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Your Air Pollution Makes Me Sick! Estimating the Spatial Spillover Effects of $PM_{2.5}$ Emissions on Emergency Room Visits Due to Respiratory Diseases in Chile

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Abstract. This study quantifies the spillover effects of $PM_{2.5}$ emissions on emergency room visits due to respiratory diseases in Chile. We use several spatial panel methods and models controlling also for the potential endogeneity of air quality. Our estimates show that the spillover effects are downward biased when this endogeneity is ignored. Furthermore, using the estimates from our preferred model, we find that about 65 per cent of the total emergency room visits in Chile are due to $PM_{2.5}$ emissions generated in the same municipality, whereas the remaining 35 per cent can be attributed to pollutants emitted in a different spatial unit. In economic terms, increasing $PM_{2.5}$ emissions in one thousand tonnes yields to an increase of USD 98,010 of annual costs for ER health facilities due to spillover effects, whereas the total costs (considering indirect and direct effects) amounts to USD 283,855.

Key words: Air pollution, $PM_{2.5}$ emissions, Spatial spillover effect, Public health, Instrumental variable, Spatial panel models

1 Introduction

Several studies across different fields have shown that air quality is highly associated with mortality and hospital admissions for respiratory and cardiovascular diseases (Brunekreef, Holgate 2002, Bernstein et al. 2004, Cohen et al. 2005, Kampa, Castanas 2008). This relationship has gained more attention with accelerating urban development, especially in developing countries where the negative impacts of air pollution on health are greater and public resources for health are scarcer compared to developed countries. Most of the recent studies have focused on atmospheric particulate matter with 2.5 micrometers in diameter ($PM_{2.5}$), which is considered one of the most dangerous pollutants for health due to its capacity to penetrate deeply into the lungs and bloodstream (Pope III et al. 2002, Xing et al. 2016). According to Brauer et al. (2015), $PM_{2.5}$ is the most frequent cause of environment-related deaths worldwide causing approximately 3.1 millions premature deaths globally in 2010 and 2.1 millions in 2013. Previous studies also suggest that long-term exposure to $PM_{2.5}$ increases the prevalence rate of respiratory diseases (Abbey et al. 1995, Pope III et al. 2002, 2004, Cohen et al. 2005), which in turn increases hospitalization rates (Ward 2015, Ostro et al. 2008) and household healthcare expenditure (Yang, Zhang 2018); whereas short-term exposures increase susceptibility to respiratory infections (Analitis et al. 2006), heart attack (Dominici et al. 2006, Madrigano et al. 2012), asthma attacks (Zanobetti et al. 2009, Hua et al. 2014, Fan et al. 2016) and acute bronchitis (Yang et al. 2019).

Most of these studies assume that air pollution has negative impacts only at the same spatial location. However, geographical units are interrelated resulting in an interregional diffusion of pollutants to other areas. This is supported by studies showing that pollutants can travel long distances (Bergin et al. 2005, Fang et al. 2019), and even continents (Hatakeyama et al. 2001), generating important unintended spatial spillover effects. In terms of $PM_{2.5}$, Li et al. (2018) show that this pollutant is the second pollutant component with the highest level of spatial interdependency in China, whereas Chen et al. (2017), Chen, Ye (2019), Hao, Liu (2016) and Ma et al. (2016) show that $PM_{2.5}$ emissions have significant diffusion effects between neighboring regions.

Given the potential externalities exerted by air pollutants, researchers have tried to estimate the spatial spillovers of air pollution on public health. For example, Zhang et al. (2017) estimates that about 73% of the total premature deaths in the world due to $PM_{2.5}$ are attributable to production activities in the same spatial unit, whereas the remaining percentage is due to air pollutants emitted in a different region. In China, Chen et al. (2017) find that an increase of ten thousand tonnes of industrial sulfur dioxide emissions in a particular city will lead, on average, to an increase in local mortalities from lung cancer and respiratory diseases of 0.035 and 0.030 per ten thousand persons, respectively, and a total spillover effect of 0.217 and 1.543 per ten thousand persons in mortalities of all its neighbors. These results imply that air pollution and its associated effects on health are a strong motivation to establish more effective air quality regulation. For example, policies aimed at reducing air pollutants in target regions might decrease emissions in neighboring regions, exerting unintended but beneficial spillover effects on public health (Fang et al. 2019).

In this context, this study tries to empirically assess the potential spillover effects of $PM_{2.5}$ emissions on emergency room (ER) visits due to respiratory diseases in Chile. In particular, the questions we try to answer are: is there a strong relationship between $PM_{2.5}$ emissions and public health? Is there evidence of spatial spillover effects? If they do exist, are they substantially large? To answer these questions, we estimate several spatial panel models for yearly data on ER visits and $PM_{2.5}$ emissions for 337 municipalities, controlling for the potential endogeneity of $PM_{2.5}$ emissions.

We focus on Chile for two reasons. First, air pollution in Chile has reached worrying levels in the Latin American context. According to the World Health Organization (WHO), the average level of $PM_{2.5}$ concentration in Chile is approximately 25 ug/m^3 (15 points greater than the recommended air quality standard of 10 ug/m^3 annual mean), placing Chile seventh out of the 33 most polluted countries in America. Furthermore, according to the 2018 World Air Quality report, Chile has 9 of the 10 most polluted cities in South America. Although these figures have led the Chilean Government to implement several prevention and decontamination plans, the air quality in many cities of the country still exceeds levels established by the WHO. Second, most of the studies documenting the detrimental effects of air pollution on Chileans' health have focused on the most polluted cities located in the central and southern regions of the country. For example, Ostro et al. (1996) find that a 10-ug/m^3 change in daily mean PM_{10} is associated with a 1% increase in total daily mortality in Santiago. Sanhueza et al. (2006), focusing in Temuco which is one of the most highly polluted cities in Chile, find that PM_{10} and $PM_{2.5}$ are statistically correlated with the daily number of deaths, hospital admissions, and ER visits for cardiovascular, respiratory, and acute respiratory infection diseases.

This work makes two potential contributions. First, and unlike previous studies in Chile, this study uses ER visits data for the entire country, which allows us to generalize our results to whole population. Moreover, it is the first study (to our knowledge) that analyzes the potential spatial spillover effects of air pollution on Chileans' health. Second, we use a spatial panel approach controlling simultaneously for the endogeneity of the spatial lag of ER visits and $PM_{2.5}$ emissions. As instruments for $PM_{2.5}$ emissions, we use the number of vehicles in each municipality and its higher-order spatial lags.

2 Methods

2.1 Model formulation and spatial mechanisms

To analyze the spillover effects of air pollution on ER visits, we propose the following spatial panel data model:

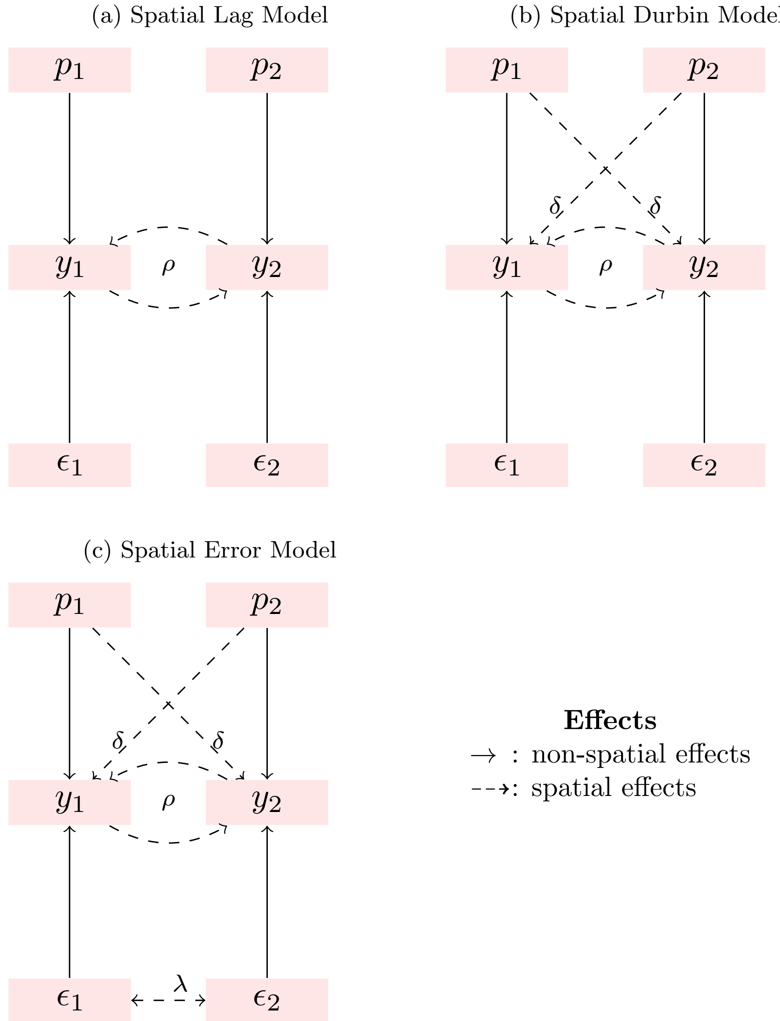
$$
\begin{aligned}
y_{it} &= \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \gamma p_{it} + \delta \sum_{j=1}^{N} w_{ij} p_{jt} + \mathbf{x}_{it}'\boldsymbol{\beta} + \sum_{j=1}^{N} w_{ij}\mathbf{x}_{it}'\boldsymbol{\theta} + \mu_i + \tau_t + u_{it}, \\
u_{it} &= \lambda \sum_{j=1}^{N} w_{ij} u_{jt} + \epsilon_{it}, \\
& \quad i = 1, ..., N; t = 1, ..., T.
\end{aligned} \tag{1}
$$

where y_{it} denotes the number ER visits due to respiratory diseases in municipality i in time t; p_{it} is the amount of $PM_{2.5}$ emissions, which we presume is endogenous; $\mathbf{x}_{it}$ is a $K \times 1$ vector of exogenous variables whose values vary over both municipalities and time; μ_i is a municipality-fixed effect which is meant to control for time-invariant variables whose omission could bias the estimates; τ_t is a time-fixed effect which eliminates omitted variable bias caused by excluding unobserved variables that evolve over time but are constant across municipalities; w_{ij} is an element of the $(N \times N)$ spatial weight matrix $\mathbf{W}$ reflecting the spatial interdependent relationship between different municipalities, so that $\sum_{j=1}^{N} w_{ij} y_{jt}$ captures the number of ER visits for respiratory diseases for i's neighbors, whereas $\sum_{j=1}^{N} w_{ij} u_{jt}$ captures the potential spatial autocorrelation in omitted variables that vary over both municipalities and time; $\sum_{j=1}^{N} w_{ij} p_{jt}$ and $\sum_{j=1}^{N} w_{ij}\mathbf{x}_{it}'$ capture air pollution and other covariates of i's neighbors, respectively. Finally, it is assumed that $\epsilon_{it} \sim iid(0, \sigma_\epsilon^2)$.

Different restrictions on the model (1) give raise to different taxonomies of the spatial relationships between ER visits and air pollution. Setting $\delta = \lambda = 0$ and $\boldsymbol{\theta} = \mathbf{0}$, we obtain the Spatial Lag Model (SLM). This model is displayed in Panel (a) of Figure 1, which considers two municipalities. Under this model, it is assumed that ER visits in municipality 1, (y_1), exerts a spatial externality on the number of ER visits in municipality 2, (y_2). If $\rho > 0$ $(\rho < 0)$, then this spatial externality is positive (negative); that is, the increase in admissions in emergency rooms due to respiratory problems in municipality 1 generates an increase (decrease) in admissions in municipality 2. ER visits might spread from municipality to municipality by a variety of mechanisms. First, there exists a vast literature in epidemiology indicating that disease transmission is inherently spatial, especially for respiratory diseases such as flu, common cold and pneumonia (Kuebart, Stabler 2020). For example, individuals have complex spatial routines in their everyday lives. Thus, it has to be considered that people tend to pass through a variety of places over time, which increase the likelihood of being infected and/or spread the disease to distant places (Kulldorff, Nagarwalla 1995, Li et al. 2003). If the transmission follows a spatial pattern and both the contagion rate and commuting is high, then we should observe spatial clusters in ER visits, especially in seasons of extreme temperatures.

Another mechanism which is observationally equivalent is the overcrowding effect. Emergency departments prioritize patients according to their severity such that low-urgency patients have a longer waiting time. Therefore, waiting times act as an implicit price ensuring that only patients who are willing to bear the cost will be treated (Sivey 2018). Thus, medical centers facing a situation of high demand or operating at or near full capacity could cause individuals with high waiting time elasticity to choose medical centers in neighboring municipalities for urgent treatment, other things equal. According to Salway et al. (2017) another potential mechanism is ambulance diversion. Ambulance diversion is a tactic used by hospitals and emergency medical services to solve the problem of overcrowded emergency departments. For example, if a given municipality is experiencing high demand for urgent treatment, nearby medical centers might also experience an increase of demand due to ambulance diversion. These mechanisms are

Figure 1: Spatial Econometric Models



relevant in the context of emergency services in Chile, which have been experiencing problems of congestion for several years (Salway et al. 2017, Becerra et al. 2020). Based on these theoretical mechanisms, we expect a positive ρ, which is consistent with the epidemiological hypothesis of contagion of diseases and/or with a potential congestion effect of emergency room departments.

Setting $\lambda = 0$ in Equation (1), we obtain the Spatial Durbin model (SDM) displayed in Panel (b) of Figure 1. Under this model, air pollution in municipality 1 not only affects municipality 2's ER visits through congestion and/or contagion, but also directly because of the transboundary characteristic of air pollution via δ (Bergin et al. 2005). As we will discuss later, although δ captures the immediate spillover effect of air pollution (local effects), if ρ equals zero, we will not be able to capture the potential spillover effects on more distant municipalities (global effects).

If $\lambda \neq 0$ gives rise to the General Nesting Spatial (GNS) model (Elhorst 2014). This model helps to control for the potential spatial dependence in the error term, which may arise because of omitted variables that are correlated across municipalities, as shown in Panel (c) of Figure 1. Spatial dependence of error terms leads to an inefficiency problem, but no bias in the estimated parameters if the omitted variables are not correlated with the included variables. Therefore, although λ does not enter in the computation of spillover effects, adjusting for spatial dependence in the error term will produce more accurate inference regarding the direct and indirect effects (LeSage 2014). Finally, if all spatial parameters are zero ($\rho, \gamma, \boldsymbol{\theta}$), except for λ, then the model is reduced to the Spatial Error (SEM) model.

2.2 Issues with model estimation

2.2.1 Fixed effect vs random effect

The idiosyncratic effect μ_i in Equation (1) can be estimated by either a fixed (FE) or a random effects (RE) model. Both methods have advantages and disadvantages discussed in detail by Elhorst (2014) and Kopczewska et al. (2017). In this study, we opt for the FE model for two reasons. First, the RE model is not appropriate when space-time data of adjacent spatial units located in unbroken study areas are used, as in our case (Elhorst 2014, p. 86). Second, the assumption of the RE model of no correlation between the municipalities' fixed (μ_i) effects and the explanatory variables is very restrictive. For instance, climate and/or geographical characteristics (or any other omitted variable in our model) may be correlated with emissions: climate may affect heating and cooling needs which in turn affects the probability of having a respiratory illness (Selden, Song 1994).

The main disadvantage of the FE model is that it does not allow to control for time-invariant geographical characteristics such as distance to the sea, elevation, distance to big cities, etc., which are known to be correlated with respiratory diseases. Therefore, we assume that all these characteristics of municipalities are captured by μ_i. In any case, the Hausman tests (displayed later) support our claim that the FE outperforms the RE model.

2.2.2 Instruments and estimation

Consider the spatial model (1) in matrix form:[1]

$$\begin{aligned} \mathbf{y} &= \rho\left(\mathbf{I}_T \otimes \mathbf{W}\right)\mathbf{y} + \mathbf{X}\boldsymbol{\beta}_1 + \mathbf{Y}\boldsymbol{\beta}_2 + \left(\boldsymbol{\imath}_T \otimes \mathbf{I}_N\right)\boldsymbol{\mu} + \mathbf{u}, \\ \mathbf{u} &= \lambda\left(\mathbf{I}_T \otimes \mathbf{W}\right)\mathbf{u} + \boldsymbol{\varepsilon}, \end{aligned} \tag{2}$$

where $\mathbf{y}' = (\mathbf{y}_1', ..., \mathbf{y}_T')$ and $\mathbf{y}_t$ is an $N \times 1$ vector in time period $t = 1, ..., T$; $\mathbf{X}' = (\mathbf{X}_1', ..., \mathbf{X}_T')$ and $\mathbf{X}_t$ is a $N \times K$ matrix of *exogenous variables*, which can also include their spatial lag; $\boldsymbol{\mu}$ is a $N \times 1$ vector of municipality-fixed effects; $\mathbf{Y}' = (\mathbf{Y}_1', ..., \mathbf{Y}_T')$, where $\mathbf{Y}_t, t = 1, ..., T$ is an $N \times H$ matrix of additional endogenous variables, which in this context collects p_{it} and $\sum_{j=1}^N w_{ij}p_{jt}$ across municipalities and time; finally $\boldsymbol{\varepsilon}' = (\boldsymbol{\varepsilon}_1', ..., \boldsymbol{\varepsilon}_T')$ is an $NT \times 1$ vector of error terms. $\mathbf{I}_N$ denotes an identity matrix of dimension $(N \times N)$, or dimensions $(T \times T)$ if the subscript T is indicated.

Estimation of model (2) imposes some complications. First, $\left(\mathbf{I}_T \otimes \mathbf{W}\right)\mathbf{y}$ generates endogeneity due to simultaneity. Second, both p_{it} and its spatial lag are potentially endogenous. For example, our measure of $PM_{2.5}$ emissions is based on self-reported emissions which might result in a potential problem of attenuation bias. Furthermore, air quality might be correlated with unobserved variables at the municipality level that affect individuals' health, creating an omitted variable bias. Therefore, we need to instrumentalize both $\left(\mathbf{I}_T \otimes \mathbf{W}\right)\mathbf{y}$ and $\mathbf{Y}$.

For the identification of the effect of air quality on ER visits, we use the number of vehicles in a given municipality as an additional pre-determined variable. According to the Chilean Ministry of Environment, vehicle emissions represent 35-50% of total national emissions. In terms of the exclusion restriction, we claim that, after taking into account the amount of $PM_{2.5}$ emissions, the only way that the number of vehicles can affect ER visits is through air quality.[2]

Following Kelejian, Prucha (1998), we use

$$\left(\mathbf{X}, \left(\mathbf{I}_T \otimes \mathbf{W}\right)\mathbf{X}, \left(\mathbf{I}_T \otimes \mathbf{W}^2\right)\mathbf{X}, ..., \left(\mathbf{I}_T \otimes \mathbf{W}^q\right)\mathbf{X}\right)$$

as instruments for $\left(\mathbf{I}_T \otimes \mathbf{W}\right)\mathbf{y}$, where $\mathbf{X}$ is the set of included exogenous variables. The intuition behind the instruments is the following: since $\mathbf{X}$ determines $\mathbf{y}$, then it must be true that $\left(\mathbf{I}_T \otimes \mathbf{W}\right)\mathbf{X}, \left(\mathbf{I}_T \otimes \mathbf{W}^2\right)\mathbf{X}, ...$ determines $\left(\mathbf{I}_T \otimes \mathbf{W}\right)\mathbf{y}$. Furthermore, since $\mathbf{X}$ is assumed to be uncorrelated with $\boldsymbol{\varepsilon}$, then $\left(\mathbf{I}_T \otimes \mathbf{W}\right)\mathbf{X}$ must be also uncorrelated with $\boldsymbol{\varepsilon}$.

[1] Note that we have dropped the time-fixed effect, τ_t, for simplicity in the exposition.

[2] As suggested by one of the reviewers, the number of vehicles can affect ER visits through other mechanisms like traffic accidents or urbanization. In our robustness checks section, we also allow for such possibilities.

We also assume that $\boldsymbol{\Phi}$ is a $NT \times R$ matrix of additional exogenous instruments for $\mathbf{Y}$, where $\boldsymbol{\Phi}$ consists of the number of vehicles. Setting $\mathbf{X}_f = [\mathbf{X}, \boldsymbol{\Phi}]$, the instruments are given by the linearly independent columns of (Drukker et al. 2013, Kelejian, Piras 2017) $\mathbf{Q} = \left[\mathbf{X}_f, (\mathbf{I}_T \otimes \mathbf{W})\, \mathbf{X}_f, \left(\mathbf{I}_T \otimes \mathbf{W}^2\right) \mathbf{X}_f, ..., (\mathbf{I}_T \otimes \mathbf{W}^q)\, \mathbf{X}_f\right]$.

Following the empirical literature we set $q = 2$ (Drukker et al. 2013, Kelejian, Prucha 1998, 2010, Fingleton, Le Gallo 2008), so that the matrix of instruments is given by following subset of $\mathbf{Q}$:

$$\mathbf{Q}_* = \left[\mathbf{X}_f, (\mathbf{I}_T \otimes \mathbf{W})\, \mathbf{X}_f, \left(\mathbf{I}_T \otimes \mathbf{W}^2\right) \mathbf{X}_f\right]_{LI}, \tag{3}$$

where LI indicates linearly independent columns of $\mathbf{Q}_*$. We use different estimation procedures in this work. First, when assuming that air pollution is exogenous, that is $\boldsymbol{\beta}_2 = \mathbf{0}$, we can estimate the GNS spatial model (Equation (2)) by Maximum Likelihood (ML) procedure assuming the full distribution of $\boldsymbol{\varepsilon}$ (Elhorst 2014). When $\boldsymbol{\beta}_2 \neq \mathbf{0}$, the ML no longer delivers consistent estimates, so we rely on GMM procedures. The full GNS model can be estimated via Generalized Spatial Two Stage Least Square (GS2SLS) (see Kelejian, Piras 2017, chapter 15 for technical specifics). The steps are the following: (1) estimate a FE effect model using a S2SLS procedure using (3) as instruments; (2) obtain the residuals from the 2SLS to consistently estimate σ^2_ϵ and λ via Method of Moments using Kapoor et al. (2007)'s equations accordingly; (3) using the consistent estimates of σ^2_ϵ and λ, the model is transformed to account for the spatial correlation in the error term, and more efficient estimates of the parameters are obtained via 2SLS using (3) as instruments. Finally, if $\lambda = 0$ the model is estimated by the traditional S2SLS.

2.3 *Computing direct and indirect effects*

Since the estimated coefficients are not directly interpretable (LeSage, Pace 2014b), we need to compute the spatial spillover effects of air pollution on ER visits, which is primary objective of this work.

To derive the marginal impacts, we follow LeSage, Pace (2009) and Elhorst (2014). Assuming that $(\mathbf{I}_{NT} - a\,(\mathbf{I}_T \otimes \mathbf{W}))$ is nonsingular for $|a| < 1$, the reduced form of model (2) is given by:

$$\mathbf{y} = \mathbf{S}^{-1}\mathbf{X}\boldsymbol{\beta}_1 + \mathbf{S}^{-1}\mathbf{Y}\boldsymbol{\beta}_2 + \mathbf{S}^{-1}\left(\boldsymbol{\imath}_T \otimes \mathbf{I}_N\right)\boldsymbol{\mu} + \mathbf{S}^{-1}\mathbf{C}^{-1}\boldsymbol{\varepsilon}, \tag{4}$$

where $\mathbf{S} = (\mathbf{I}_{NT} - \rho\,(\mathbf{I}_T \otimes \mathbf{W}))$ and $\mathbf{C} = (\mathbf{I}_{NT} - \lambda\,(\mathbf{I}_T \otimes \mathbf{W}))$. Taking the expectation of (4) yields:

$$\mathbb{E}(\mathbf{y}) = \mathbf{S}^{-1}\mathbf{X}\boldsymbol{\beta}_1 + \mathbf{S}^{-1}\mathbf{Y}\boldsymbol{\beta}_2.$$

Since $\mathbf{Y}$ collects both air pollution and its spatial lag, the impact on the expected value of location j given a change in air pollution in location i, also known as the indirect effects, is:

$$\frac{\partial \mathbb{E}(y_i)}{\partial p_j} = \mathbf{G}_p(\mathbf{W})_{ij}, \quad \forall i \neq j, \tag{5}$$

where $\mathbf{G}_p(\mathbf{W})_{ij}$ is the i, jth element of the following matrix:

$$\begin{aligned}\mathbf{G}_p(\mathbf{W}) &= \begin{pmatrix} \frac{\partial \mathbb{E}(y_1)}{\partial p_1} & \frac{\partial \mathbb{E}(y_1)}{\partial p_2} & \cdots & \frac{\partial \mathbb{E}(y_1)}{\partial p_N} \\ \frac{\partial \mathbb{E}(y_2)}{\partial p_1} & \frac{\partial \mathbb{E}(y_2)}{\partial p_2} & \cdots & \frac{\partial \mathbb{E}(y_2)}{\partial p_N} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial \mathbb{E}(y_n)}{\partial p_1} & \frac{\partial \mathbb{E}(y_n)}{\partial p_2} & \cdots & \frac{\partial \mathbb{E}(y_n)}{\partial p_N} \end{pmatrix}, \\ &= \left(\mathbf{I}_{NT} - \rho\,(\mathbf{I}_T \otimes \mathbf{W})\right)^{-1}\left(\mathbf{I}_{NT}\gamma + \delta\,(\mathbf{I}_T \otimes \mathbf{W})\right).\end{aligned} \tag{6}$$

Note that $\boldsymbol{\beta}_2' = [\gamma, \delta]$, where γ represents the coefficient for air pollution and δ denotes the coefficient for the spatial lag of air pollution in Equation (1).

Equation (5) is known as the indirect effect which reflects that air pollution in a given municipality not only has a direct or spatial-localized effect on its inhabitants' ER visits, but also in those of neighboring municipalities. It can be noticed from Equation (5) that every off-diagonal element of (6) represents an indirect effect. Therefore, indirect effects do not occur if both $\rho = 0$ and $\delta = 0$ (Elhorst 2014). Furthermore, it is important to distinguish between global and local indirect effects (LeSage, Pace 2009). Local spillovers occurs if $\delta \neq 0$ and represent a situation where the impact of air pollution on individuals' ER visits falls only on immediate neighbors, dying before they impact municipalities that are neighbors to the neighbors. Global spillovers occur when $\rho \neq 0$ and arise when changes in the air quality of one municipality impact all municipalities' ER visits. This applies even to the municipality itself as the impacts of the air pollutants can pass to its neighbors and back to the municipality itself. Thus, the simultaneous interactions produced by global spillovers lead to a scenario where changes in air quality in one municipality set in motion a sequence of adjustments over time in all municipalities in the sample such that a new long-run equilibrium arises (LeSage, Dominguez 2012, LeSage, Pace 2014b).

The impact of the expected value of municipality i's ER visits, given a change in air pollution for the same municipality is given by:

$$\frac{\partial \mathbb{E}(y_i)}{\partial p_i} = \mathbf{G}_p(\mathbf{W})_{ii}, \quad \forall i. \tag{7}$$

The effect on Equation (7) is known as the direct effect and includes the effect of feedback loops where municipality i affects municipality j and municipality j also affects municipality i.

It is important to highlight three important issues. First, if both $\rho = 0$ and $\delta = 0$, both global and local effects cannot be separated from each other (Elhorst 2014). Second, the SLM model has the disadvantage that the ratio between the indirect and direct effects is the same for all variables considered in the model, which might be unrealistic in our application. This shortcoming does not occur in the SDM or GNS model. Third, given that the change of air quality in each municipality implies N^2 potential marginal effects (as shown in Equation (6)), we report the average marginal effects as suggested by LeSage, Pace (2009). Assuming that our instruments are valid, both the average direct and indirect marginal effects represent the effects of $PM_{2.5}$ emissions for the compliers, i.e., those municipalities whose $PM_{2.5}$ is affected by the instruments (in our case, the sub-population of municipalities who would increase their $PM_{2.5}$ emissions because the number of vehicles had increased). This is known as the local average treatment effect (LATE).

2.3.1 Spatial weight matrix

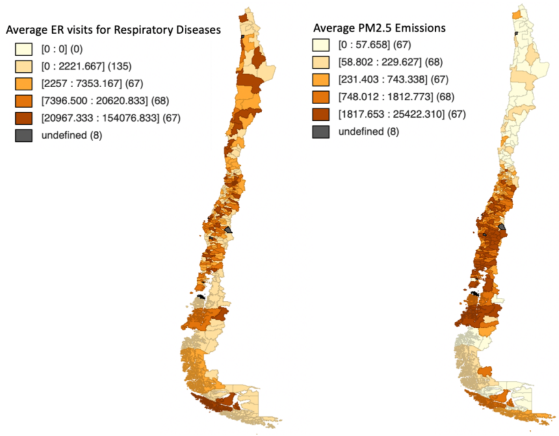
Since pollutants can be transported to geographical locations 1000 kilometers away (Bergin et al. 2005), or even to other continents (Hatakeyama et al. 2001, Liu et al. 2020), in this study we chose an inverse distance weighting scheme. Specifically, we assume that:

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}^2} & i \neq j \\ 0 & i = j \end{cases}, \tag{8}$$

where d_{ij} is the distance between municipality i and j. Thus weights are given by the reciprocal of the distance, such that the larger the distance between municipalities, the lower the spatial connection.

Instead of using the inverse of the distance, as Chen et al. (2017), we use the inverse squared-distance since we expect that the neighboring relationships are nonlinear and decline faster than proportionally to the distance. According to Kopczewska et al. (2017), this weighting scheme allows for both local and global clusters: it is global because it captures interactions between all units under the Chilean territory, and it is local because the spatial links are stronger for closer spatial units. For all the estimations, we use the row-standardized version of $\mathbf{W}$. This ensures that all weights, w_{ij}, are between 0 and 1 and facilitates the interpretation. This also guarantees that the spatial parameters are comparable between models (Anselin 2001).

In the robustness check section, we also consider the following alternative weight matrix: (1) the inverse of the distance, where the weights are given by $1/d_{ij}$, (2) the



Notes: The values represents the average over 2009-2014 period.

Figure 2: Spatial distribution of ER visits and PM2.5 emissions at municipality level.

10- and 7-closest neighbors for each municipality. We do not consider the simple binary geographic unit matrix since it is hard to argue that air pollution only affects first order neighbors. For a similar reasoning see Chen et al. (2017).

3 Data

We use a panel dataset comprising 337 municipalities in Chile over the period 2009-2014. Our main dependent variable is the yearly number of emergency room visits collected from the Statistic and Health Information Department (DEIS in Spanish) of the Health Ministry of Chile. DEIS records daily ER visits in health care facilities of the country that have an emergency service. Since pollutants have been widely associated with various diseases related to the respiratory system, we focus on ER visits due to respiratory diseases coded according to the International Classification of Diseases, 10th Revision (ICD-10).

Panel (a) in Figure (2) shows the spatial distribution of the average number of ER visits due to respiratory diseases for all ages over the 2009-2014 period. A slightly positive spatial autocorrelation can be detected: that is, there is a tendency for municipalities to be surrounded by municipalities with similar numbers of ER visits.

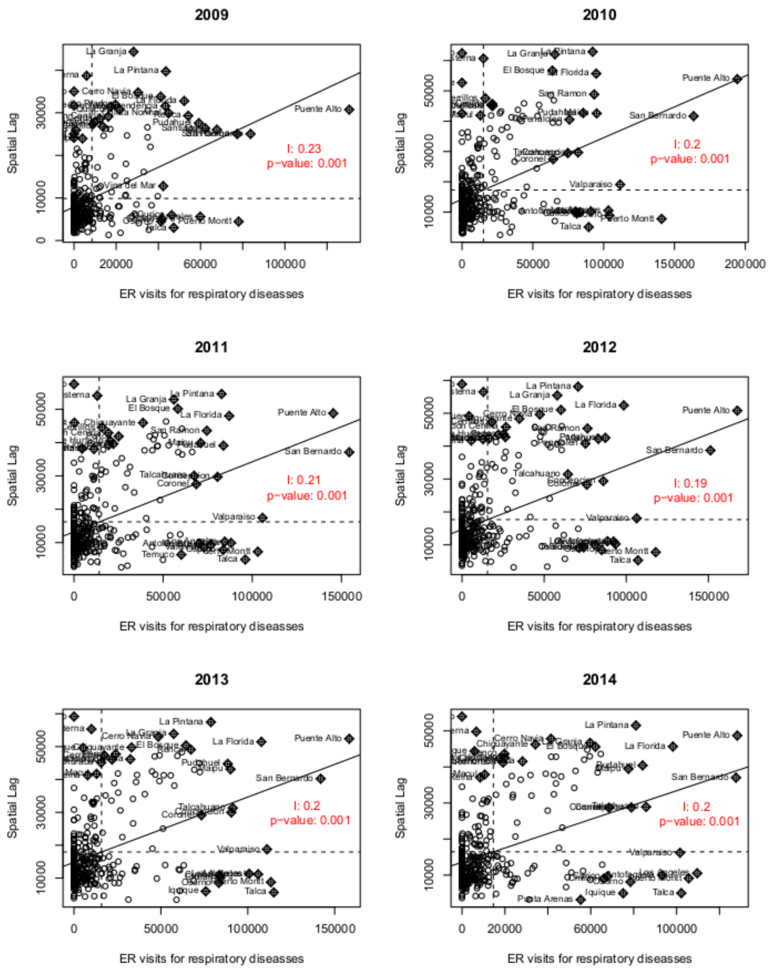
To statistically test this global spatial association, we perform a Moran's test calculated from the following formula:

$$I = \frac{n\sum_{i=1}\sum_{j=1} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{S_0\sum_i (y_i - \bar{y})^2},$$

where $S_0 = \sum_i \sum_j w_{ij}$. Moran's I values range from -1 (perfect dispersion) to 1 (perfect correlation). Positive values indicate positive spatial autocorrelation; that is municipalities with similar values have a tendency to be spatially clustered; whereas negative values indicate negative spatial autocorrelation, that is municipalities with high (low) values tend to be surrounded by municipalities with low (high) values of y. A zero value indicates a random spatial pattern.

Figure 3, shows the the Moran's scatterplot for ER visits along with the Moran's I and the p-value for the null hypothesis of spatial randomness for each year in the sample.[3] The idea of the Moran's scatterplot is to display the variable for each municipality against the standardized spatial weight average. Therefore, the Moran's I is equivalent to the slope coefficient of a linear regression of $\mathbf{Wy}$ on $\mathbf{y}$ measured as deviation from their mean. The results reveal a moderate degree of positive spatial autocorrelation with a Moran's I fluctuating between 0.19 and 0.23. For all years, the null is rejected at the 5% level.

[3]The p-values are computed using Monte Carlo simulation with 999 rearrangement of spatial configurations.



Notes: p-values for Moran's I statistic are based on Monte Carlo simulation using 999 permutations.

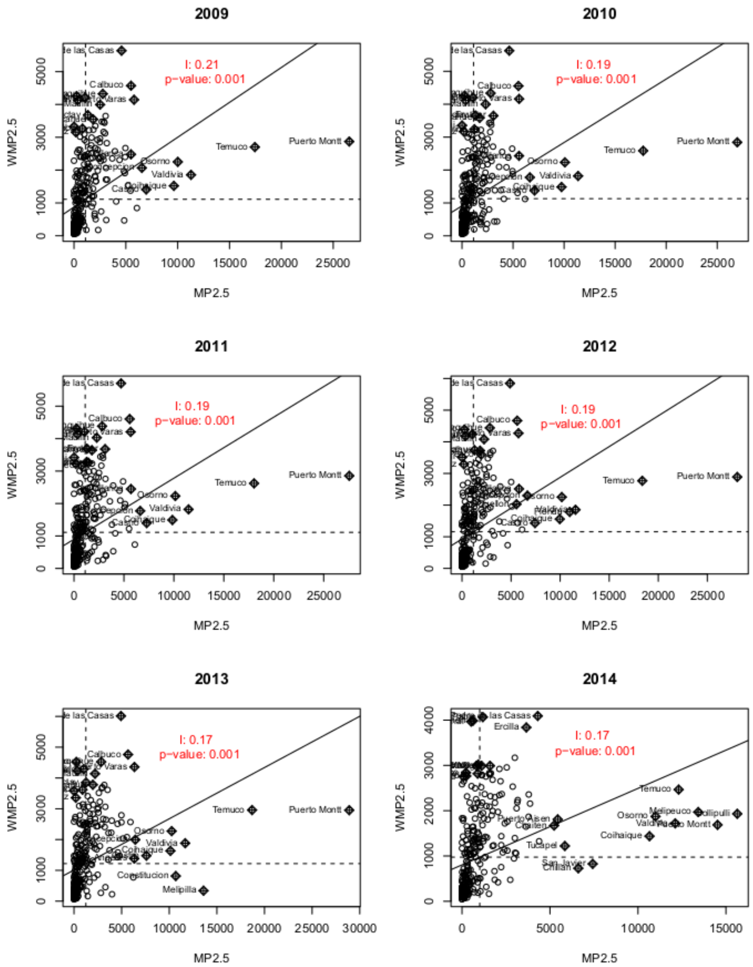
Figure 3: Moran's scatterplots for average ER visits for respiratory diseases: Moran's I test and p-value by year.

These results gives us a first insight on the adequacy of including the spatial lag of ER visits on Equation (1).

$PM_{2.5}$ emissions are obtained from the database of the Record of Emissions and Contaminant Transfer (RETC) from the Chilean Ministry of the Environment. The environmental information associated with each source is collected by different organizations with environmental competence, which in May of each year must be sent to the central node of the RETC. All the information declared through RETC comes from different sectoral systems associated with the self-reporting of point-sources discharges, in addition to the estimation of air emissions from diffuse sources (road transport, agricultural burning, forest and urban fires, and residential firewood), which then are validated and consolidated for each year.

Panel (b) of Figure 2 shows the spatial distribution of $PM_{2.5}$ emissions in tonne averaged over the period 2009-2014. A strong cluster of municipalities high emissions on central and southern part of Chile can be observed. This is further corroborated by Figure 4, which shows a significant positive spatial autocorrelation according to the Moran's I test. Importantly, Puerto Montt, Valdivia, Osorno and Temuco stand out as the municipalities with the highest levels of emissions.

Following the existing literature (e.g. Chen et al. 2017, Analitis et al. 2006, Brunekreef, Holgate 2002, Xing et al. 2016, to mention a few) and the availability of data, we control for the following variables: population, poverty rate, the expenditure on health inversion



Notes: p-values for Moran's I statistic are based on Monte Carlo simulation using 999 permutations.

Figure 4: Moran's scatterplots for average $PM_{2.5}$ emissions: Moran's I test and p-value by year.

and medical human resources, the number of ambulances, medical health facilities and medical laboratories at the municipal level. All these control variables come from the Chilean government's National System of Municipality Indicators (SINIM). The summary statistics are presented in Table 1.

4 Results

4.1 Models and diagnostic test

Although the most preferred model and estimation procedure should be selected on theoretical grounds (see LeSage, Pace 2014b, LeSage 2014, LeSage, Dominguez 2012, Golgher, Voss 2016, for further discussion), we first present several diagnostics and statistical tests for different models and methods, so that we can focus on the estimated spillover effects in the next section. In particular, we test: (1) whether a fixed effect model is more suitable than a model with random effects, 2) what type of spatial structure fits our data better; and finally (3) the ability of the instruments to deal with the potential endogeneity of $PM_{2.5}$ emissions.

Table 2 presents the diagnostic tests for different spatial panel models with FE. Each model (SLM, SDM, and GNS) is estimated by ML and S2SLS/G2SLS. The extended S2SLS/G2SLS additionally controls for the endogeneity of $PM_{2.5}$ emissions (SLM) and its spatial lag (SDM and GNS model).

Table 1: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Emergency room visits for respiratory disease:					
Children < 1 year	2,022	1,298.532	2,458.911	0	20,961
Children 1-4 years	2,022	3,385.774	6,163.631	0	56,526
Adults 15-64 years	2,022	5,506.554	9,505.077	0	71,311
Adults > 65 years	2,022	890.385	1,418.220	0	8,467
All	2,022	13,964.210	24,049.280	0	194,310
Controls:					
$PM_{2.5}$ (tonne)	2,022	1,130.821	2,331.553	0	28,898.720
Poverty rate	2,022	16.288	8.055	0	50.900
Population / 1000	2,022	508.128	866.759	1.340	9,312.110
Expend. health investment	2,022	0.399	2.287	0	38
Expend. medical human resources	2,022	18.274	9.013	0	82.610
Number of ambulances	2,022	2.202	1.861	0	12
Number of health facilities	2,022	0.790	1.513	0	12
Number of medical laboratories	2,022	0.334	0.521	0	4
Instrument:					
Number of vehicles	2,022	11,172.770	17,798.620	0	118,830

Notes: Expend. ... Expenditures. All variables are computed at municipal level.

To discriminate between the FE and RE model, we performed a Hausman test under the null of no systematic difference between the two set of estimates for the three models considered: SLM, SDM and GNS model. For each of them, we strongly reject the null hypothesis with a χ^2 test statistic equal to 1317, 271 and 704, respectively. Thus, the FE is the preferred model based on both theoretical and statistical reasoning.

We also performed Wald tests for testing whether $\rho = 0$ and/or $\lambda = 0$ across all models and estimation procedures. Looking at Table 2, it can be observed that ρ is positive and highly significant across all models revealing a positive spatial dependency of ER visits and corroborating the Moran's test results, except when the GNS is estimated by ML. According to Elhorst (2014), the GNS model usually tends to overparameterize the spatial relationship, resulting in low z-values of the coefficients. Thus, the lack of statistical significance of λ, together with the erratic behavior of ML estimates, lead us to discard the GNS model in the following sections in pursuit of a more parsimonious model.

Next, we focus on the selection of the spatial structure following the strategy suggested by LeSage, Pace (2009) and Elhorst (2010). Starting with the SDM model, we can apply some restrictions to analyze whether the SLM or SEM model fits our data better. Consider a SDM model by assuming that $\lambda = 0$ in Equation (1), and the following restrictions:

$$\begin{aligned} H_0^1 :& \delta = 0, \\ & \theta_k = 0, \quad \forall k = 1, ..., K, \end{aligned} \tag{9}$$

and

$$\begin{aligned} H_0^2 :& \gamma + \delta\rho = 0, \\ & \theta_k + \beta_k\rho = 0 \quad \forall k. \end{aligned} \tag{10}$$

If (9) is not rejected, then the SDM can be reduced to the SLM. If (10) holds then the SDM can be reduced to the SEM. If both restrictions hold, then the SDM is equivalent to a non-spatial panel model (LeSage, Pace 2009, Elhorst 2010). Table 2 shows that all tests point towards a SDM model: both tests are strongly rejected, except for the extended S2SLS model where H_0^2 is rejected at the 10% level. These results indicate that, in general, the fixed-effect SDM model outperforms the SLM and SEM model, even though we are considering a relatively short period of time.[4]

[4]Elhorst (2014) argues that it is often difficult to reject H_0^1 when using cross-sectional data or panel data over a relatively short period of time.

Table 2: Tests for model specification and instruments

Method:	ML			S2SLS/G2SLS			Extended S2SLS/G2SLS		
Model:	SLM	SDM	GNS	SLM	SDM	GNS	SLM	SDM	GNS
Hausman test: FE vs RE	1316.800	270.700	703.820						
(χ^2 statistic and p-value)	0.000	0.000	0.000						
H_0^1: *SDM vs SLM*		105.010	109.400		119.380	89.084		104.050	96.693
(χ^2 statistic and p-value)		0.000	0.000		0.000	0.000		0.000	0.000
H_0^2: *SDM vs SEM*		163.640			151.210			14.845	
(χ^2 statistic and p-value)		0.000			0.000			0.062	
$\widehat{\rho}$	0.310	0.273	-0.069	0.220	0.201	0.121	0.231	0.203	0.142
Wald test $\rho = 0$	144.080	103.030	1.909	44.993	34.373	7.748	47.095	33.375	9.608
(χ^2 statistic and p-value)	0.000	0.000	0.167	0.000	0.000	0.005	0.000	0.000	0.002
$\widehat{\lambda}$			0.685			0.012			0.022
Wald test $\lambda = 0$			247.530			1.700			1.645
(χ^2 statistic and p-value)			0.000			0.722			0.511
Hausman test of regressors exogeneity							60.300	10.390	10.390
(χ^2 statistic and p-value)							0.000	0.000	0.000
Test of instruments relevance									
$PM_{2.5}$							115.000	31.830	31.830
F statistic and p-value							0.000	0.000	0.000
Spatial lag of $PM_{2.5}$								232.160	232.160
F statistic and p-value								0.000	0.000
Sargan-Hansen test of instrument orthogonality							10.672	22.991	27.982
(χ^2 statistic and p-value)							0.223	0.083	0.083

Notes: The additional pre-determined variables (instruments) for $PM_{2.5}$ and its spatial lag are vehicles and its first and second spatial lag. The Extended S2SLS/G2SLS controls for the endogeneity of $PM_{2.5}$ (SLM) and its spatial lag (SDM and GNS model). The Hausman test of regressors exogeneity and the test of instruments relevance (power of instruments) are the same for the SDM and GNS model. All test where performed under the FE model, except for the Hausman test for the comparison between FE and RE model.

Now we turn our attention to the analysis of models using additional instruments (Extended S2SLS/G2SLS). The over-identifying restrictions tests gives a Hansen-Sargan test statistics equal to $\chi^2_2 = 10.672$, $\chi^2_1 = 22.991$ and $\chi^2_1 = 27.982$ for the SLM, SDM and GNS model, respectively. The p-value for the SLM model (p-value = 0.223) indicates that the orthogonality conditions hold strongly, whereas the results for the SDM and GNS model (p-value = 0.08) indicate that we cannot reject the null at the 5% level. Regarding the power of the additional pre-determined variables (cars, and its first and second order lag), we find that the joint F statistics from the first-stage are sufficiently large in both the SLM and SDM model to reject the null that the instruments are weak. Finally, the Hausman test of regressors exogeneity allows us to reject the null that $PM_{2.5}$ (in the SLM) and both $PM_{2.5}$ and $WPM_{2.5}$ (in the SDM) are not correlated with the error term, suggesting that both variables are indeed endogenous.

In summary, statistical tests cast doubt on the suitability of the GNS model and favor the SDM model. There is also strong evidence that the RE model's estimates are inconsistent. Finally, the tests carried out show that: (1) both $\mathrm{PM}_{2.5}$ emissions and their spatial lag are endogenous[5]; (2) the instruments used have sufficient power; and finally (3) there is moderate evidence that the instruments are valid.[6]

4.2 Spillover effects of PM2.5 emissions on ER visits

Given that our main interest is in spatial spillover effects, we report the direct, indirect and total effects of $\mathrm{PM}_{2.5}$ emissions on the number of admissions to ERs due to respiratory diseases.[7] The models' point-estimates are presented in Table A.1.

Table 3 shows the average cumulative direct, indirect and total effect of $\mathrm{PM}_{2.5}$ for the SLM and SDM models using the spatial panel FE estimator.[8] To show the consistency of the results, we also report the average effects using the ML, S2SLS and the extended S2SLS method. The standard errors in all the specifications and models are computed simulating the distribution of the direct and indirect effects using the estimated asymptotic variance-covariance matrix as proposed by LeSage, Pace (2009). In particular, we use 50,000 simulated parameter drawn from the multivariate normal distribution and compute Equations (5) and (7) using the following Leontief approximation: $(\mathbf{I}_{NT} - \rho(\mathbf{I}_T \otimes \mathbf{W}))^{-1} \approx \sum_{i=0}^{\infty}(\rho\mathbf{W})^i$.

It is important to recall that these average effects should be interpreted as the changes in ER visits that would take place in the long-run as all changes—due to the simultaneous changes in the $\mathrm{PM}_{2.5}$ emissions and ER visits—reach a new equilibrium (see Elhorst 2014).[9] These cumulative effects measure the average impact on all municipalities that arise from changes in the $\mathrm{PM}_{2.5}$ emissions in each spatial unit.

Considering either the ML or S2SLS estimates, the direct and indirect effects of $\mathrm{PM}_{2.5}$ emissions show the expected positive sign when the SLM or SDM model are fitted to our data. Both models show very similar direct effects, whereas the indirect effects are lower when the S2SLS method is used (columns 2 and 3). Another noticeable difference is that the average indirect effect is statistically insignificant when they are obtained from the SLM model.

When endogeneity of $\mathrm{PM}_{2.5}$ is taken into account (columns 5 and 6), the results reveal interesting findings. First, the indirect effects of the SDM model become significant at the 10% (p-value = 0.08). Second, the average effects are higher when both $\mathrm{PM}_{2.5}$ and its spatial lag are instrumentalized. For example, considering just the total (LATE) effects,

[5] However, this result depends on the validity of our instruments

[6] Since we fit an overidentified model, it is important to highlight that rejection of over-identification tests does not mean that instruments are invalid as all could be valid but give different compliers populations.

[7] The partial changes of the rest of the variables are available upon request

[8] All the estimations were carried out using the splm package in R (Millo, Piras 2012).

[9] As suggested by one of the reviewers, we also estimated a Dynamic SDM with FE assuming that $\mathrm{PM}_{2.5}$ is exogenous as in Elhorst (2014). The results (available upon request) show that the point-estimate for ρ is 0.379, which is higher than our estimates in A.1. The point-estimate for $\mathbf{W}\mathbf{y}_{t-1}$ is negative and significant, indicating that an increase in ER visits in neighboring municipalities in the previous year reduces ER visits in each municipality in the current year. The point-estimates for $\mathrm{PM}_{2.5}$ and $WPM_{2.5}$ are not significant, which casts doubt as to the exogeneity of air pollution.

Table 3: Effects of $PM_{2.5}$ on ER visits due to respiratory diseases

	ML		S2SLS		Extended S2SLS	
Effects	*SLM*	*SDM*	*SLM*	*SDM*	*SLM*	*SDM*
Direct	1.857	2.164	1.812	2.169	1.837	3.379
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Indirect	0.816	0.875	0.503	0.606	0.543	1.782
	(0.000)	(0.107)	(0.000)	(0.268)	(0.001)	(0.088)
Total	2.673	3.038	2.315	2.775	2.380	5.161
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: These results should be interpreted as the average impact of increasing $PM_{2.5}$ in one tonne on the number of ER visits due to respiratory diseases. The effects are computed using the estimated coefficients from a FE model. The Extended S2SLS method controls for the endogeneity of $PM_{2.5}$ (SLM) and its spatial lag (SDM). The estimated partial effects are computed using the 50,000 draws from the estimated asymptotic variance-covariance matrix of the coefficients as proposed by LeSage, Pace (2009). Simulated p-value in parenthesis.

the SDM estimates under the Extended S2SLS are 86% (5.161 vs 2.775) higher than the S2SLS estimates. Since the emissions are self-reported, this result suggests that a measurement-error problem might exist, implying that ignoring the endogeneity of air quality may lead to underestimating the total effects.

Considering the extended S2SLS estimates, the average estimates imply that increasing $PM_{2.5}$ emissions has a positive direct, indirect and total impact on the ER visits. The positive direct effect indicates that an increase in own-$PM_{2.5}$ emissions is associated with increased ER visits due to respiratory diseases. The magnitude of the effect also indicates that a one tonne increase in $PM_{2.5}$ emissions is associated with an increase of 3.4 ER visits, on average, considering the potential feedback effects. In other words, an increase of about 1000 tonnes (the average of emissions in the sample) would imply that ER visits would increase by about 3,400, on average. Since the coefficient for $PM_{2.5}$ is 3.359 and the direct effect is 3.379, the feedback effect amounts to 0.0204.

The indirect effects are found to be 0.543 (SLM) and 1.782 (SDM), respectively, accounting for approximately 23% and 35% of the total effect. This difference between the SLM and SDM can be explained by two factors. First, the SDM also includes local average effects. Second, the SLM has the restriction that the ratio between the indirect and direct effects is the same for every explanatory variables. Thus, the SLM might be unnecessarily rigid to model spillover effects adequately (Elhorst 2010). The positive indirect effects show that, on average, increasing $PM_{2.5}$ emissions in municipality i leads to higher ER visits not only in that municipality itself but also in that of its neighboring municipalities. Taking into consideration the SDM estimates, an increase of one thousand tonnes in $PM_{2.5}$ emissions in a municipality leads to an increase of 1,728 ER visits of all its neighboring municipalities due to respiratory diseases.

Summarizing, our results show that $PM_{2.5}$ emissions have a significant negative effect on public health. Furthermore, the direct, indirect and total effects of air pollution can be underestimated when endogeneity is not taken into account. Moreover, and unlike Chen et al. (2017), we found that the direct effects are larger than the indirect effects. Using the estimates from our preferred model, we find that about 65% of total PM2.5-related emergency room visits in Chile are due to $PM_{2.5}$ emissions generated in the same municipality, whereas the remaining 35% can be attributed to pollutants emitted in a different spatial unit.

4.3 Policy implications

What are the economic impacts of $PM_{2.5}$ emissions on ER health facilities? Although knowing the impacts of air quality on public health and its spillover effects is useful, it would also be interesting to translate these estimates into terms of monetary costs. Considering that the cost per person in ER services is approximately USD 55, our average estimates from the SDM model imply that an increase of one thousand tonnes in $PM_{2.5}$

emissions in all municipalities would produce an average annual cost of USD 283,855 (approximately 20% of the municipalities' average annual health expenditures), holding other factors constant, from which USD 98,010 (35%) corresponds to spatial spillover effects.

The previous figures represent the expected average effects on monetary costs and ER visits if all municipalities increased their $PM_{2.5}$ emissions by one tonne. However, policy makers might be interested in applying a certain policy to reduce $PM_{2.5}$ emissions in those municipalities with a greater potential impact. A potential solution would be to select the municipality with the greatest total impact, such that resources are spent in the most efficient way after considering both spatial spillover and feedback effects.

To find such municipalities, we compute the total impact from an observation (Kelejian et al. 2006, LeSage, Pace 2009, Anselin, Le Gallo 2006, Golgher, Voss 2016), which is computed as the sum across the jth column of $\mathbf{G}_p$. Each of these j-values represent the total impact over all municipalities' ER visits from increasing the $PM_{2.5}$ emissions by one tonne in the jth municipality.

Figure 5, shows the ranking of the first 20 municipalities with the highest total impact using the estimates from the SDM. Panel (a) and (b) shows the total impact from each municipality assuming that $PM_{2.5}$ emissions are exogenous and endogenous, respectively. The first important result is that the spillover effects emerging from each municipality are larger when we control for the endogeneity of $PM_{2.5}$ emissions, which is in line with the results from the previous section. For example, the effects emanating from San Ramón municipality is approximately 7.4: twice as high as the effects when $PM_{2.5}$ emissions are considered exogenous. This is because the effects depend on the strength of the spatial dependence measured by ρ, and the magnitude of the parameters γ and δ in Equation (1). These parameters are higher when controlled by the potential endogeneity of air pollution; especially γ and δ (see Table A.1).

Considering the cost per person in ER services, reducing $PM_{2.5}$ emissions in San Ramón municipality by about one thousand tonnes would imply an average annual cost reduction of about USD 407,000 considering both the effects in the same municipality and the spillover effects. This cost reduction would be USD 357,500 if the same policy with the same expected result in terms of emissions reduction is applied to the municipality of Cerrillos.

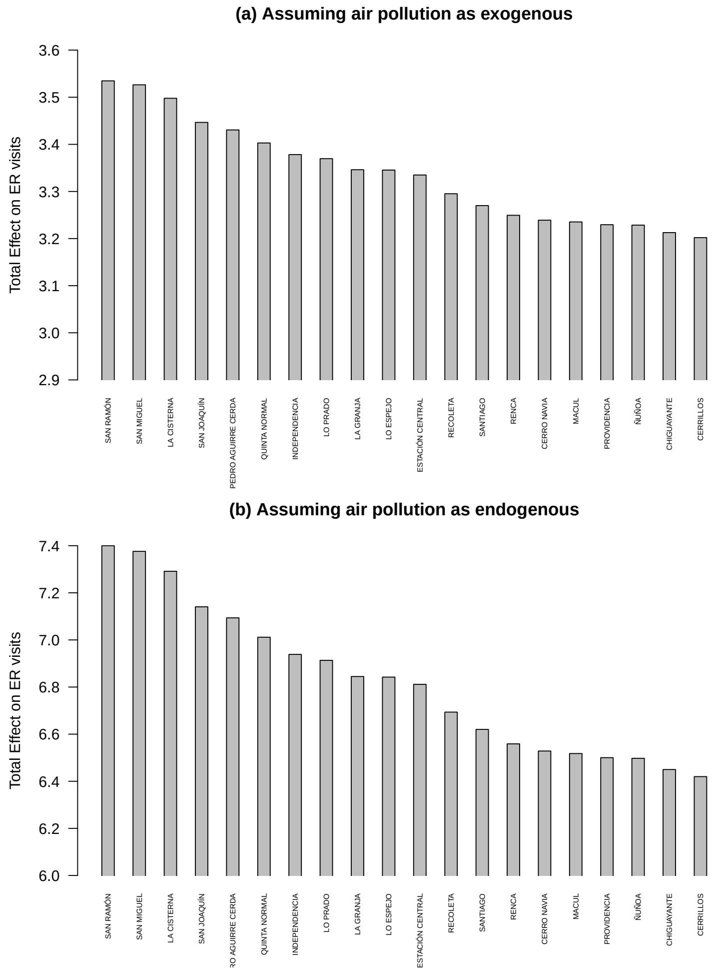
A surprising result is that the municipality with the highest total impact is not that with the highest level of emissions. In fact, all the municipalities in Figure 5 belong to the Metropolitan Region, which captures around 40% of the total Chilean population and is located in the center of the country. However, it should be noted that the magnitude of the spatial spillovers also depend on the position of the municipality in space and the degree of connectivity among municipalities represented by $\mathbf{W}$ (LeSage, Pace 2009).

5 Robustness checks

In this Section, we provide two additional robustness checks to previous results. First, we examine the sensitivity of the marginal impacts to variants of $\mathbf{W}$. Then, we analyze whether heterogeneous effects exist in the relationship between $PM_{2.5}$ and ER visits considering different age-groups. Finally,

Table 4 shows the direct, indirect and total effects using the following spatial weight matrices: (1) inverse-distance, (2) 10-nearest neighbors, and (3) 7-nearest neighbors. Column (4) provides a specification where $\mathbf{WX}$ and $\mathbf{Wy}$ are modeled using the squared-inverse distance (dense) matrix and 10-nearest neighbors (sparse) matrix, respectively. This latest specification is intended to limit the spatial scope of ER visits to municipalities nearby, while at the same time allowing PM2.5 to have more far-reaching local spatial effects. The estimates come from a SDM model with fixed effects using the extended S2SLS method.

The average direct effects are very close among the different spatial connectivity structures, ranging from 2.78 to 3.76, and highly statistically significant. These estimates are also similar to our preferred model (column 6 of Table 3). Thus, the marginal direct impacts are not overly sensitive to alternative weight matrices.



Notes: This graph shows the first 20 municipalities with the highest total impacts using the estimates from the SDM model. The impacts are computed as the sum across the jth column of $\mathbf{G}_p$

Figure 5: Municipalities that generates the higher total impacts.

On the other hand, the indirect effects are more sensitive to spatial structure. The magnitudes are greater when more dense matrices are considered. For example, the average indirect effects using the inverse-distance matrix is 3.074 and statistically significant at 5%, which is greater than the indirect effect using the squared inverse-distance matrix. This result is expected since the inverse matrix does not assume that the neighboring relationship declines faster than proportionally, so that it captures global effects more than local ones. The 10-nearest neighbors matrix produces an average indirect effect closer to the SDM model using the squared-inverse distance, but it is estimated with less precision. Finally, the spillover effects are reduced significantly when the 7-nearest neighbors matrix is assumed. These results agree with the LeSage, Pace (2014a)' results in the sense that the indirect effects for models considering more neighbors are generally higher and that the marginal direct impacts should not be too sensitive to the spatial connectivity imposed.

We also use the J-test proposed by Kelejian, Piras (2016) for panel models. It is important to emphasize that, although informative, the J-test was not developed in the context of spatial models with additional endogenous variables. The model under the H_0 is our SDM-extended S2SLS in Table 3, whereas the alternative models H_1 are those estimated in each column of Table 4. At the 5% level, the J test is not able to reject the model under the null since the Chi-squared variables are lower than the critical value 3.841. These results corroborate previous studies showing that matrices based on

Table 4: Sensitivity of partial effects to different spatial weight matrices

	Inverse distance	10-nearest neighbors	7-nearest neighbors	10-nearest neighbors & squared-inverse distance
Direct	3.222	3.239	3.761	2.777
	(0.000)	(0.000)	(0.000)	(0.000)
Indirect	3.074	1.607	0.479	2.321
	(0.010)	(0.110)	(0.649)	(0.008)
Total	6.295	4.846	4.239	5.098
	(0.000)	(0.000)	(0.000)	(0.000)
J-test (χ^2_1)	2.662	3.342	2.982	3.328

Notes: These results should be interpreted as the average impact of increasing $PM_{2.5}$ in one tonne on the number of ER visits due to respiratory diseases. The effects are computed using the estimated coefficients from a SDM model with fixed effects using the Extended S2SLS method. The estimated partial effects are computed using the 50,000 draws from the estimated asymptotic variance-covariance matrix of the coefficients as proposed by LeSage, Pace (2009). Simulated p-value in parenthesis.

Table 5: Effects of $PM_{2.5}$ on ER visits due to respiratory diseases for age-groups

	< 1 year		1-4 years		15-64 years		> 64 years	
Effects	*SLM*	*SDM*	*SLM*	*SDM*	*SLM*	*SDM*	*SLM*	*SDM*
Direct	0.210	0.455	0.488	1.015	0.594	0.924	0.136	0.241
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Indirect	0.089	-0.013	0.140	0.111	0.162	1.230	0.055	0.031
	(0.001)	(0.936)	(0.001)	(0.695)	(0.003)	(0.002)	(0.000)	(0.667)
Total	0.299	0.442	0.628	1.126	0.755	2.154	0.191	0.272
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: These results should be interpreted as the average impact of increasing $PM_{2.5}$ in one tonne on the number of ER visits due to respiratory diseases. The effects are computed using the estimated coefficients from a SDM-FE model using the Extended S2SLS method. The estimated partial effects are computed using the 50,000 draws from the estimated asymptotic variance-covariance matrix of the coefficients as proposed by LeSage, Pace (2009). Simulated p-value in parenthesis.

distance perform better than more restrictive spatial connectivity matrices when it comes to modeling the spillover effects of air pollution (see for example Cheng et al. 2017, Chen et al. 2017).

The literature shows that the effects of $PM_{2.5}$ on health are heterogeneous. For example, individuals with pre-existing lung or heart disease, as well as elderly people and children are particularly more vulnerable to air pollutants. To analyze the potential heterogeneous effect of $PM_{2.5}$ on ER visits, we re-estimate the SDM model by the extended S2SLS using the ER visits of: infants, children aged 1-4, adults aged 14-64 and adults age 64 and over as the dependent variable.

Looking at Table 5, we can observe that for all age groups, the total average effects are positive and highly significant: a one thousand tonne increase in $PM_{2.5}$ would increase ER visits of infants, children aged 1-4, adults aged 14-64 and adults age 64 and over by about 442, 1126, 2154 and 272, respectively, under the SDM model. These findings corroborate previous findings for Chile (Sanhueza et al. 2009, Cakmak et al. 2007, Ostro et al. 2008). With regards to the average indirect effects, substantial spillover effects are only found for adults aged 14-64 and children aged 1-4, but are only significant for the former. Therefore, the findings from column 6 of Table 3 are mainly driven by adults aged 14-64.[10]

[10] One of the reviewers suggested that our instruments (the number of vehicles and their spatial lag) might be correlated with variables such as car accidents and the level of urbanization. Given this concern, we re-estimated our Extended S2SLS model including the number of ER visits due to car accidents and its spatial lag as additional covariates, along with density (as a proxy for urbanization) and its spatial lag to control for urbanization. The results (available upon request) show that the point-estimates for ρ and $PM_2.5$ are reduced, whereas the estimate for $WPM_{2.5}$ increases and turns out significant.

6 Conclusion

$PM_{2.5}$ has been considered one of the most dangerous pollutants to human health due to its ability to penetrate deeply into lungs and bloodstream, causing various diseases related to the respiratory and circulatory system. Furthermore, the literature has shown that this pollutant has the ability to travel large geographical distances, producing negative effects on public health not only in the city where the pollution is emitted, but also in more distant cities. Not taking into consideration these spillover effects might lead to under- or overestimation of the effects of environmental or economic policies that are spatially blind.

In this paper, we contribute to the empirical literature on the effects of air pollution on public health by quantifying the direct and indirect effects of $PM_{2.5}$ emissions on emergency room visits due to respiratory disease in Chile. To do so, we use different spatial panel models and methods for 337 municipalities over the period 2009-2014. To give more accurate estimates of the effect of air quality on public health, we use an instrumental variables approach using the number of vehicles in each spatial unit as exogenous variability.

Our results provide evidence that the marginal partial effects are downward-biased when not controlling for the potential endogeneity of air pollution. This result supports both that emissions may be measured with error or that there may be omitted variables that are negatively correlated with municipal emissions. According to our results, the bias is higher for the average indirect effects than the direct effects: the average direct and indirect effects are respectively 1.5 and 3 times lower when $PM_{2.5}$ emissions are considered as exogenous. Assuming both that our instruments are valid and that a high proportion of municipalities are compliers, our results suggest that estimates based on traditional spatial panel data are likely to be misleading.

In addition, the magnitude of our preferred model indicates that increasing $PM_{2.5}$ emissions by one thousand tonnes would imply, on average, a total increase of approximately 5161 ER visits due to respiratory diseases, holding time-invariant idiosyncratic effects and other relevant factors constant. Of this total (LATE) change, 1782 ER visits are due to the spillover effects, which represents 35% of the total effect. The robustness checks show that the direct effects are relatively unvarying under different spatial weight specifications, whereas the indirect are higher and statistically significant when spatial connectivity is based on the inverse-distance between municipalities rather than limiting the spatial association to a certain number of neighbors.

When considering age-group specific ER visits, the estimated average impacts reveals that an increase of $PM_{2.5}$ emissions by one thousand tonnes would increase the ER visits of infants, children aged 1-4, adults aged 14-64 and adults age 64 and over by about 442, 1126, 2154 and 272, respectively. However, substantial spillover effects are only found for adults aged 14-64 and children aged 1-4.

Although the indirect effects are proportionally lower than the direct effects, they are still economically significant. For example, the average indirect effects of an increase of one thousand tonnes of $PM_{2.5}$ emissions yield to an increase of USD 98,010 of annual costs for ER health facilities, whereas the total costs (considering indirect and direct effects) amounts to USD 283,855. Furthermore, we show that policies that aim to reduce $PM_{2.5}$ emissions would have a greater impact (considering both direct and spillover effects) if they are applied to municipalities located in the Metropolitan Region. For example, considering the municipality that generates the highest total effects (San Ramón), reducing the $PM_{2.5}$ emissions by one thousand tonnes would imply an average annual cost reduction of about USD 407,000.

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A Appendix:

Table A.1: Spatial panel models with fixed effects

	ML		S2SLS		Extended S2SLS		ML		S2SLS		Extended S2SLS	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
$PM_{2.5}$	1.844***	(0.126)	1.806***	(0.140)	1.830***	(0.328)	2.151***	(0.138)	2.162***	(0.153)	3.359***	(0.462)
Poverty	89.856**	(36.168)	83.115***	(40.000)	82.855**	(42.960)	212.260***	(52.503)	215.940***	(58.093)	235.350***	(59.547)
City size	17.638***	(0.427)	18.054***	(0.469)	17.991***	(0.515)	17.121***	(0.432)	17.304***	(0.473)	16.250***	(0.641)
Investment on health	63.534	(122.840)	83.568	(135.655)	81.540	(135.620)	36.774	(120.370)	45.199	(133.020)	54.047	(136.120)
Investment on medical HR	-62.744*	(32.828)	-74.481***	(36.374)	-72.926***	(36.446)	-71.040**	(33.215)	-75.272***	(36.742)	-60.904	(37.722)
Number of ambulances	1537.977***	(176.516)	1569.781***	(195.263)	1570.723***	(207.288)	1115.400***	(179.460)	1107.700***	(198.500)	1249.900***	(211.470)
Number of health facilities	1129.107***	(224.754)	1216.661***	(249.924)	1204.440***	(251.475)	1276.200***	(224.940)	1322.900***	(249.540)	1141.500***	(268.150)
Number of medical laboratories	381.006	(559.349)	299.931	(618.426)	296.874	(645.975)	879.900	(553.630)	876.190	(612.230)	390.380	(636.520)
Year 2010	6316.011***	(883.623)	6306.715***	(976.726)	6308.921***	(976.008)	6876.500***	(873.340)	6837.900***	(966.000)	7006.600***	(988.270)
Year 2011	6361.261***	(912.359)	6494.853***	(1009.426)	6478.681***	(1008.575)	2424.900*	(1241.000)	2432.000**	(1372.500)	3446.100***	(1431.600)
Year 2012	7678.957***	(911.779)	7804.514***	(1008.574)	7788.076***	(1008.032)	3374.600***	(1222.800)	3400.100***	(1352.500)	4072.700***	(1400.200)
Year 2013	7828.567***	(913.128)	7932.988***	(1009.886)	7916.302***	(1011.228)	3349.800***	(1254.700)	3341.700***	(1387.600)	3911.900***	(1429.200)
Year 2014	6586.191***	(920.687)	6721.775***	(1018.455)	6704.799***	(1017.701)	1247.800	(1307.600)	1269.200	(1446.200)	2096.800	(1497.800)
Spatial Lags												
$PM_{2.5}$							0.059	(0.402)	0.056	(0.443)	0.752	(0.804)
Poverty							-113.130	(90.598)	-119.340	(100.240)	-271.680***	(110.790)
City size							3.233**	(1.649)	4.166***	(1.849)	5.021***	(2.177)
Investment on health investment							-196.900	(588.950)	-180.000	(651.400)	-210.870	(669.560)
Investment on medical HR							215.170**	(109.040)	177.290	(121.400)	165.290	(124.260)
Number of ambulances							2813.900***	(632.330)	2821.100***	(699.340)	3442.400***	(834.700)
Number of health facilities							-3933.300***	(796.370)	-4012.700***	(881.190)	-3236.400***	(916.610)
Number of medical laboratories							-8487.200***	(1996.900)	-8653.000***	(2209.900)	-13059.000***	(2478.200)
ρ	0.310***	(0.026)	0.220***	(0.033)	0.231***	(0.034)	0.273***	(0.027)	0.201***	(0.034)	0.203***	(0.032)

Notes: Robust standard errors in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$.