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Spotlight on Spatial Environmental Policy Spillovers:

An Econometric Analysis of Wastewater Treatment in Mexican Municipalities

Abstract

The objective of this paper is to analyze whether successful environmental policies spread across geographical space. We examine the existence of such environmental spatial policy spillovers using the example of wastewater treatment in Mexican municipalities. Untreated wastewater is a key pollution source in many developing and emerging countries, also in Mexico. However, wastewater treatment levels also differ greatly among the 2,456 Mexican municipalities. We apply spatial econometrics to explain differences in wastewater treatment. Our main finding is that a municipal administration is more likely to treat wastewater if neighboring municipalities do so. This insight seems of broader relevance to environmental policy-making. In developing and emerging countries, governments frequently lack capacities to solve environmental problems. Consequently, they may often rely on learning spillovers from nearby success cases. We recommend to implement environmental pilot projects which may then trigger domino effects.

JEL-Codes: Q010, Q530, Q580.

Keywords: spatial policy spillover, wastewater treatment, spatial econometrics, Mexico, social factors.

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1. INTRODUCTION

In the year 2000, all 191 United Nation member states committed to help achieve the Millennium Development Goals (MDGs) by 2015. The MDGs contain eight goals with 21 targets, and a series of measurable health indicators and economic indicators for each target. The target of MDG 7 "Ensuring Environmental Sustainability" is to integrate the principles of sustainable development into national policies and programs. Despite many achievements and progress in this field, the environmental pollution and degradation levels are still generally high in most developing and emerging countries. However, substantial variations exist across regions, nations, and within countries. The Environmental Performance Index (EPI), which indicates the current state and trends of water quality, biodiversity, forestry, and greenhouse gas emissions for different countries, shows substantial heterogeneity among countries (see e.g. Jabbour et al. 2012 and Hsu et al., 2014). As to subnational levels, World Health Organization (WHO) data on outdoor air quality in 1,600 cities across 91 countries reveals higher variation among cities within developing countries than within their counterparts in developed countries (WHO, 2014). Similarly, the quality of inland waters differ substantially among river basins (UNEP, 2016). These variations beg the question of what determines the level of environmental pollution and degradation in developing and emerging countries, and in particular, what are the reasons that some countries or regions are more successful than others in coping with environmental problems.

To answer this question, studies investigated the impact of socioeconomic, demographic and institutional factors on environmental pollution. Many authors scrutinized the nexus between income levels and environmental performance addressing areas such as air pollution (e.g. Grossman and Krueger, 1991; Narayan et al., 2010), water pollution (e.g. Shafik, 1994; Wong and Lewis, 2013) and deforestation (e.g. Culas, 2007; Choumert et al., 2013). Others analyzed the relationship between environmental performance and institutional factors such as the decentralization of governmental decisions (e.g. Fredriksson and Wollscheid, 2014), corruption levels in the public sector (e.g. Halkos and Tzeremes, 2014), the prevalence of democratic participation or autocratic government regimes (see Wan-Hai et al., 2015 or Farzanegan and Markwardt, 2018), and the efficiency and soundness of institutions (e.g. Costantini and Monni, 2008). Further emphasis has been put on the role of demographic and socioeconomic factors such as racial and ethnic composition of the population (e.g. Zwickl et al., 2014), gender discrimination (e.g. Germani et al., 2014), differences in education levels (e.g. Meyer, 2015), and income inequality (e.g. Berthe and Elie, 2015).

In this paper, we focus on a factor that has received very little attention in explaining environmental policy differences, namely, spatial policy spillovers. Our main hypothesis is that the likelihood of adopting an environmental policy in a specific region is positively influenced by the existence of this policy in neighboring regions. This hypothesis can be motivated by three possible reasons (Simmons et al., 2006). (1) Spatial contiguity may catalyze the diffusion of political ideas as it allows territorial authorities to learn from each other or mimic each other's behavior. (2) Competition for residents among contiguous municipalities may result in a race to the top in the provision of clean and safe living environments. (3) Pollution spillovers among neighboring jurisdictions may lead a jurisdiction that implements an environmental policy to exert some pressure on its neighbors to follow this policy to overcome pollution at the regional level. Although it is a well-known hypothesis that policymaking spreads geographically (Hosseini and Kaneko, 2013; Amin, 2016), empirical studies that scrutinize the spatial spillover potential of environmental policies rarely exist (notable exceptions include Sauquet et al., 2012 and Amin, 2016). We contribute to filling this research gap by examining empirically whether there is a policy spillover of municipal wastewater treatment among neighboring Mexican municipalities.

Our study focuses on an environmental problem of high relevance. Water pollution continues to be a key environmental threat in a developing and emerging country context. According to Wang and Yang (2016), 2.3 billion people, 2.2 billion of which live in less-developed regions, suffer annually from waterborne diseases. On average, contact with polluted water kills approximately 5 million people every year, mainly in such regions (Azizullah et al., 2011). In addition, the damage caused to aquatic ecosystems is severe (Diaz and Rosenberg, 2008; Corcoran et al., 2010). A major pollution source is the discharge of untreated wastewater (Malik et al., 2015) with 2 million tons of untreated sewage being released into waters every day (Azizullah et al., 2011). This issue is particularly severe in developing countries where cities continue to discharge 80 to 90% of wastewater without prior treatment (Corcoran et al., 2010). Even in emerging economies and upper middle-income countries, only 25% of collected municipal wastewater receives some kind of treatment (Baum et al., 2013). The EPI for wastewater treatment performance shows that treatment patterns vary among countries (Malik et al., 2015), and that, in many cases, observed heterogeneity is mirrored at subnational levels. The severity of water pollution and the heterogeneity of wastewater treatment provide a highly relevant case study to investigate the factors and mechanisms that propagate the implementation of successful environmental policies and to explain variations in the success rate at the local level.

Mexico is well suited to be a case study as treatment levels differ greatly among the 2,456 Mexican municipalities. Water pollution poses a major environmental threat and the discharge of untreated municipal wastewater is one of the major pollution sources (Semarnat, 2008). In 2012, only 43.5% of the 7.24 km^3 of municipal sewage received some kind of treatment that removed 35.2% of the 1.96 million tons of BOD_5 loads (Conagua, 2014a).

We apply a spatial econometrics approach for our empirical analysis and control for socioeconomic, demographic and institutional characteristics to identify further factors that influence municipal wastewater treatment. We find strong empirical evidence that municipal wastewater treatment spills over across neighboring jurisdictions. Our empirical results rule out similarities in the socioeconomic, demographic and institutional structure of contiguous municipalities as a single explanation for similar policies in neighboring municipalities. This suggests that municipal wastewater treatment spatially spreads as a successful environmental policy. In addition, we find that per capita GDP, income distribution, urbanization, education level, the creation of a public water utility and the municipality's location in a particular federal state have a significant influence on the probability that a Mexican municipality will treat wastewater.

The remainder of the paper is organized as follows. Section 2 briefly reviews the theoretical discussion and the previous empirical literature. Section 3 discusses the econometric specification and the underlying data. Section 4 presents the estimation results and robustness checks. Section 5 discusses the policy implications of our results and presents our conclusions.

2. LITERATURE REVIEW

(a) *Policy spillovers*

Learning, mimicking, competition and strategic response to transboundary pollution flows are mechanisms that are often discussed as reasons for spatial policy spillovers (see e.g. Hosseini and Kaneko, 2013; Amin, 2016).

According to learning theories, policymakers can learn from other governments by investigating their experiences with policy implementations (Shipan and Volden, 2008). Once they learn that a policy is successful in other jurisdictions, they may decide to adopt it in their own jurisdictions as well (Simmons et al., 2006). However, as acquiring knowledge is costly, the access of policymakers to information from alien entities is restricted. Particularly, policymakers in developing and emerging countries may face heavy restrictions in the systematic collection of information due to the widespread lack of administrative, technical and financial capabilities (Barkin, 2011). Hence, policymakers may rely primarily on already established communication and exchange channels to inform themselves on policy successes (March and Simon, 1993). Often, those channels exist with administrations in spatial proximity (Hosseini and Kaneko, 2013). Generally, the spillover of knowledge and innovation requires cognitive and cultural similarity among the innovating and adopting entity (Verdolinia and Galeotti, 2011; Costantini et al., 2013). Economic and social agents may find it difficult to absorb new knowledge from others if they do not share a similar knowledge level. Thus, public administrations of neighboring municipalities might be more predisposed to exchange knowledge successfully as they are likely to match each other better in terms of shared norms and beliefs than with peers in entities located further away (Simmons et al, 2006).

Whereas the approach of policy learning assumes that policymakers ground their action on rationality (Simmons et al, 2006), other authors point out that policymakers might simply mimic successful policies (Drezner, 2001; Perkins and Neumayer, 2009). In this case, policymakers copy policy agendas from elsewhere without completely understanding their repercussions. They might simply follow the policies of others in order to avoid appearing old-fashioned or underdeveloped (Shipan and Volden, 2008; Perkins and Neumayer, 2009). As with learning, public administrations of neighboring municipalities might be more prone to mimicking each other than more distant peers, since they may maintain closer relations that enable them to be better informed about each other's activities. Or, they may identify more with each other.

Another possible reason for spatial policy spillovers is that competition may force political units to adopt successful policies from neighboring administrations. Competing to attract industries, investments or residents incentivizes jurisdictions to align their policies with the highest-performing competitors. Otherwise, businesses or residents are motivated to 'vote with their feet' and move to places that better meet their demands (Tiebout, 1956). To the extent that jurisdictions compete for the same kinds of businesses or residents with the same preferences, competition should result in the convergence of policies, including environmental policy (Holzinger et al., 2008). Geographic proximity may again reduce information costs to acquire knowledge on policies in other jurisdictions (Hosseini and Kaneko, 2013).

Strategic responses to transboundary pollution flows may be another reason why spatial patterns in the adoption of policies emerge (Maddison, 2007). The negative externality character of transboundary pollution and the resulting public good character of abatement policies may induce neighbors to align environmental policies for an effective protection of the environment. Once a municipality abates pollution it gives a positive example of proper environmental conduct, which may help to put pressure on neighbors to follow (Amin, 2016).

(b) *Socioeconomic, demographic and institutional factors*

The nexus between environmental performance and socioeconomic, demographic and institutional factors is diversely discussed in the literature. Income is considered to be a key factor in explaining environmental performance. Assuming that environmental quality is a normal good (Bo, 2011), a positive relation exists between average per capita income and efforts to improve environmental quality (see e.g. Dinda, 2004). Previous studies found, in part, an inverted U-shaped relation as postulated by the environmental Kuznets curve framework (e.g. Wong and Lewis, 2013). Beside income levels, some studies suggest that income distribution has an impact on environmental performance (Wisman, 2011). Based on the assumptions that the richer part of the population has more political power in societies and that preferences for environmental quality increase with increasing income, it has been postulated that more unequal societies have a higher level of environmental quality than those that are more equal (Scruggs, 1998). However, the impact is the subject of a controversial debate in the literature (Berthe and Elie, 2015).

The ethnic composition of a population may be a factor that potentially influences environmental performance. Ethnic homogeneity has been hypothesized to promote social cohesion. This facilitates, in turn, cooperation that is required for the provision of public goods such as environmental quality. In addition, it may reduce a society's propensity to externalize harm (Alesina et al., 1999 and 2003; Alesina and La Ferrara, 2005). Accordingly, several previous studies assumed a negative linear relationship between ethnic heterogeneity and environmental performance (see Grafton and Knowles 2004; Videras and Bordoni, 2006; Das and DiRienzo, 2010).

Following Meyer (2015), the level of education has an impact on the adoption of environmental policies. With an increasing level of education, individuals are often better informed about the risk of pollution for human health and the environment. Therefore, with more education, the population may increasingly urge policymakers to implement policies to improve environmental quality.

Some studies stress the importance of population density (e.g. Massoud et al., 2009, Wong and Lewis, 2013). *Ceteris paribus*, urbanization leads to higher pollution levels. This may result in intensified efforts to offset pollution (Wong and Lewis, 2013). In addition, with a growing population, economies of scale might be present in abatement measures (Massoud et al., 2009).

Institutional quality has a positive impact on environmental performance. Studies suggest that transparent, democratic, well-functioning and non-corrupt bureaucracies tend to deliver effective environmental regulation (Bernauer and Koubi, 2009; Leitão, 2010; Hosseini and Kaneko, 2013). In many developing countries, corporatization of public service provisions has been propagated in recent decades with the aim of improving institutional quality by promoting a more managerial orientation, and by curbing corrupting political influence (Barkin, 2011; Herrera and Post, 2014).

In addition, it has been debated whether female participation in politics affects environmental performance (Xiao and Mc Cright 2015). Surveys of Europeans and North Americans revealed a more pro-environment attitude among women (Xiao and McCright, 2015; Vicente-Molina et al., 2018). It has been hypothesized that this general attitude causes female politicians to implement more environmentally friendly policies (Sundström and Mc Right, 2013).

3. DATA AND ECONOMETRIC METHODOLOGY

As mentioned before, our main research objective is to analyze whether environmental policy in a specific region positively influences the adoption of this policy by neighboring regions. Our sample consists of 2,299 Mexican municipalities in the year 2010 (Conagua, 2010).

(a) *The institutional setting of wastewater treatment in Mexico*

The empirical analysis focuses on wastewater treatment in Mexican municipalities. The constraint of a single country is preferred to avoid conceptual issues from differences in institutional frameworks between different countries. Article 115 of the Mexican Constitution mandates municipal administrations to provide the services of potable water, sanitation, sewage systems, treatment and disposal of municipal wastewater. Despite the clear assignment of responsibility on paper, the legal and administrative framework of municipal water governance remains highly complex in Mexico, as all three government tiers – national, state, and municipal – are heavily involved (Pineda Pablos and Salazar Adams, 2008). Municipalities are often overburdened by the responsibility of service provision as they lack financial resources, and administrative and technical capabilities (Barkin, 2011). With this background, the National Water Commission (CONAGUA - *Comisión Nacional de Agua*) launched co-financing programs for the municipal water supply and sanitation sector. With the support of state governments, municipal administrations and public water operators frequently apply for federal government funding to establish, operate and maintain municipal wastewater treatment infrastructure (Conagua, 2013a/b).

(b) *Dependent variable*

We take as the dependent variable ("*wt*") whether a municipality treats wastewater or not. The dependent variable assumes a value of one if treatment takes place. Otherwise, it is zero. A total of 1,526 or 66.4% of the municipalities in our sample had no treatment plants at all. The remaining 773 municipalities had plants that treated wastewater in amounts ranging from single-digit percentages to full coverage. Figure 1 displays the locations of municipal wastewater treatment plants in 2010. Small circles represent plants with low treatment capacities; larger circles represent plants with higher treatment capacities (Conagua, 2012a). Over the past two decades, the number of wastewater treatment plants in Mexico grew steadily from 394 to 2,186 in 2010 (Conagua, 2011).

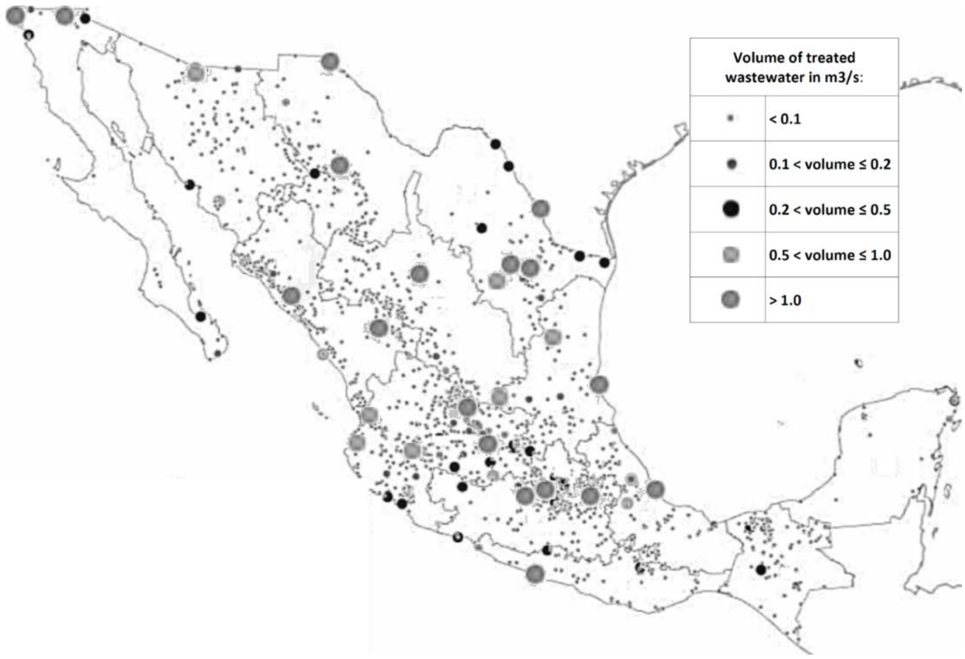

Figure 1: *Municipal Wastewater Treatment Plants in Mexico, 2010.* S*ource: adapted from Conagua (2012a).*

(c) *Independent variables*

In line with our theoretical discussions and the literature survey presented in Section 2, we developed hypotheses on the influence that treatment performance of neighboring municipalities, the income level and distribution, education, urbanization, the ethnic homogeneity, the female participation in municipal politics and the institutional quality have on the probability that wastewater treatment takes place in a Mexican municipality.

Table 1 provides summary statistics of included variables and provides the data source and year for which the respective data is available. The overall sample size includes 2,299 municipalities. Data are derived from several sources in the Mexican federal government.[1]

We use per capita GDP ("*GDPpc*") as the measure for economic development. The variable "*GINI*" refers to the Gini coefficient as a measurement for income inequality after tax and transfers in the Mexican municipalities. "*Education*" represents the UNDP education index. It compares achievements across Mexican municipalities in the fields of average schooling of cohorts older than 24 years and expected (scheduled) schooling for cohorts between 6 and 24 years. Its score ranges from 0 to 100 with higher scores representing higher levels of education. For a detailed explanation of the index see UNDP (2014). "*Femadmin*" stands for female participation in municipal politics. It measures the share of female members in municipal administrations in Mexico.

The variable "*Urban*" measures the degree of urbanization. It is specified as the share of the municipal population living in settlements of 30,000 or more inhabitants. In this, we follow

[1] In total 2,456 municipalities existed in 2010 in Mexico. Out of this total, data for all included variables was only available for 2,299 municipalities.

the classification of the National Information System on Mexican Municipalities that considers settlements of this population size as urbanized (SNIM, 2014). As a measure for the degree of heterogeneity in population composition, we include the Fractionalization index[2] ("*FracIndex*") that was specified by Papyrakis in 2013. In our calculation of the Fractionalization index, we differentiate between speakers and non-speakers of indigenous languages. Overall, approximately 6.9% of the Mexican populations speak at least one indigenous language (INEGI, 2010).

Table 1: General descriptive statistics of dependent and explanatory variables

Variables	Description	Mean	Min	Max	Obs.	Sources
wt	Dummy for municipal wastewater treatment with *wt* = 1 --> yes	0.34	0	1	2,299	CONAGUA (2010)
GDPpc	per capita GDP in thousands of US Dollars in 2010	5.926	1.467	33.813	2,299	PNUD (2014); INAFED (2015)
GINI	Gini coefficient after tax and transfers in 2010	41.19	28.57	59.08	2,299	CONEVAL (2015)
Education	UNDP Education index in 2010	76.77	35.86	92.94	2,299	UNDP (2014)
Urban	Percentage of urbanized municipal population in 2010	8.92	0	100	2,299	SNIM (2014)
Femadmin	Percentage of female members in municipal government in 2005	16.67	80.00	0	2,299	PNUD (2005); SNIM (2014)
FracIndex	Ethnic fractionalization index for 2010	12.25	50.00	0	2,299	SNIM (2014)
WaterUtility	Dummy variable for the existence of a public water utility in 2010	0.18	1	0	2,299	CONAGUA (2014b)
StateBelonging	Dummy variables for belonging of a municipality to a federal Mexican state	-	1	0	2,299	(CONAGUA, 2014a)

As a proxy for institutional quality, we include the dummy variable "*WaterUtility*". It assumes the value of one if a public water utility exists in a municipality. Otherwise, it is zero. Since 1990, 457 of the 2,456 Mexican municipalities created public water utilities (Conagua, 2014b) to corporatize municipal water supply and sanitation service with the aim of better service quality provision (Barkin, 2011). In the remaining municipalities, municipal water supply and sanitation management continues to be under the auspices of the general municipal administration. We hypothesize that improvements in the institutional structure of municipal water supply and sanitation management may also translate into better wastewater treatment performance.

Finally, "*StateBelonging*" represents dummy variables for the affiliation of a municipality to one of the 31 federal Mexican states or the Federal District of Mexico-City. A dummy variable for a certain state is one if a municipality belongs to this state. Otherwise, it is zero. In Mexico, governments of federal states pursue independent municipal water supply and sanitation policies (Conagua, 2014a). This requires controlling for cluster effects stemming

[2] The ethnic fractionalization index captures the probability of two randomly chosen individuals from the general population belonging to different social groups. Smaller values of "*FracIndex*" indicate lower degrees of ethnic fractionalization.

from state sanitation policies or unobserved heterogeneity by including dummy variables for the affiliation of a municipality to a federal state. Otherwise, we run the risk of incorrectly associating observed spatial dependencies among Mexican municipalities to policy spillovers at the municipal level.

(d) *Econometric methodology*

We parse our research question by estimating variants of probit models that account for the binary outcome character of the dependent variable. To provide a benchmark case, we first estimate a general probit model including the socioeconomic, the demographic and the institutional variables. In this baseline regression we do not incorporate any spatial relationship among neighboring municipalities. The conventional probit model is specified as follows:

$$wt = X\beta + \varepsilon \qquad (1)$$

where wt represents our dependent variable with a binary outcome character. X is a $n \times k$ matrix of independent variables whereby n is the number of included observations and k is the number of included independent variables. β is a $k \times 1$ vector of corresponding parameters.

In a second step, we consider the spatial dependence between the different observations in our sample of Mexican municipalities. We make use of a spatial auto-regressive probit model (SAR probit). The reasons for using this type of model are the omitted variables that exhibit a structure of spatial dependence and are correlated with variables included in the model. The estimation equation now takes the form:

$$wt = \rho Wwt + X\beta + \varepsilon \qquad (2)$$

SAR probit includes the term ρWwt into the general probit model. Wwt is the spatial lag of the latent dependent variable. It contains the weighted average of the dependent variable of observations j with $j \neq i$ and $i, j \in n$. W is a $(n \times n)$ spatial weight matrix which maps the spatial relations among observations n. Its main diagonal contains only zeros while other values in the matrix depend on how contiguity is defined. Several definitions of contiguity exist (for an overview, see Hosseini and Kaneko (2013)). In this paper, we follow the k-*nearest approach*, which considers spillovers to occur to the k observations that are nearest to observation i. Observations $j \neq k$ are not considered to exert influence on observation i. Thus, standardized W entails zeros for observations $j \neq k$ and $1/k$ for observations k. We rely on the k-*nearest approach* as the National Information System on Mexican municipalities (SNIM) provides longitudes and latitudes of the centers of Mexican municipalities (SNIM, 2014). This information allows us to calculate distances and identify the k-nearest municipalities for each municipality.

Finally, the scalar parameter ρ in equation (2) measures the strength of dependence, with a value of zero indicating independence. Clearly, a conventional non-spatial probit model emerges when $\rho = 0$. This term captures the interdependency among neighboring observations and may indicate the presence of policy spillovers if estimates are significant (LeSage, 2011; Wilhelm and de Matos, 2013).

To scrutinize whether spatial proximity facilitates environmental policy spillovers we estimate the SAR probit model for different specifications of k. In different model runs, we set k to the 5, 10, 15, 20, 50, 100 and 500 nearest neighbor municipalities. If proximity of municipal wastewater treatment matters, the model should estimate significant and positive dependence parameters ρ for small k values. In addition, the magnitude and significance of ρ estimates are expected to decrease if numbers of municipalities considered as neighbors increase. Furthermore, parameter estimates and significance levels of the included independent variables should converge with the results of the general probit model.

(e) *Endogeneity issues*

Endogeneity in the underlying data might be an issue. First, empirical studies suggest that that improved sanitation has a reverse positive impact on economic growth (Minh and Nguyen-Viet, 2011; Hepworth et al., 2013) and education (Hepworth et al., 2013). Thus, using data on municipal wastewater treatment, per capita GDP and the education index of the same year, as this study does, may produce biased estimation results due to possible correlation of independent variables with the error term. However, previous research did not find endogeneity being a particular issue in the Mexican data (see Hecker, 2017).

More severe might be the consequence of including a spatial lag of the dependent variable as an explanatory variable. Primarily, a possibly resulting endogeneity issue could be solved by lagging the data on municipal wastewater treatment of neighboring municipalities in time by one or two years, for instance (see e.g. Hosseini and Kaneko, 2013). However, the stock character of the dependent variable makes this approach unfeasible for our analysis. From 2009 to 2010, the number of municipal wastewater treatment plants in operation increased only slightly from 2,029 to 2,186 in Mexico (Conagua, 2011 and 2012b). That means, the large majority of municipalities treating wastewater in 2010 also did so in 2009. As a result, including a time lag of one year does not produce tremendously different estimation results. We therefore decided to include a spatial lag of the dependent variable of the same year. A further caveat of the study is that estimation results are to some extent inevitably biased as information on longitudes and latitudes are missing for 145 out of the 2,456 Mexican municipalities. We dropped municipalities with missing longitudes and latitudes from our sample, but included their neighbors if information on their longitudes and latitudes was available. Consequently, the specification of the *k*-nearest neighbors are only approximately correctly, in some cases.

4. EMPIRICAL RESULTS

(a) *Baseline results*

Table 2 presents the estimation results. Column (1) contains the estimated parameter of the general probit model of socioeconomic, demographic and institutional factors. Columns (2) to (8) present the respective parameters and ρ-values for the SAR probit model for different specifications of k.

Table 2: *Regression results*

	General probit	SAR-probit						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable		*k*=5	*k*=10	*k*=15	*k*=20	*k*=50	*k*=100	*k*=500
GDPpc	0.048** (0.019)	0.044** (0.018)	0.043** (0.019)	0.043** (0.018)	0.044** (0.019)	0.049** (0.019)	0.048** (0.019)	0.049*** (0.019)
Education	0.014** (0.007)	0.012* (0.006)	0.013** (0.006)	0.013** (0.006)	0.014** (0.006)	0.015** (0.007)	0.015** (0.007)	0.015** (0.007)
GINI	0.032*** (0.009)	0.031*** (0.010)	0.036*** (0.009)	0.033*** (0.010)	0.033*** (0.009)	0.033*** (0.010)	0.032*** (0.010)	0.032*** (0.010)
Femadmin	0.0004 (0.003)	0.0005 (0.003)	0.0003 (0.003)	0.0003 (0.003)	0.0001 (0.003)	0.0002 (0.003)	0.0005 (0.003)	0.0002 (0.003)
Urban	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)
FracIndex	-0.001 (0.003)	-0.0004 (0.003)	-0.0003 (0.003)	-0.0003 (0.003)	-0.0002 (0.003)	-0.0008 (0.003)	-0.001 (0.003)	-0.001 (0.003)
WaterUtility	0.331*** (0.109)	0.342*** (0.109)	0.333*** (0.108)	0.334*** (0.110)	0.335*** (0.109)	0.330*** (0.107)	0.331*** (0.112)	0.333*** (0.107)
StateBelonging	yes[a]	yes	yes[a]	yes	yes	yes	yes	yes
Intercept	-1.359** (0.660)	-1.397** (0.629)	-1.477** (0.634)	-1.510** (0.640)	-1.470** (0.651)	-1.490** (0.736)	-1.422** (0.713)	-1.449** (0.722)
Rho (ρ)	-	0.162*** (0.051)	0.172*** (0.063)	0.189*** (0.069)	0.161* (0.073)	0.066 (0.091)	-0.055 (0.102)	0.060 (0.100)
Observations	2,299	2,299	2,299	2,299	2,299	2,299	2,299	2,299

Note: *** significant at 1%, ** significant at 5%, * Significant at 10%, Figures in parentheses are standard deviations of coefficients

[a] The complete results can be found in the appendix.

As for independent variables, the general probit model and the SAR probit model for all k specifications display relatively similar estimation results in terms of magnitude and significance. Our socioeconomic, demographic and institutional control variables show the expected signs. Per capita GDP has a significant positive impact on the likelihood of municipal wastewater treatment. This supports the hypothesis that a more affluent society increases efforts to improve environmental quality. Additionally, the parameter estimates of the Gini coefficient are significant and positive. Together with the previous finding that preferences for environmental quality increase with increasing income, this result suggests that the wealthier part of the population has enough political power to force policymakers to increase environmental quality according to its demands. The positive and significant parameter estimate of the education index confirms the hypothesis that more educated people demand better environmental performance than less educated people. The estimated positive and significant relationship between the degree of urbanization of a municipality and the likelihood of wastewater treatment gives empirical credit to the assumption that higher population densities require, *ceteris paribus*, higher pollution abatement efforts. The significant and positive parameter of the dummy variable for the existence of a public water utility in a municipality indicates that corporatization of municipal water supply and sanitation service increases chances of wastewater treatment in a municipality.

Estimates for female participation in municipal politics and ethnic fractionalization display the expected positive and respectively negative signs. However, they are not statistically significant on conventional levels. Hence, our empirical findings do not allow us to conclude that more female participation and ethnic homogeneity lead to more pollution abatement efforts as postulated by our hypotheses. For the vast majority of the included dummy variables, the parameter estimates for a municipality's location in a particular state are significant and negative. As a reference case, we omitted six Mexican states – Aguascalientes, Baja California, Baja California Sur, Colima, Nuevo León, and Sinaloa. Within those jurisdictions, all municipalities perform treatment activities. Accordingly, it is not surprising to see that a municipality located in another state negatively affects the probability of municipal wastewater treatment, in most cases (see appendix). Differences in state sanitation policies and unobserved heterogeneity may explain these findings.

The SAR-probit models in columns (2) to (8) in Table 2 provide insights on spatial relationships. Models that specify k as 5, 10 or 15 produce estimates of the spatial dependence parameter ρ that are of similar positive magnitude. All of them are significant at the 1% level (see (2), (3) and (4) in Table 2). This indicates that Mexican municipalities whose immediate neighbors ($k \leq 15$) treat municipal wastewater are significantly more likely to do so as well. Significance and magnitude of ρ estimates fade away once the number of municipalities considered as neighbors is extended to 20 or more. For $k = 20$ significance reduces to 5%. The magnitude, however, remains at a comparable level (see column (5) in Table 2). If the 50, 100 and 500 closest municipalities are considered as neighbors significance vanishes completely. Moreover, estimated magnitudes are much smaller in cases where contiguity is defined more broadly ($k > 20$; columns (5) to (8) in Table 2). These findings confirm our expectation that municipalities further away do not exert significant influence on the municipal wastewater treatment performance of a municipality. This finding is further backed by the fact that in SAR-models with higher k-specification parameter magnitudes of independent variables approximate the respective estimates of the general probit model (see column (1) in Table 2).

(b) *Interpreting the model estimates*

The non-linearity of probit models prevents us from interpreting the parameter estimates β directly. Interpreting the way in which changes in the explanatory variables in the matrix X affect the probability of wastewater treatment in the municipalities requires some care. It is common practice to calculate the marginal effect by quantifying the effect of a unit change in an explanatory variable. However, in the presence of spatial spillovers, this is not feasible (LeSage, 2011). In this case, a change in the explanatory variable x_i in an observation i alters not only the dependent variable in observation i but additionally in observations j ($j \neq i$). The marginal effects do not account for that. LeSage and Pace (2009) therefore developed a method that calculates the direct, indirect and total effect of an x_i-change. The direct effect measures the impact a unit change in x_i has on average on wt of the observation within which the x_i change takes place. For instance, by how much the treatment probability changes on average in a municipality whose per capita GDP changes by one unit. The indirect effect quantifies the impact that a unit change in x_i has on average on wt of observations within which the x_i change does not take place. If, for instance, the treatment probability in a municipality has changed due to a change in its GDP per capita, the indirect effect then measures by how much the changed treatment probability in this municipality alters on average the treatment probability in other municipalities. Finally, the total effect is defined as the sum of direct and indirect effects (LeSage and Pace, 2009; LeSage, 2011; Wilhelm and de Matos, 2013).

Table 3: *Estimates of the direct, indirect and total effects for SAR probit with k = 10*

Variable	Direct effect	Indirect effect	Total effect
GDPpc	0.01**	0.002*	0.012**
Education	0.003**	0.001	0.004**
GINI	0.008***	0.002*	0.01***
Femadmin	0.0001	0.00002	0.0001
Urban	0.001***	0.0003*	0.001***
FracIndex	-0.00007	-0.00001	-0.00008
WaterUtility	0.078***	0.016*	0.094***
StateBelonging	not reported	not reported	not reported

Note: *** significant at 1%, ** significant at 5%, * significant at 10%

Table 3 provides the estimates of the direct, indirect and total effects for the SAR probit model when k is specified as 10. It shows that changes in the treatment probability that are induced by changes in the independent variables only partly spill over. Although direct and indirect effects have same signs for all independent variables, magnitudes and significance levels are generally reduced for the indirect effects. While significance levels of direct effects and β estimates match each other throughout, estimates of the indirect effect are significant at the 10% level, at most.

An increment of one thousand US$ of GDP per capita in a municipality increases, for instance, the overall treatment probability by 1.2%. While the probability increases directly by 1.0%, the indirect effect is 0.2%. Similarly, a unit change of the Gini coefficient alters the overall treatment probability by 1.0%. However, its indirect effect is also only 0.2%. Furthermore, treatment is on average 0.1% more likely in a 1%-more-urbanized municipality. Simultaneously, treatment probability increases slightly by 0.03% in neighboring municipalities. The insignificance of the indirect effect of a unit change in the education index suggests that changes in the education level do not provoke spillovers at all. Finally, the establishment of an independent water utility increases the overall treatment probability by 9.4%. A municipality's decision to create this entity within its boundaries has a direct impact of 7.8% on its treatment probability. In addition, it triggers a 1.6% probability increase in neighboring municipalities. Like the estimates of the β parameters, the estimated direct and indirect effects of the ethnic fractionalization and female participation in municipal politics are not significant.

(c) *Robustness tests*

The empirical results in the previous sections suggest that the probability of a municipality to treat wastewater increases if surrounding municipalities engage in wastewater treatment. Spatial spillover effects, in the form of the diffusion of a successful environmental policy of municipal wastewater treatment, could be an explanation for observed spatial correlation patterns. However, there is no guarantee that this cause-and-effect relationship is truly at work.

Alternatively, the observed clustering of municipal wastewater treatment across municipalities could also arise from similarities in the socioeconomic, demographic and institutional structure of contiguous municipalities. In this case, decisions of neighboring municipalities rather coincide than depend on each other. For instance, similarities in treatment performance could simply result from similarities in per capita GDP across neighboring municipalities or be a consequence of the fact that economic performance spills over among neighboring municipalities. Several studies confirmed the existence of economic spillovers (Abreu et al., 2005; Ahmad and Hall, 2017). The significant estimates of the indirect effect of GDP per capita, the Gini coefficient and urbanization in Section 4b of this paper also does not exclude that social characteristics may contribute, at least to some extent, to the observed spillover patterns.

The difficulties in differentiating between spatial spillovers and non-causal correlation are extensively discussed in the literature (Jaffe et al., 1993). Proposed solutions do not solve the identification issue perfectly (Keller, 2004). Our strategy is to control for the influence of social characteristics on observed spatial patterns. For this, we apply the spatial Durbin probit model (SDM) and regress in alternative runs the dependent variable additionally on the spatial lags of independent variables (LeSage and Pace, 2009; Lacombe and LeSage, 2013). The SDM probit model is specified as follows:

$$wt = \rho Wwt + X\beta + \theta WX + \varepsilon \qquad (3)$$

It includes the term ρWwt into the SAR probit model with WX being the spatial lag of independent variables. WX contains the weighted average of the dependent variable of observations j with $j \neq i$ which are considered as neighboring observations. The term θ captures the influence of spatially lagged independent variables on the dependent variable.

Table 4: *Results for the SAR probit and the SDM model with k = 5 and k = 10*

	Spatial lag probit		Spatial Durbin probit	
Variable	*k*=5	*k*=10	*k*=5	*k*=10
GDPpc	0.044** (0.018)	0.043** (0.019)	0.040** (0.020)	0.041** (0.020)
Education	0.012* (0.006)	0.013** (0.006)	0.013* (0.008)	0.014* (0.007)
GINI	0.031*** (0.010)	0.036*** (0.009)	0.034*** (0.010)	0.031*** (0.010)
Femadmin	0.0005 (0.003)	0.0003 (0.003)	0.0001 (0.003)	0.000 (0.003)
Urban	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)
FracIndex	-0.0004 (0.003)	-0.0003 (0.003)	0.001 (0.003)	0.001 (0.003)
WaterUtility	0.342*** (0.109)	0.333*** (0.108)	0.376*** (0.111)	0.354*** (0.110)
Spatial Lag GDPpc			0.038 (0.033)	0.047 (0.041)
Spatial Lag Education			-0.006 (0.010)	-0.008 (0.011)
Spatial Lag GINI			-0.015 (0.017)	0.006 (0.021)
Spatial Lag Femadmin			0.005 (0.005)	0.009 (0.007)
Spatial Lag Urban			0.002 (0.004)	-0.000 (0.005)
Spatial Lag FracIndex			-0.002 (0.004)	-0.002 (0.005)
Spatial Lag WaterUtility			-0.627*** (0.231)	-0.795*** (0.284)
StateBelonging	yes	yes	yes	yes
Intercept	-1.397** (0.629)	-1.477** (0.634)	-0.547 (0.977)	-1.235 (1.128)
Rho (ρ)	0.162*** (0.051)	0.172*** (0.063)	0.180*** (0.057)	0.180** (0.072)
Observations	2,299	2,299	2,999	2,999

Note: *** significant at 1%, ** significant at 5%, * significant at 10%

We hypothesize that similarities in the socioeconomic, demographic and institutional structure are less likely to be the reasons for the observed spatial patterns if parameter estimates of spatial lags lose or do not show any significance in explaining the variance of the dependent variable in comparison to parameter estimates of the independent variables. Consequently, similarities in the socioeconomic, demographic and institutional structure may be ruled out in favor of spatial spillovers of successful environmental policies as the cause of observed clustering of municipal wastewater treatment across contiguous municipalities (Jaffe et al., 1993; Keller, 2004; Ahmad and Hall, 2017).

Table 4 contrasts the estimation results of the SAR model and the SDM probit model for the specifications of the *k*-nearest neighbors to 5 and 10. Including lagged independent variables does not significantly change magnitude and significance estimates of independent variables. Only the estimate for the measure for education reduces significance from the 1% to 5% level, when the 10 closest municipalities are considered as neighbors. With the exception of the lag of the dummy variable for the existence of a public water utility, none of the included lags of independent variables show any significance. Furthermore, the spatial dependence parameter "rho"(ρ) remains significant in the SDM models. Only for the k = 10-specification does it reduce slightly from the 1% to the 5% level.

The non-significance of the spatial lags supports the hypothesis that spatial patterns emerge not merely due to correlations in socioeconomic, demographic and institutional social characteristics across neighboring Mexican municipalities. Moreover, the significant "rho" estimate at the 5% level supports the hypothesis that other factors such as the proximity of a successful environmental policy cause spatial patterns. Somewhat puzzling though is the finding that the establishment of public water utilities in surrounding jurisdictions negatively affects the treatment performance of a municipality. An explanation for that might be that the service of municipal water supply and sanitation is delivered more efficiently in municipalities with a public water utility. The aim of creating public water utilities was to provide better service quality in the Mexican municipal water sector (Barkin, 2011). Accordingly, municipalities whose neighbors established a public water utility may then take advantage of their neighbors' higher efficiency in wastewater treatment. Instead of treating wastewater by themselves, they may find it more attractive to outsource the task of wastewater treatment and channel their untreated wastewater to treatment plants in neighboring jurisdictions.

Tests on the model suitability do not reject the hypothesis that the proximity of a successful environmental policy positively affects the treatment performance of a municipality. Although log likelihoods of the SDM probit models are slightly higher than log likelihoods for the SAR probit models, the insignificance of the LR-test in Table 5 does not indicate that the spatial Durbin probit model is favored over the spatial lag probit model. Thus, controlling for spatial lags of independent variables does not contribute to explaining observed variations in the underlying data. In addition, the AIC and BIC values for the SAR probit models are slightly lower than for the SDM probit model for the specification of *k* to 5 and 10 (see Table 5). In conclusion, one can exclude that similarities in socioeconomic, demographic and institutional characteristics are the only cause for spatial patterns across neighboring municipalities. Also random shocks in the error term, which are another potential cause for spatial correlation patterns, are unlikely to explain observed spatial autocorrelation across neighboring municipalities in the Mexico. The AIC and BIC values for spatial error probit models are significantly higher than the values for the SAR and SDM probit model (see Table 5). Overall, these findings provide the freedom to interpret empirical results by assigning a pivotal role to the spillover of successful environmental policies.

Table 5: *Test statistics for SAR, spatial Durbin and spatial error probit model*

Model specification	*k*=5	*k*=10
Log Likelihood for spatial lag model	-981.9314	-982.9027
Log Likelihood for spatial Durbin model	-976.2887	-977.5163
Degrees of freedom	7	7
LR test statistics	11.285	10.683
AIC for spatial lag model	2033.863	2035.805
AIC for spatial Durbin model	2035.398	2039.033
BIC for spatial lag model	2234.771	2236.714
BIC for spatial Durbin model	2276.488	2280.122
AIC for spatial error model probit	2237.514	2264.834
BIC for spatial error model probit	2444.163	2471.482
Log Likelihood for spatial error model probit	-1082.757	-1096.417

Note: *** significant at 1%, ** significant at 5%, * significant at 10%

5. DISCUSSION AND CONCLUSIONS

In this paper, we focus on a factor that has received very little attention in explaining environmental policy differences and similarities - spatial policy spillovers. We take municipal wastewater treatment as an example for an environmental policy and analyze different factors for 2,299 Mexican municipalities that affect a municipal administration's decision to treat wastewater in the year 2010. We find strong empirical evidence that the effects of municipal wastewater treatment spill over across neighboring jurisdictions. Our empirical results rule out similarities in the socioeconomic, demographic and institutional structure of contiguous municipalities as a single explanation for similar policies in neighboring municipalities. This suggests that municipal wastewater treatment spatially spreads as a successful environmental policy. Several possible reasons may explain these spatial policy spillovers. Geographic proximity may i) enable administrations to learn best practices from each other or to imitate each other's policies, ii) provide incentives to copy successful policies in response to increased competition for residents among neighboring communities, and iii) lead municipal administrations to coordinate environmental policies to fight environmental pollution effectively to avoid environmental spillovers from neighboring municipalities.

We believe that our finding that spatial policy spillovers matter for wastewater treatment in Mexican municipalities is of broader relevance to environmental policymaking in developing and emerging countries. In these countries, governments frequently lack administrative, technical and financial capacities to individually develop targeted solutions to environmental problems. As a result, they may rely on learning spillovers from nearby success cases. This hypothesis is supported by Amin's (2016) findings on biodiversity conservation policymaking in developing and emerging countries. For a sample of 48 sub-Saharan countries, she finds that biodiversity conservation policies spill over among contiguous countries. To better understand under what conditions spatial policy spillovers exist, further research may investigate the interconnectedness of environmental policymaking of neighboring administrations in more detail to better understand by which of the three abovementioned channels a successful environmental policy travels across contiguous political entities.

In addition to spatial policy spillovers, we contribute to the debate on what factors impact the implementation of environmental policies in several ways. Our results confirm widely held views in the literature on positive relations between pollution abatement efforts and per capita GDP, urbanization, and education level (Wong and Lewis, 2013; Meyer, 2015). In the more controversial discussion on the impact of income inequality on environmental performance (Heerink et al., 2001; Berthe and Elie, 2015), our empirical results support those who see a positive influence of income inequality on environmental performance. A possible explanation of our finding is that wealthier people 1) have a higher preference for environmental goods, and 2) exert, on average, more influence on politics than the poorer elements of society. This allows them to lobby successfully for environmental measures such as wastewater treatment in the political arena.

In another controversial area - the impact of the population's ethnic composition on environmental policy - we could not detect a significant negative impact of ethnic heterogeneity, in contrast to other studies (Grafton and Knowles, 2004; Videras and Bordoni, 2006; Papyrakis, 2013). A possible explanation for our finding is that in Mexico, selection criteria for national aid programs for the establishment of wastewater treatment infrastructure favor, to some extent, municipalities with a high percentage of indigenous population (Olivares and Sandoval, 2008).

Regarding the controversial debate on the impact of female participation in politics on the outcome of environmental policy, such as Fielding et al. (2012), we do not find a significant impact of female participation in politics on the environmental conduct. This contradicts to some extent the findings of Sundström and Mc Right (2013), who found that female politicians in municipal and county councils in Sweden have stronger environmental concerns than their male colleagues. To some extent, our measure of female participation may explain our result. We use the representation of female members in municipal administrations as an indicator. However, in the Mexican system, the municipal president assumes the leading role and sets political agendas. However, including the gender of municipal presidents was not feasible as data was not comprehensively available.

As for institutional quality, we find that outsourcing municipal water administration from the municipal administration to a public water utility increases the probability of wastewater treatment. This lends support to the hypothesis that corporatization of public service provision improves institutional quality by promoting a more managerial orientation and by curbing corrupting political influence. Corporatization has been recommended for developing countries to improve public services in the field of municipal water supply and sanitation (Barkin, 2011; Herrera and Post, 2014).

Regarding methods, unlike many previous studies, we use spatially explicit econometric regression technics such as the spatial auto-regressive model and the spatial Durbin probit model to account for spatial autocorrelation of water pollution. In this way, we avoid the biased estimates and inconsistent parameters of independent variables that conventional regression approaches produce if spatial autocorrelation is present (Hao and Liu, 2016).

Although we control for spatial autocorrelation in the data, our results potentially suffer from endogeneity issues, as independent, dependent and respective spatial lags may be prone to reversed causation. Future research might consider changes in time in a panel data regression analysis to overcome potential shortcomings and to further deepen insights on the mechanisms of the diffusion of successful environmental policies, and the role that social factors play in this regard for good environmental performance. Due to a lack of data, we restricted our analysis to cross-sectional data.

As a measure for treatment performance, our study uses the treatment probability of municipal wastewater. Alternatively, future research may consider using the share of treated municipal wastewater as a measure for checking the robustness of our findings. We did not include this alternative measure in our study as the calculation of the actual share of treated municipal wastewater has been impaired in the Mexican context due to a lack of data. For the majority of Mexican municipalities, only the treated volumes and not the generated volumes of municipal wastewater are known (Conagua, 2010).

Based on our findings, we suggest as a policy recommendation the implementation of pilot projects in different parts of a developing country. Our results indicate that establishing success cases in areas without wastewater treatment has a significant spatial impact at the regional level. As shown in the study of Lewis et al. (2011) on organic dairy farming, the adoption of new practices by neighbors significantly decreases information acquisition costs and uncertainty for new adopters. Thus, neighbors and their actions have a pivotal role. However, Lewis et al. also conclude that results of spatial spillovers differ within the same sector, because spatial spillovers are present in different degrees. Future research needs to investigate in more detail under which circumstances wastewater treatment pilot projects in particular, and environmental policy in general, may or may not lead to spatial spillovers to ensure that pilot projects trigger domino effects in adjacent areas.

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APPENDIX

Table A.1: *Regression results including dummy variables for belonging of a municipality to a certain federal state*

	General probit	SAR-probit	
Variable		*k*=5	*k*=10
GDPpc	0.048** (0.019)	0.044** (0.018)	0.043** (0.019)
Education	0.014** (0.007)	0.012* (0.006)	0.013** (0.006)
GINI	0.032*** (0.009)	0.031*** (0.010)	0.036*** (0.009)
Femadmin	0.0004 (0.003)	0.0005 (0.003)	0.0003 (0.003)
Urban	0.006*** (0.002)	0.006*** (0.002)	0.006*** (0.002)
FracIndex	-0.001 (0.003)	-0.0004 (0.003)	-0.0003 (0.003)
WaterUtility	0.331*** (0.109)	0.342*** (0.109)	0.333*** (0.108)
Federal state of Campeche	-2.452*** (0.520)	-2.234*** (0.530)	-2.160*** (0.527)
Federal state of Coahuila	-2.103*** (0.356)	-1.986*** (0.344)	-1.988*** (0.359)
Federal state of Chiapas	-2.405*** (0.326)	-2.117*** (0.313)	-2.072*** (0.335)
Federal state of Chihuahua	-0.850** (0.336)	-0.827*** (0.304)	-0.806** (0.322)
Federal District (DF)	-2.102*** (0.486)	-1.988*** (0.454)	-1.982*** (0.461)
Federal state of Durango	0.423 (0.503)	0.434 (0.487)	0.423 (0.490)
Federal state of Guanajuato	-1.265*** (0.345)	-1.142*** (0.327)	-1.105*** (0.339)
Federal state of Guerrero	-1.742*** (0.328)	-1.528*** (0.319)	-1.510*** (0.329)
Federal state of Hidalgo	-2.540*** (0.326)	-2.270*** (0.315)	-2.253*** (0.332)
Federal state of Jalisco	-1.287*** (0.304)	-1.176*** (0.287)	-1.168*** (0.302)
Federal state of Mexico	-1.716*** (0.302)	-1.557*** (0.288)	-1.537*** (0.306)
Federal state of Michoacan	-2.476*** (0.316)	-2.241*** (0.311)	-2.219*** (0.320)
Federal state of Morelos	-1.609*** (0.366)	-1.435*** (0.344)	-1.441*** (0.361)
Federal state of Nayarit	0.144 (0.586)	0.296 (0.584)	0.310 (0.601)
Federal state of Oaxaca	-2.516*** (0.297)	-2.188*** (0.291)	-2.151*** (0.320)
Federal state of Puebla	-1.903*** (0.297)	-1.670*** (0.280)	-1.631*** (0.306)
Federal state of Queretaro	-0.652 (0.450)	-0.518 (0.445)	-0.515 (0.442)
Federal state of Quintana Roo	-1.229* (0.720)	-0.789 (0.742)	-0.646 (0.757)
Federal state of San Luis Potosi	-2.044*** (0.340)	-1.885*** (0.325)	-1.863*** (0.345)

Federal state of Sonora	-0.894*** (0.334)	-0.822*** (0.314)	-0.821** (0.327)
Federal state of Tabasco	-0.022 (0.571)	0.336 (0.612)	0.333 (0.595)
Federal state of Tamaulipas	-1.430*** (0.372)	-1.292*** (0.354)	-1.291*** (0.371)
Federal state of Tlaxcala	-1.561*** (0.331)	-1.346*** (0.315)	-1.332*** (0.334)
Federal state of Veracruz	-2.274*** (0.301)	-2.015*** (0.287)	-1.981*** (0.310)
Federal state of Yucatan	-3.239*** (0.391)	-2.846*** (0.339)	-2.803*** (0.407)
Federal state of Zacatecas	-1.023*** (0.337)	-0.962*** (0.330)	-0.936*** (0.342)
Intercept	-1.359** (0.660)	-1.397** (0.629)	-1.477** (0.634)
Rho (ρ)	-	0.162*** (0.051)	0.172*** (0.063)
Observations	2,299	2,299	2,299

Note: *** significant at 1%, ** significant at 5%, * Significant at 10%, Figures in parentheses are standard deviations of coefficients