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The Demand for Air Quality: A Case study in Bogotá, Colombia

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Abstract

Using a (second stage) hedonic housing model, this paper identifies an inverse demand function for air quality in Bogota, the fourth most polluted city in Latin America (annual average of PM10 52 mg/m^3). We use precipitation and distance to monitoring stations as instruments for pollution. We found that the monthly benefits of compliance with the U.S Environmental Pollution Agency standard (50 mg/m^3 – annual average), and the far more stringent World Health Organization standard (20 mg/m^3 – annual average) are U$7.12 and U$72.91per household respectively. Accordingly, these values represent about 1% and 8% of the average household income.

Key words: air pollution, hedonic models, housing markets

JEL: Q51 Q53 R31

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Demanda por Calidad Ambiental: Un Estudio de Caso en Bogotá, Colombia

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Resumen

A partir de un modelo hedónico de segunda etapa, este documento identifica una función inversa de demanda por calidad ambiental en Bogotá, la cuarta ciudad más contaminada de Latinoamérica (promedio anual de PM10 de 52 mg/m^3). Para las estimaciones usamos precipitación y distancia a las redes de monitoreo como instrumentos de contaminación. Encontramos que los beneficios mensuales promedio por hogar debidos al cumplimiento de los estándares de contaminación de la Agencia Ambiental de Estados Unidos (50 mg/m^3 – promedio anual) y de la Organización Mundial de la Salud (20 mg/m^3 – promedio anual) son de U$7.12 y U$72.91 respectivamente. Estos valores corresponden al 1% y 8% del ingreso promedio mensual de los hogares.

Palabras claves: contaminación ambiental, modelos hedónicos, mercados de vivienda.

JEL: Q51 Q53 R31

I. INTRODUCTION

According to a recent report from the World Health Organization (WHO), air quality in most cities that monitor ambient air pollution fail to meet WHO standards for safe levels. Almost half of the monitored urban population worldwide is exposed to air pollution levels at least 2.5 higher than those recommended by WHO. Further, the Organization has estimated that ambient (outdoor) air pollution caused about 3.7 million deaths of people under 60 in 2012.

Data collected by the WHO also suggests that the burden of urban air pollution is concentrated mainly in cities from middle and low-income countries (WHO, 2014). In Latin America, for example, Mexico City, Santiago, Lima and Bogotá rank as highly polluted cities. In particular, high concentrations of particulate matter less than 10 micrometers (PM10) remain an issue of public concern in the latter. Some authors have discussed that air pollution problems originate mainly from the city´s rapid economic growth that entailed a greater demand for energy and fossil fuels (Gaitán, Cancino, & Behrentz, 2007; Uribe, 2005). The local environmental authority argues that urban air pollution is mainly caused by industry, mining, illegal burns, poor condition of roads and the increasing stock of public and private vehicles, which amounted to near a million by year 2011 (SDA, 2011). In a diagnostic of Bogota´s air quality based on the analysis of ten years´ readings from Bogotá´s monitoring network for several pollutants, authors showed that most stations recorded admissible levels for Carbon Monoxide (CO), Sulfur (SO2) and Nitrogen Dioxides (NO2), and Ozone (O3). However, as judged by the local pollutants' standards, readings for Particulate Matter (PM10) exceeded the annual local air quality standard of 50 micrograms per cubic meter, especially in Puente Aranda, the city´s main industrial area (Gaitan et al, 2007).

The observed levels of PM10 in the city has called the attention of local environmental and health authorities due to the likely detrimental effects of pollution on human wellbeing. The epidemiological and economic literature have extensively documented the effects of air quality on two wellbeing areas: the first bulk of the literature has examined the effect of air pollution on human health, focusing on both the relationship between pollution levels and hospital admissions´ rates due to Acute Respiratory Infection. This literature has also expanded to carry out economic valuations of improved air quality due to reductions in morbidity and mortality rates. Several studies in these areas have been conducted in Bogotá, finding a positive relationship between PM10 concentrations and the number of medical visits due to acute respiratory infections, especially among children and the elderly (Arciniegas et al, 2006; Montealegre, 1993; Urdaneta, 1999; Lozano, 2004). Local Studies estimating economic benefits from reducing morbidity and mortality rates focused on willingness to pay measures for air pollution reductions based on health production functions or contingent valuation studies (Rodríguez, 1999; Castillo, 2010; Larsen, 2004). Nonetheless, economic benefits (costs) from improved (degraded) air quality conditions are not limited to health; poor air quality may also affect individual preferences for clean air, buildings by damaging construction materials, and the livelihood of individuals in polluted neighborhoods. Thus, the second bulk of literature relating the effects of air quality on wellbeing has documented welfare benefits from property value capitalizations that arise from better air quality conditions (Chattopadhyay,1999; Palmquist,1983; Smith & Huang 1993). Most studies are based on the hedonic model framework (Rosen, 1974) using the so-called First Stage (FS) estimation where residential prices are a function of structural characteristics and neighborhood and environmental amenities surrounding the housing unit location. The research here reported belongs to this bulk of the literature.

Previous hedonic applications in Bogotá have found a consistent negative correlation between air quality and housing prices from first stage models (Carriazo et al., 2013; Morales and Arias, 2005). Although these studies are useful to understand how air quality improvements capitalize into property values, and are informative as an exploratory tool to determine implicit prices for marginal pollution reductions, they are not necessarily suitable to determine welfare effects from non-marginal changes in air quality. Calculating welfare effects from non-marginal changes is important because the local environmental agency has done some efforts to curve pollution levels, mostly based on command and control policies such as the programmed reduction of sulfur on diesel fuels. However, very little is known on the potential welfare effects of air quality improvements. Neither welfare nor cost benefit analysis has been done to quantify these potential welfare effects in Bogotá.

Our study contributes to welfare analysis of air quality improvements in Bogotá by identifying a demand function for air quality from a Second Stage (SS) hedonic application. First Stage welfare estimations are not suitable for air quality welfare measures because air quality changes are non-marginal. Estimating the demand function allow us to improve the reliability of these measures. The SS of the hedonic method combines air pollution quantities and the implicit prices of pollution, derived from the First Stage hedonic model, to identify a demand function for air quality.

Second Stage estimations of the hedonic model are scarce in the non-market valuation literature due in part to challenging data requirements and estimation complexities regarding two specification issues: identification and endogeneity. To our knowledge, this study is the first application of the hedonic model in Bogotá using a SS model proposing a market segmentation strategy and an Instrumental Variables (IV) estimation for solving these specification issues. For identification, we propose separate real-estate markets within an urban area based on three types of properties: namely, apartments, houses, and houses belonging to condominiums. Analysis of welfare effects related to changes in ambient quality based on a demand function identified from a second stage hedonic model could be an important tool for environmental policy decision makers: first, by identifying a demand function for air quality, consumer surplus measures due to the compliance of emission standards can be calculated, and second, social benefits can be incorporated into cost-benefit analyses of environmental investments and pollution control policies. Our final analysis includes counterfactual scenarios to calculate potential welfare effects derived from pollution control policies aimed to comply with The U.S Environmental Pollution Agency (EPA) standard, and the World Health Organization (WHO) standard. Estimation of Total Willingness to Pay (TWTP) for particulate matter reductions suggest average per household monthly benefits of U$7.12 for the compliance of the EPA´s standard and of U$72.91 for the compliance of the WHO standard.

The remaining of this paper is organized as follows: Section II discusses First and Second Stage hedonic models applied to air quality. Section III presents the proposed econometric model to identify the air quality demand and proposed welfare measures. Section IV describes the study area and the data used for estimations. Section V presents empirical results and Section VI includes a final discussion.

II. HEDONIC PRICING MODELS AND AIR QUALITY

This research uses Rosen´s (1974) hedonic pricing theoretical framework to identify the demand for air quality in Bogotá. In the so-called First Stage of the model the well-known Hedonic Price Function (HPF) is estimated. Theoretically, this function gives us information on the equilibrium points where the marginal bid a consumer places for a characteristic (i.e number of bathrooms, rooms) of a composite good such as housing, equals the marginal price for that characteristic. Rosen showed that at the optimum, the marginal bid, also known as the implicit price of the characteristic, equals the marginal rate of substitution between the characteristic and a Hicksian bundle of goods. In equilibrium, the implicit price of the housing characteristic also equals the suppliers´ marginal cost. The hedonic price function gives the locus of equilibrium points where a consumer and a supplier of a dwelling are willing to pay and accept, respectively, the same amount of money for each of the housing characteristics. The theoretical hedonic equilibrium condition describing first stage implicit prices and the so-called second stage demand relationship between implicit prices and the level of a characteristic has been thoroughly addressed in the economic literature (Rosen, 1974; Freeman, 1979; Taylor, 2003; Palmquist, 2005). In the following subsections we review some FS and SS hedonic pricing models for air quality.

First Stage Studies

Most empirical hedonic applications exploring the relationship between property values and environmental quality to estimate marginal implicit prices for air quality are based on FS hedonic models, where the hedonic price function is empirically estimated by regressing housing prices as a function of its characteristics, including the environmental quality of the surrounding area. The estimated derivative of the price function with respect to a characteristic (i.e neighboring air pollution levels) is usually interpreted as its implicit price.

Even before Rosen´s (1974) seminal work where he developed the theoretical framework of the hedonic equilibrium, the earliest application that examined the relationship between property values and air pollution, to our knowledge, is Ridker and Henning (1967). This early classic work has inspired a myriad of studies dealing with methodological aspects of empirical estimations to identify marginal implicit prices for air quality. Extensive reviews of early works reporting marginal implicit prices for air pollution are found in Smith and Huang (1993, 1995), Boyle and Kiel (2001), and Freeman (2003).

More recent applications valuing accrued implicit prices from air quality include Kim et al. (2003), Chay and Greenstone (2005), Bayer et al (2006), Anselin and Le Gallo (2006), Neill et al (2007), Anselin and Lozano-Gracia (2008), Vasquez et al (2011), Minguez et al. (2012), Carriazo et al. (2013). All this studies have reported implicit prices for air quality addressing different methodological issues: Kim et al explored the possible spatial dependence in the hedonic price function and specified a spatial hedonic model showing the validity of a spatial lag specification for the housing market in Seoul. Their results suggest that the marginal willingness to pay for a permanent improvement of 4% in air quality is about 1.43% of the mean house value. Chay and Greenstone focuses in two identification problems: 1) potential endogeneity of the pollution variable due to correlation between pollution and unmeasured neighborhood characteristics and 2) self-selection based on preferences. The authors found evidence on the capitalization of air quality into housing values, estimating that a unit ($\mu g/m^3$) reduction of Total Suspended Particles increases mean housing values between 0.2 and 0.4%. Bayer et al (2006) also explores possible endogeneity of the pollution variable and proposes and IV approach, using the contribution of distant sources to local air pollution as an instrument for air quality. These authors found an elasticity for the implicit price of air quality of 0.34-0.42.

Anselin et al (2006) explore different interpolation techniques for the ozone pollution variable in the South Coast Quality Management District of Southern California. They suggest that Kriging outperforms other methods of interpolation such as Thiessen polygons, inverse distance weighting, and splines. Using similar data, Anselin et al (2008), evaluate the sensitivity of marginal willingness to pay estimates to another source of the endogeneity of the pollution variable; they argue that interpolated values of pollution may result in a prediction error that may be correlated to the overall model disturbance leading to an “error in variables” problem. To correct this endogeneity they propose an explicit two-stage spatial lag model, including a polynomial spatial trend of for the coordinates of housing locations. Minguez et al (2012) compare subjective and objective measures of pollution in a hedonic model application in Madrid. For comparisons they use as a reference a spatial

Durbin model. They found that subjective measures of pollution outperformed the objective indicator based on the expected sign of the coefficients and significance of the parameter, finding positive and insignificant parameter for the objective measure. Neil et al (2007) compare the performance of traditional OLS method with the maximum likelihood spatial estimator (MLE). They found that MLE coefficients for PM10 tend to be higher by 0.4% to 0.9% than the OLS coefficients suggesting some superiority of MLE over the OLS with respect to predictive performance. Carriazo et al (2013) propose a stochastic frontier model to mitigate possible omitted variable bias in hedonic estimations of air quality. They found that in the presence of omitted variables, OLS estimations tend to overestimate the pollution variable's parameter. The OLS estimated price elasticity for PM10 is 59% larger than the estimate from the Hedonic Frontier Model. Vásquez et al (2011) examine price compensating differentials in the housing and labor markets of Chile originated by air pollution and crime. These authors asses the sensitivity of estimated parameters in the presence of i) selection bias ii) the simultaneity between labor and housing market decisions iii) the presence of endogenous amenities and iv) clustered data of crime and pollution finding important effects on parameter estimates' magnitudes and their variance in the presence of these methodological issues. They found marginal implicit prices for the air pollution, PM10, ranging from U$3 to U$6 depending on the estimation method.

Even though First Stage (FS) hedonic applications are useful to recover the implicit prices of non-marketable characteristics, they are of limited applicability to calculate welfare benefits for non- marginal changes because FS only recovers a point of the demand curve of each agent in the market. The Second Stage hedonic model solves in part this problem by identifying a demand function (willingness to pay function) that allows the monetary valuation of non-marginal changes in air quality.

Second Stage Studies

Second Stage Hedonic models are less common in the empirical literature that use the hedonic framework to value benefits from environmental quality improvements. Kuminoff and Pope (2012) claim that Rosen's second stage entails methodological challenges due to the identification and endogeneity problems in estimations, in addition to the incredibly high demand on data. These complications explain, in part, the very few empirical applications of this stage of the model. To our knowledge, with the exception of Harrison and Rubinfeld (1978) who identified a demand for NOx in Boston, most of the hedonic studies conducted, at least until 1993, estimated only the relationship between housing prices and air quality but not completed Rosen´s second stage (Smith & Huang, 1993). This stage involves the estimation of the demand for well-differentiated characteristics using hedonic prices (Taylor, 2003). The Second Stage of the HPM recovers the demand for a given characteristic by combining implicit prices, derived from the FS Hedonic Price Function (HPF), with socio-economic data that could reflect consumers' preferences for their houses. Particularly, with this estimations welfare measures could be derived, even by defining the utility parameters for a given utility function or by using the demand function for deriving a lower bound of total benefits to changes of a specific attribute.

Posterior to Smith and Huang (1993) thorough review of hedonic applications for air quality, we found that second stage approach is very limited in the literature. In fact, most examples of this approach are not very recent, some of them focused on structural characteristics such as number of available bathrooms (Palmquist, 1984), and others on the physical condition of a neighborhood (Bartik, 1987). Few studies have explored the second stage estimation for environmental amenities; Boyle, Poor and Taylor (1999) use a linear, Semilog and Cobb Douglass structure for their estimation of an inverse demand for water clarity for properties nearby a lake in Maine, pointing out linear, semilog and linear Cobb-Douglas models as preferred.

In practice, identification methods of the second stage consist of the estimation of the hedonic price function (first stage) for several markets and the construction of pooled data base of implicit prices from the first stage regressions from several markets to estimate an inverse demand function (Palmquist 1984, Bartik, 1987). Definition of a housing submarket is not trivial and in many cases its implication on hedonic estimations has been ignored. Using a single metropolitan market to identify parameters of the Hedonic Price Function when in reality there are several submarkets may lead to erroneous parameter estimates (Palmquist, 2005; Goodman y Thibodeau, 2003)

We identified just two post-Smith and Huang (1993) studies applying the second stage approach for estimating welfare benefits from air quality improvements, using two different methods for solving the identification issue (Chattopahyay, 1999; Zabel and Kiel, 2000);

within the first approach, the demand is identified essentially by regressing the marginal implicit price from first stage hedonic function as a function of the marginal rate of substitution, the theoretical equilibrium condition, that results from a predefined functional form of the hedonic price function and of the utility function. The second approach identifies the demand function by using information from different markets, as it is suggested by Taylor (2003). Traditionally, market segments in SS hedonic applications are defined by temporal variation or spatial variation. Implicitly, this approach assumes that consumers with similar socio economic characteristics have the same preferences, independently of the housing submarket where they belong (Palmquist, 2005). Taylor (2003) reports that the number of housing markets that have been used for identification vary from two to thirteen, highlighting that, even though there is not a rule of thumb for the number of submarkets to be used in estimations, it is important that the hedonic function varies among markets.

Chattopahyay (1999) uses the theoretical equilibrium condition to estimate welfare changes from air quality improvements in the Chicago housing market. The author uses PM10 and sulfur dioxide as measures for air quality. Their estimates of marginal willingness to pay for PM10 ranges from $268 to $363 in dollars of 1989-90. Non-marginal benefits from a 25% reduction of PM10 levels ranged from $2,037 to $3,350. For the case of sulfur pollution, the mean marginal willingness to pay ranged from $878 to $1036 while non-marginal benefits from a 25% reduction of sulfur pollution ranged from $1353 to $1925 in dollars of 1989-90.

Zabel and Kiel (2000) estimate the demand for air quality using the American Housing Survey Chicago, Denver, Philadelphia, and Washington D.C. Second stage estimation assumes each city is a submarket, exploiting temporal variation of housing prices and pollution levels. Results from the demand for air quality are used to estimate non-marginal benefits from increasing air quality to meet the U.S Ambient Air Quality Standards. They found benefits ranging from $171 million in Denver to $953 million in Philadelphia.

In summary, our literature survey suggests that FS hedonic model still remains as the most prevalent empirical estimation of the hedonic model. This body of literature focuses on important methodological issues, being those related to spatial structure of the hedonic equation the most recent research. The attempts to estimate SS demand equations for air quality still is scant. This is probably explained in part by the extremely detailed data requirements to carry out SS estimations. We did not find, to our knowledge, recent works estimating Second Stage models for air quality in the last ten years. Although, implicit marginal prices have been estimated in emerging economies like Colombia or Chile, we did not find, studies implementing SS hedonic models to value non marginal benefits from air quality improvements in the context of emergent economies. Our research intends to fill these gaps in the literature.

III. ECONOMETRIC MODEL

The econometric model to measure the willingness to pay for air quality improvements lies on the theoretical assumption that households consider structural characteristics, neighboring attributes and pollution levels in their housing choices, as it is extensively detailed in the economic literature (Rosen, 1974; Freeman, 1974; Taylor, 2003; Palmquist, 2005).

Let Z a vector of housing characteristics $(z_1, z_2, \ldots, z_n)$, including housing characteristics, neighborhood attributes, and air pollution concentrations. Let X a Hicksian bundle of other goods and Y household monetary income. The theoretical model assumes that households maximize $U(Z, X)$ subject to the budget constraint $X + P(Z) = Y$. $P(Z)$ is the price of a house with attributes Z, described by the housing HPF. In the optimum, a household would choose a level of attribute so that $\frac{\partial P}{\partial Z} = \frac{\partial U/\partial Z}{\partial U/\partial X}$. In this framework, the optimal condition states that a household´s willingness to pay for say a marginal change in air pollution equals to the marginal rate of substitution between air quality and other goods. To recover this willingness to pay for the marginal change in air pollution we can calculate, in a FS, the derivative of the hedonic price equation with respect to air pollution. When this derivative is calculated separately for each household, this derivative is an estimate of the marginal willingness to pay for an improvement in air quality. In our case, where a multiple market approach is used for solving the identification issue, the hedonic price equation P(Z) takes the general form:

$$\ln(P_{ij}) = \beta_{0j} + \beta'_{Zj} \cdot Z_{ij} + \beta'_{Kj} \cdot A_{ij} + \beta_j PM10_{ij} + u_{ij} \quad \forall\, j \in J \qquad (1)$$

Where, P is the price of housing i (i=1, 2, …, n) belonging to submarket j (j={1,2,3}), Z_{ij}=($z_{1ij}, z_{2ij}, \dots, z_{Z_j ij}$) is a vector of z_j structural characteristics of housing for each dwelling i in submarket j. A_{ij}=($a_{1ij}, a_{2ij}, \dots, a_{K_j ij}$) is the vector of k_j neighborhood attributes for house i in submarket j, and a semi-log (log-lin) relation is assumed. Particulate matter less than 10 μg/m^3 (PM10) is the variable we use as a measure for environmental quality, our variable of interest in this research. $\beta_0, \beta_Z', \beta_K', \beta_j$ are parameters to be estimated for each market j and u_{ij} a random error $\sim N(0, \sigma^2{}_j)$. Assuming a semi-log (log-lin) specification allows us to capture non linearities in prices. This functional form also has been used widely in FS hedonic price applications. For this functional form, the marginal willingness to pay for air quality in each market j, is given by:

$$\frac{\partial P_{ij}}{\partial PM10_{\text{ij}}} = -\hat{\beta}_j P_{ij} = W(PM10_{\text{ij}}) \qquad (2)$$

Where $W(PM10_i)$ denotes the marginal willingness to pay for air quality or its implicit price, of agent i in submarket j.

The FS hedonic model thus encompasses the estimation of equation (1) and the calculation of (2) for each housing market. For estimations, we assume that the city is not a unique housing market but rather composed by three submarkets. We propose housing market segmentation in Bogotá based essentially on the type of properties, namely houses, houses in condominiums and apartments.

Market segmentation is an important feature of our model because it allows for variation in price schedules that is needed for the identification of the demand function for air quality. Most research uses an urban area as a single market without discussing its consequences (i.e. (Palmquist, 1984); (Bartik, 1987); (Chattopadhyay, 1999); (Zabel & Kiel, 2000); (Boyle, Poor, & Taylor, 1999)). It is a common practice also to merge data from different time periods. Some authors have also considered that a market can be defined by year, so the same city in x years are considered x different markets (i.e. Zabel & Kiel, 2000). This may be a particular common strategy on those works were authors expect to estimate the HPM Second Stage. In the absence of data for different time periods, we propose market segmentation based on the type of properties discussed above, thus separating markets by a structural attribute rather than by time. Intuitively, this segmentation makes sense because each type of property offers different amenities for different consumers; for example, condos are likely to have better security conditions than detached houses, or better quality of nearby green areas, whereas apartments may provide nicer views and higher security that detached homes and condos. Households living in each type of dwelling are revealing preferences for housing attributes. A similar strategy for market segmentation was used by Poudyal et al (2009), who segmented the housing market of the City of Roanoke (VA) for estimating the demand for urban recreational parks.

In the results session, we discuss Chow tests to validate the different structure of the proposed submarkets. To externally validate this housing market segmentation, we also performed a cluster analysis for cadastral data containing residential uses in both commonhold property such as apartments and houses in condos, and non-commonhold properties (houses), to examine if cluster analysis shaded some light on housing submarkets within the city. Results from this analysis are discussed in the following section. Because of clustering in prices and pollution at the census tract level, we correct for correlation at the interior of each census tract, relaxing the assumption of independent observations by estimating cluster-robust standard errors (Rogers, 1993).

However, FS, as it was mentioned before, is not suitable to determine each household´s willingness to pay for non-marginal improvements of air quality. To do so, we need to estimate in a second stage the relationship between air pollution levels PM10 and the marginal implicit price $W(PM10)$ for this characteristic. Thus the willingness to pay equation is a uncompensated inverse demand function for air quality estimated by regressing households' marginal implicit prices in (2) on air pollution levels, household's socio economic characteristics and other demand shifters such as household income. Thus, our specification for the willingness to pay function for air quality (inverse demand) is given by

$$W\left(PM10_{\mathrm{ij}}, Y_{ij}, S_{ij}\right) = \beta_0 + \beta_1 PM10_{ij} + \beta_2 Y_{ij} + \beta_{\mathrm{S}}' \mathrm{S}_{\mathrm{ij}} + \varepsilon_{ij} \qquad (3)$$

The left hand side of equation (3) is the implicit price for air quality from the first stage hedonic price function, PM10 is our proxy for air quality and Y is household income and S is a vector of S socio economic characteristics of the households in each defined submarket. Subindex i=1…n refers to household and j=1,2,3 refers to housing submarket. OLS estimation of (3) may be inconsistent due to the problem of endogeneity associated with the simultaneous determination of the marginal implicit price and the level of air quality. Thus, the level of pollution is correlated with the error term in the second stage OLS estimation of the inverse demand equation (3). We propose a 2SLS to correct for this endogeneity and instrument PM10, using precipitation and distance to monitoring stations as instruments. Haussmann tests for suitability of instruments are presented in the results session below.

IV. STUDY AREA AND DATA

Our study area for the estimation of the demand for air quality is Bogotá D.C. In 2013 Bogotá had 7,877,041 people (Secretaria Distrital de Planeación, 2013) in its urban area of 307.36 km^2. Its production represents almost 25.8% of 2013 national GDP[1] and during the last ten years its economy has growth in average 4.65% per year.

Renting and Socio-Economic Data

Data used for estimations come mainly from Bogotá's Multiple Purpose Survey of 2011 (EMB, 2011), which randomly sampled the household population. Jointly, The National Statistic Department (*Departamento Administrativo Nacional de Estadística* – DANE) and the District Planning Office (*Secretaría Distrital de Planeación* – SDP) developed this survey to describe the socio economic conditions of households in the city, and to learn about households' decisions and their lifestyles. Table 7 to 9 describe the most important socio demographic variables. Head of households (HH) are mainly men (61.6%) 48 years old in average. More than half of HH are married or live with their partner (59.65%). Average family size is 3.38 people and has in average 1.29 sons. 64.8% of HH reported not to have technical or professional studies, almost 71.7% are employed and the average monthly income per household is of COP$ 1,664,386 (US$ 901.14[2]).

EMB also reports information on dwelling´s structural characteristics, as well as the most relevant neighborhood characteristics (see Table 10 and Table 11). Apartments are the most common type of dwelling, with almost 62.4% of the market, followed by no-condo houses

[1] Constant prices of 2005. Values reported by the National Statistic Department (DANE)
[2] 2011 mean exchange rate was COP$ 1,846.97 for each US$.

(31.6%) and condo houses (5.9%). In the average, each house has 3.63 rooms and 1.59 bathrooms, in an area of almost 135 m^2. 41.09% of the residences in Bogotá has a garage, 40.84% has a garden and 29.49% easy access to green areas. Regarding tenure, most households are owners, only 38.65% are renters. Average rent is COP$ 464,159.5 per month (US$ 251.3), which represents 35.72% of the Head of Household income and 22.33% of the Household aggregated income. The survey asked owners how much they would pay for rent for their own house. Average hypothetical rent value was COP$ 730,643.6 per month (US$ 395.59), 38.54% and 23% of HH and all household members´ income respectively.

Urban Amenities and Crime

The EMB information is the main source of data for this study, but several sources were used to complete, as much as possible, information on dwelling´s characteristics, and neighborhoods´ amenities, including air quality data. Bogotá has 19 urban localities, divided in 5,145 neighborhoods, each of them with 8.25 blocks on average. The EMB survey information was available at the block level, which allowed us to geo-reference and to join data with block level cadastral data. We included from the latter mean constructed area, mean Cadastral Score, an indicator of construction quality, among other variables (see Table 12). Our data also included geo-referenced amenities such as schools, clinics and hospitals, and touristic attractions, which we use to calculate euclidean distances from housing to the closest amenity. Crime data collected by the police for the period 2000-2013 and shared with us under confidentiality agreement through the Secretary of Government of Bogotá was included; we used ESRI geocoder to identify the number of homicides and the number of home, cars or people burglaries at the Thiessen polygon level where the house belongs.

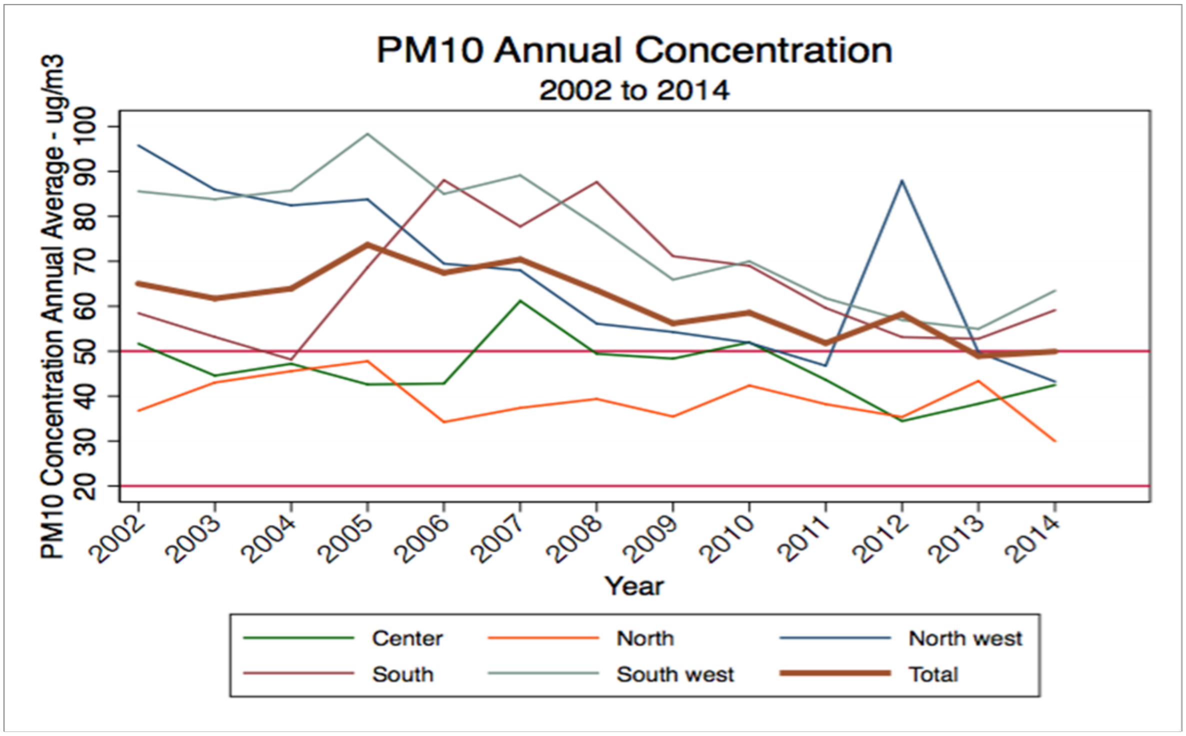
Air Quality

Bogotá's air quality, our variable of interest, has been one of the main public concerns and one of the most important issues on the city's environmental agenda. The current maximum permissible limit for Bogota immission was established by Resolution 610 of 2010 from the Ministry of the Environment, Housing and Territorial Development (the environmental national authority). The local environmental agency-SDA (2011) states that Colombia determines their standards based on the international leading standards: the World health Organization (WHO), the United States Environmental Protection Agency (EPA) and the World Bank´s proposed limits. Table 6 in the appendix presents a comparison between the international standards and Bogotá's defined limits.

Particularly, the high levels of PM10 during several years make particulate matter the main contaminant and the focus of the most important air quality measures. Gaitán et al. (2007) diagnose air quality based on data provided by Bogotá's Air Quality Monitoring Network (*Red de Monitoreo de Calidad del Aire* – RMCAB) between 1997 and 2007. The authors claim that Bogotá does not have pollution problems of SO_2 (annual standard for the city : 26ppb), NO_2 (annual standard for the city: 53ppb), CO (standard 8 hours for the city: 9611ppb) and O_3 (time standard for the city: 87ppb). PM10 is a criteria pollutant that exceeds the air quality city standards (annual standard for the city: 55µg/m^3), particularly in Bogotá's main industrial area (the locality of Puente Aranda). This result agrees with the SDA´s (2011) assessment that relates this phenomenon with the use of fossil fuels, especially diesel of high sulfur content.

PM10 continues to be the most important air quality pollutant in Bogotá. Figure 1 and Figure 3 present updated data. Figure 3 (in Appendix) uses the same methodology proposed by Gaitán et al. (2007), which tries to compare annual average per RMCAB station with the national and international standards. As it is observed, 7 of the 11 reported stations present levels over the national and EPA's standards in 2011 and all of them report levels higher than the suggested limit by WHO. Even so, Figure 1shows important reductions of PM10 going from an annual mean concentration of 65 µg/m^3 in 2002 to 52 µg/m^3 in 2014. The city average is still above the permissible limits. Figure 1 also reveals important differences of PM10 concentrations within the city.

Figure 1. PM10 Mean Annual Concentration from 2001 to 2014



For this empirical exercise, RMCAB data for 2011 was gathered so it could be merged as our air quality variable for estimations of the Hedonic Pricing Model. Using PM10 concentration as a measure of air quality data offer two advantages: first, it allowed us to work with the city's most relevant pollutant, and second, it is one of the most visible, helping to mitigate possible biases due to households´ subjective perception of pollution. For obtaining a measure of air quality for each of the households in our sample of the EMB we use Inverse Distance Weighted interpolation from the monitoring readings, a standard interpolation technique. Figure 4 shows the results of the interpolation showing the spatial variability suggested in Figure 1. Even though, our study area encompasses a single urban area, we identified some spatial variation of pollution levels: important PM10 concentrations are observed in the south and southwest areas of the city, while the north and center areas presented relatively low measures. Additional measures of air quality were gathered so that we could test for robust results. Particularly, the Voronoi Neighborhood Averaging methodology is used for replicating the interpolation of monitoring data method used by EPA's Environmental Benefits Mapping and Analysis Program (RTI International, 2015). For both interpolation methods we used the mean annual stock of concentrations as the variable to proxy air quality. A detailed description of air quality variables is available in Table 13.

V. EMPIRICAL RESULTS

First Stage Estimation – The Hedonic Price Function

The Hedonic Price Function was estimated using a semi-log (log-lin) functional form. Rental prices are used as our housing value. For owner occupied dwellings, we used imputed rent, thus the natural logarithm of rents is the dependent variable in all of the estimations of the Hedonic Price Function. Additionally all estimations include a rent dummy (*arriendo* variable) and interactions between independent variables and rent (X_arr for all X variables) so that possible bias from the imputed value could be corrected.

Table 1 presents a summary of the Price Schedule for Bogotá's dwelling market. Column (1) presents the results for all the market, without differentiating the type of dwelling. Columns (2), (3) and (4) show the submarket´s estimation results for apartments, houses in condos and no-condos houses respectively. All the four models include variables related to structural dwelling characteristics (Structural) and neighborhood characteristics' variables related to security (Security), distances to principal amenities (Distance), structural characteristics of the near houses (Cadastral), among others. Results suggest a consistent negative relationship between PM10 concentration (*meanStock* variable) and the rent price. The model predicts that an increase of 1 µg/m3 is accompanied by a monthly average rent reduction of 0.48% for apartments, of 0.59% for condos and of 0.33% for houses. An increase in 9.29 $\mu g/m^3$ (the standard deviation of the PM10 concentration by household) reduces rent price in 4.46% in the first submarket, 4.71% in the second submarket and 2.70% in the third one (1.68%, 2.05% and 1.15% of HH monthly income, respectively). The complete specification of the Hedonic Function estimation is shown in Table 14 of Appendix 1 debajo de.

Table 1. Hedonic Price Function Estimation

	(1) All	(2) Apart.	(3) House in Condos	(4) House no Condos
PM10	-.0044232***	-.004801***	-.005864***	-.0032885***
	(0.0006)	(0.0008)	(0.0021)	(0.0010)
Structural	Yes	Yes	Yes	Yes
Security	Yes	Yes	Yes	Yes
Distance	Yes	Yes	Yes	Yes
Cadastral	Yes	Yes	Yes	Yes
Other char.	Yes	Yes	Yes	Yes
Owner bias	Yes	Yes	Yes	Yes
R-Square	.71078	.7496	.70758	.62982
N	11,492	7,160	684	3,648
Var. Est.	ols	ols	ols	ols

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We test for the validity of the estimators significance due to potential spatial residual autocorrelation of the Hedonic Price estimations by correcting the variances estimators for clustering, which take into account that observations are grouped by blocks, so same blocks dwelling residuals might be correlated due to non-observable variables. As it may be seen in Table 2 all PM10 concentration estimators are significant at least to the 5% of confidence after this variance correction.

All specifications are shown in Table 15 and an additional correction by White robust errors is shown in Table 16 in appendix. Coefficient results for other variables had the expected sign. The dwelling number of rooms (*numCuartos*) has a positive effect over the rents, increasing them from 1.17% to 10.58% for each new room. An increase in one bathroom (*banios*) increases rent from 15.97% to 31.05%. The model also shows that an increase in one case of homicide in the block is associated with a decrease in the rent in 0.03% to 6.70%. Interestingly, the models show that disamenities like noise did not have a statistical effect in rent prices.

Table 2. Hedonic Price Function Correcting Variance Estimator

	(1) All	(2) Apart.	(3) House in Condos	(4) House no Condos
PM10	-.0044232***	-.004801***	-.005864**	-.0032885***
	(0.0008)	(0.0010)	(0.0023)	(0.0012)
Structural	Yes	Yes	Yes	Yes
Security	Yes	Yes	Yes	Yes
Distance	Yes	Yes	Yes	Yes
Cadastral	Yes	Yes	Yes	Yes
Other char.	Yes	Yes	Yes	Yes
Owner bias	Yes	Yes	Yes	Yes
R-Square	.71078	.7496	.70758	.62982
N	11,492	7,160	684	3,648
Var. Est.	Cluster	cluster	cluster	Cluster

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Second Stage Estimation – Reduction on Air Pollution Demand

Based on the predicted effect of the PM10 concentration on property rents, the implicit price for the reduction of air pollution ($W(PM10_{ij})$) is calculated. Because defining the apartment, condo houses and no-condo houses submarkets already solves SS identification issue by estimating information of multiple markets, the only problem that stills unresolved is the endogeneity issue. A two stage least squares (2SLS) method is used to obtain consistent estimations of the demand parameters under a linear specification. Optimum instrumental variables could be defined based on those variables that affect the PM10 concentration but it may not be affecting the houses' prices. The selected instruments are the raining rates, and the distance to the air quality monitoring network.

Table 3. Demand for Air Quality Estimation

	(1) First Stage PM10	(2) Second Stage
Reductions in PM10		-.019147***
		(0.0040)
Income	-.0001018**	.0002206***
	(0.0000)	(0.0000)
Rainfall	-.14822***	
	(0.0081)	
RMCAB dist.	-.0002314	
	(0.0002)	
R-Square	0.367	0.513
N	10,981	10,981
Hausman pValue		0.013
Relevance pValue		0.000
Hansen pValue		0.509
Var. Est.	robust cluster	robust cluster

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

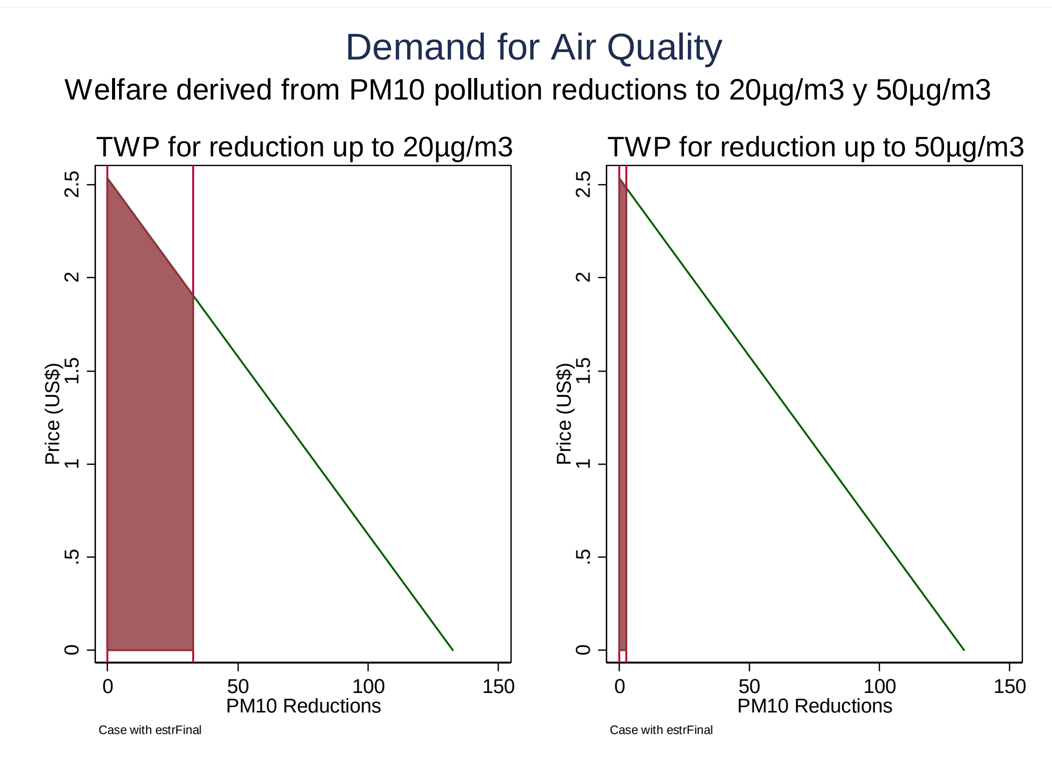
Table 3 shows a summary of the 2SLS first stage results in column (1) and the second stage in column (2), correcting again by clusters in the estimation (the complete estimation is shown in Table 17 Appendix 2). Consistent estimations where found on both estimations. As it was expected, more rain (*precipitacion*) is associated with less concentration of PM10, as well is distance to the monitoring network (distRMCAB). Hausman test, instruments relevance test and Hansen's J statistic for over-identification are reported also in Table 3. All three tests suggest that the model is well specified.

Second column also shows expected results to the estimation of the linear demand for reduction in air pollution. The results show that air pollution reduction is a normal good, meaning that it is affected positively by the income (*ingresos*). Also, the estimation shows that the demand for Air Quality might satisfy the law of the demand, and in the mean the demand for air quality will decrease in 1.5% by an increase of 1% in the price. Table 17 shows the influence of other variables on the demand for air quality. The estimation shows that greater levels of education and age of HH are related to increasing marginal willingness to pay. Model also suggests some gender differences: if a head of household is male, willingness to pay is lower than females´. Time of residence in the city also explains willingness to pay; the longer a household has been living in Bogotá the lower the willingness to pay for air quality.

Welfare Measures

For some attributes like air quality, first stage hedonic estimation is not enough to calculate welfare measures. Taylor (2003) states that welfare measures for non-localized amenities, such as dwellings' features whose changes affect all agents in the market, should be calculated based on the demand from the Second Stage. The area under the derived demands will show the total willingness to pay for a certain reduction of PM10.

Figure 2. Demand for Air Quality



Source: the authors

Figure 2 shows the demand curves estimated on Table 3. The shaded areas of the graphs show the total monthly willingness to pay per household for an air quality that respectively satisfies the WHO standard (left) and the national standard (right). To reduce air pollution of PM10 up to 50 µg/m3 will have a total willingness to pay of US$ 7.12 per month per family, 0.79% on monthly income. The total willingness to pay for a PM10 reduction up to 20 μg/m3 amounts to US$ 72.91 per month per family, which represents 8.09% of HH's monthly income. Table 4 presents these results and disaggregates the effects by low, medium and high socio-economic strata.

Table 4. Welfare measures

	Elasticity (%)	TWP for 20um/m3		TWP for 50um/m3	
General	-1.502415	72.91	[8.09]	7.12	[.79]
Low Strata	-.6770902	56.28	[13.84]	11.59	[2.85]
Med Strata	-1.770291	78.12	[7.35]	2.92	[.27]
High Strata	-6.516673	106.17	[3.27]	-29.2	[-.9]

Percentage of monthly income in square brackets

Robustness Checks

There are at least two identification issues to consider: the evidence in favor of the existence of three submarkets defined by the type of dwelling, and how results might change using an alternative measure of air quality or different functional forms for the Hedonic Price Function.

A Chow test was used to check for structural changes in the Hedonic Price Function among the housing submarkets. Although it does not have the traditional structure because in this case we have three groups instead of two.[3] The calculated statistic is 4.31which have a p-value of 0.000, so with at a significant level of 99% we could affirm that exist a structural change between the three submarkets based on the specified functional form. Poudyal et al. (2009) use segmentation also for identifying and estimating the demand for urban

[3] In this case the statistic should be calculated by using the expression

$$Chow = \frac{\frac{RSS - (RSS_1 + RSS_2 + RSS_3)}{2 * (k+1)}}{\frac{RSS_1 + RSS_2 + RSS_3}{n - 3 * (k+1)}}$$

, where RSS refers to the residual sum of squares without disaggregating by submarkets, RSS_j $j \in \{1,2,3\}$ to the RSS of regressions using only data for j sub market, k is the number of independent variables in the regression without differentiating between submarkets, and n is the number of observations in it. Under the null hypotheses, where there is not difference between the Hedonic Price Function of the submarkets, the f statistic distributes $F\big(2 * (k+1), n - 3 * (k+1)\big)$.

recreational parks. By using the same proposed clustering method, the Two Step Clustering, we estimated the optimum number of clusters and the clusters structure using cadastral data, which is a census of all Bogotá's dwellings. Table reports the output of the cluster methodology. As can be seen the methodology predicts three submarkets, apartments (cluster 1), houses without horizontal property (cluster 2), and houses with horizontal properties, which is similar to the market structure that this document is using. (See table 18 A in appendix)

We also used as a robustness check different functional forms of the hedonic function. As suggested by Cropper et al (1988) and Kuminoff et al. (2010) simple functional forms such as semilog or log models are preferred when there is not an explicit strategy for control for omitted variables. Table 18 presents the estimation of the air quality parameter obtained for each submarket using the four simplest functional forms (Log-Lin, Log-Log, Lin-Lin and Lin-Log). As seen, under most of the functional forms and submarkets the air quality parameter is negative and significant. A similar result is obtained by changing the air quality variable. Table 19 reports the air quality estimated parameter using annual PM10 concentration average (column 1, the same results reported in Table 2), daily mean concentration during EMB's field work (column 4), mean maximum daily concentration (column 5) and annual PM10 concentration by using the Voronoi Neighborhood Averaging (VNA) interpolation method[4]. For all variables and submarkets the relation still negative and almost all are statistical significant at least at 10%.

VNA interpolation method is also used for checking for robustness of SS estimations to changes in air quality variable. The estimator of the demand's slope change from -0.019147 to -0.031665, although the elasticities and TWP values may not change significantly (see Table 5 below and Table 20 in appendix). The negative relation between the implicit price and the air quality is apparently robust to the functional form, as it is shown in Table 21 and Table 22 in appendix.

[4] Proposed by EPA to the BenMap Tool, for air quality assessment.

Table 5. Welfare Measures with VNA

	Elasticity (%)	TWP for 20um/m3		TWP for 50um/m3	
General	-1.064818	82.17	[9.12]	-4.55	[-.5]
Low Strata	-.4426667	72.42	[17.8]	5.68	[1.4]
Med Strata	-1.192467	88.57	[8.33]	-4.52	[-.43]
High Strata	-4.837325	113.99	[3.51]	-43.46	[-1.34]

Percentage of monthly income in square brackets

VI. FINAL DISCUSSION

Results from the first stage hedonic confirm that air quality capitalize into property values. However, these capitalizations vary from one housing submarket to another. A Chow test concludes in favor of separate housing submarkets and therefore this test also suggests a non-unique hedonic price function for Bogotá. Capitalizations seem to have a larger effect in condominiums compared to housing in other submarkets (apartments, and houses not in condominiums). Further research on the nature of housing submarkets within a city is still an unexplored area of research and further investigations on this issue would be part of future work.

The proposed market segmentation within the city helped us to estimate a Second Stage hedonic model to identify a demand for air quality relying on information obtained from the market process. We address identification and endogeneity issues by using housing submarkets and an IV econometric strategy. Results of the Second Stage confirm the demand law and the hypothesis that Air quality is a normal good. An identification of a demand function for air quality is a suitable and very flexible tool for policy makers interested in identifying non-marginal benefits (costs) from air quality improvements (deterioration). We illustrated how the demand function can be flexibly used to calculate benefits for various ambient quality scenarios: benefits from compliance to the EPA standard amount to U$ 8/month/household whereas the compliance of the more stringent WHO standard brings as a result benefits close to U$73/month/household. These benefits are to be interpreted as a lower bound since the identification of preferences from the hedonic model does not capture potential impacts on health. Nonetheless, our estimated values from revealed preferences could be incorporated in cost benefit analysis concerning regulatory policies to control urban air pollution. Our results are suggestive but not conclusive. Further research comparing revealed preference estimated with state preferences methods to account for subjective perceptions of pollution are required, we hope to address these issues in future research.

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VIII. APPENDIX

Appendix 1. Tables and Figures

Table 6. Air Contamination Limits by Type of Pollution and Regulation

Pollutant	Maximum Allowable Limit				Reference Period
	EPA Standards	WHO Standards	Resolución 601/2006	Resolución 610/2010	
Carbon monoxide	9ppm		8.8ppm 10mg/m3	8.8ppm 10mg/m3	8-hours average
	35ppm		35ppm 40mg/m3	35ppm 40mg/m3	1-hour average
Nitrogen dioxide	0.053ppm	40µg/m3	0.053ppm 100µg/m3	0.053ppm 100µg/m3	Annual average
			0.08ppm 150µg/m3	0.08ppm 150µg/m3	Daily average
		200µg/m3	0.106ppm 200µg/m3	0.106ppm 200µg/m3	1-hour average
Ozone	0.08ppm		0.041ppm 80µg/m3	0.041ppm 80µg/m3	8-hours average
	0.12ppm	100µg/m3	0.061ppm 120µg/m3	0.061ppm 120µg/m3	1-hour average
Sulfur dioxide	0.03ppm		0.031ppm 80µg/m3	0.031ppm 80µg/m3	Annual average
	0.14ppm	20µg/m3	0.096ppm 250µg/m3	0.096ppm 250µg/m3	Daily average
			0.287ppm 750µg/m3	0.287ppm 750µg/m3	3-hours average
		500µg/m3			10 minutes
PM2.5	15µg/m3			25µg/m3	Annual average
	65µg/m3			50µg/m3	Daily average
PM10	50µg/m3	20µg/m3	70µg/m3	50µg/m3	Annual average

	150µg/m3	50µg/m3	150µg/m3	100µg/m3	Daily average
TSP			100µg/m3	100µg/m3	Annual average
			300µg/m3	300µg/m3	Daily average
Lead	1.5µg/m3				Quarterly average

Figure 3. Mean Annual PM10 Concentration by RMCAB Stations

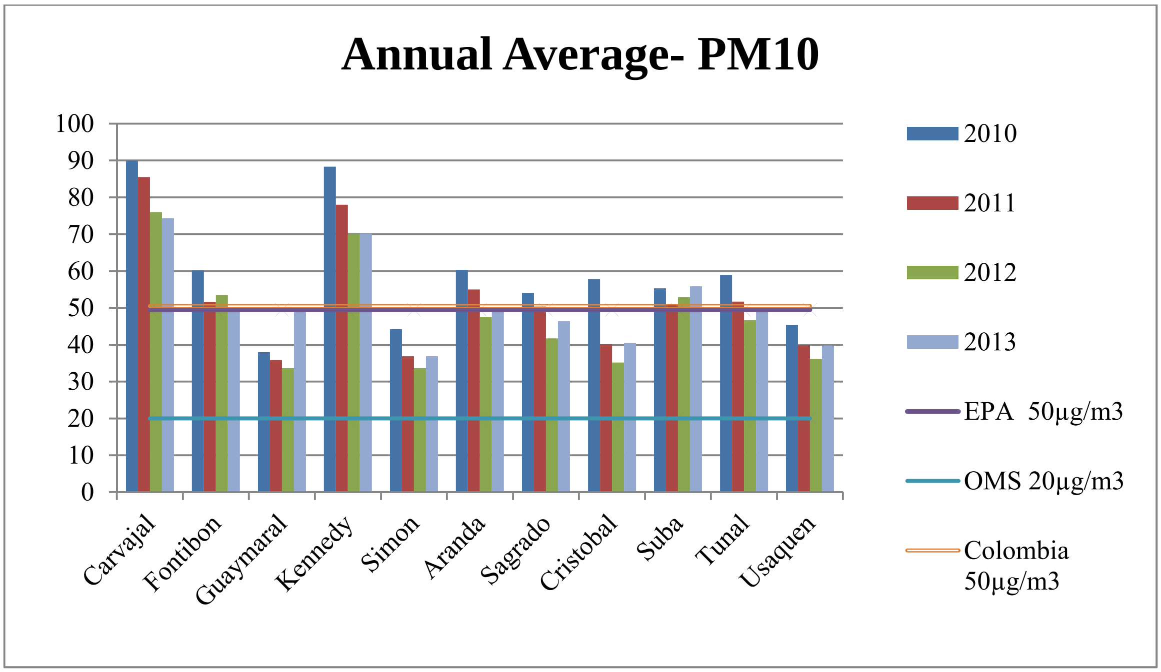

Figure 4. PM10 Concentration interpolated with IDW

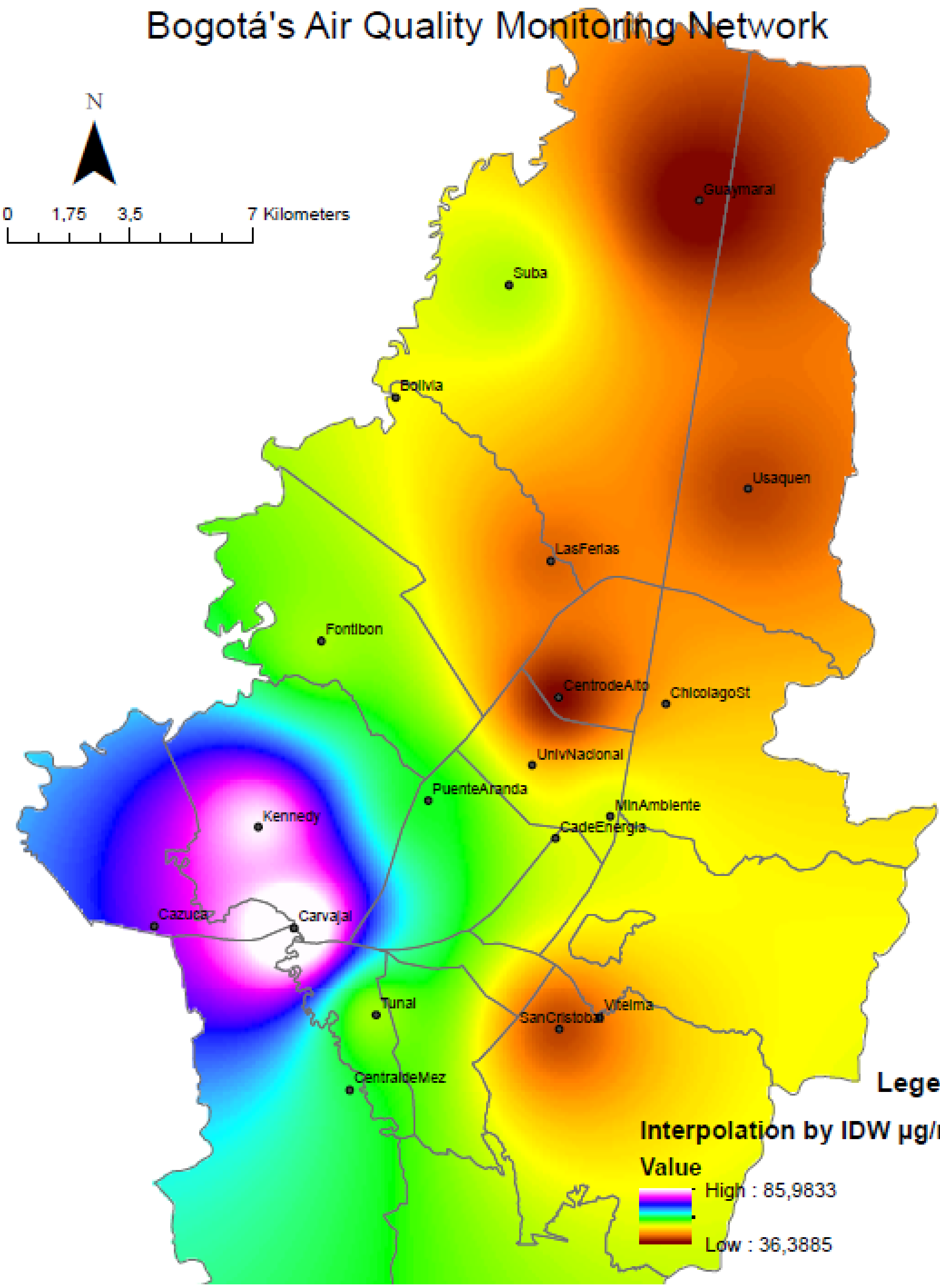

Table 7. HH Marital Status – edoCivJH

	Total Perc (%)	Low Strata Perc (%)	Medium Strata Perc (%)	High Strata Perc (%)
Living with a partner (<2 y)	2.9	3.6	2.6	0.9
Living with a partner (>2 y)	22.7	34.1	15.5	4.7
Widower	9.2	7.9	10.2	9.8
Separated or divorced	14.4	15.6	13.4	15.3
Single	16.7	12.8	19.4	20.7
Married	34.1	26.1	38.9	48.6
N	11643	4870	6111	662

Table 8. HH Highest Education Level – educMasAlta

	Total Perc (%)	Low Strata Perc (%)	Medium Strata Perc (%)	High Strata Perc (%)
None	1.5	2.6	0.7	0.2
Kinder	0.2	0.4	0.0	
Primary	21.6	35.1	13.1	0.9
High School	41.5	49.9	37.6	15.6
Technical	7.9	6.2	9.7	3.6
Technological	2.8	1.9	3.7	2.4
Undergraduate	15.6	3.0	22.8	40.5
Graduate	9.0	0.9	12.4	36.9
N	11643	4870	6111	662

Table 9. Description of Socio Demographic Variables

Variable	Description	N	Mean	SD	Min.	Max.
sexoJH	Sex of HH (1=man)	11,643	.616	.4864	0	1
edadJH	Age of HH	11,643	48.23	15.09	16	99
meanAge	Mean age within families	11,643	35.97	15.49	8	92
tiemBogJH	Time living in Bogotá (years)	11,643	37.14	19.77	0	99
perHog	Number of people per house	11,643	3.382	1.64	1	19
hog_hijos	Number of sons	11,643	1.297	1.127	0	9
ingresos	Income (US$)	10,993	901.1	1,554	0	54,143
menores_5	Number of children under 5y	11,643	.2286	.4987	0	4
men5Tos	Children under 5y with cough during the last week	11,643	.0931	.3228	0	3
men5DifRes	Children under 5y with breath difficulties during the last week	11,643	.02499	.1683	0	3
hog_orgAmb	Number of family members in environmental organization	11,643	.01589	.1369	0	3
trabaja	Marital status of HH	11,507	.717	.4505	0	1

Table 10. Type of Dwelling- VivPH

	Freq	Perc (%)	Cum. (%)
Apartment	7,270	62.4	62.4
Condo houses	691	5.9	68.4
No-condo houses	3,682	31.6	100.0
Total	11,643	100.0	

Table 11. Structural and Neighborhood Characteristics

Variables	Description	N	Mean	SD	Min.	Max.
arriendo	Type of dwelling	11,643	.3865	.487	0	1
numCuartos	Living in rent (Yes or no)	11,643	3.63	1.324	1	15
banios	Number of rooms	11,631	1.593	.8211	1	9
garaje	Number of bathrooms	11,643	.4109	.492	0	1
arriendoReal	Garage (Yes or no)	4,500	251.3	219.5	12	3,790
arriendoAuto	Rent for renters (US$)	7,143	395.6	380.7	14	3,790
PArrien	Hypothetical rent (US$)	11,643	339.8	335.4	12	3,790
ascensor	Aggregated rent (US$)	11,643	.1328	.3394	0	1
terraza	Elevator (Yes or no)	11,643	.2854	.4516	0	1
zonVerdes	Terrace (Yes or no)	11,643	.2949	.456	0	1
numTelFijo	Green spaces (Yes or no)	11,643	.8012	.5068	0	5
internet	Number of fixed phones	11,643	.4738	.4993	0	1
conjunCerr	Internet (Yes or no)	11,643	.3007	.4586	0	1
jardin	In a residential complex (Yes or no)	11,643	.4084	.4916	0	1
pisos	Garden (Yes or no)	11,643	3.479	2.909	1	30
plancha	Number of levels in the building	11,544	.8482	.3588	0	1
humedad	Plate (Yes or no)	11,619	.3581	.4795	0	1
inseguridad	Moistness (Yes or no)	11,643	.757	.4289	0	1
ruido	Insecurity (Yes or no)	11,643	.3673	.4821	0	1
malOlor	Noise (Yes or no)	11,643	.3832	.4862	0	1
indComSer	Odor (Yes or no)	11,643	.3728	.4836	0	1
anunciosExc	Near industry, commerce or services (Yes or no)	11,643	.08142	.2735	0	1
invasionAndenes	Advertising (Yes or no)	11,643	.1611	.3677	0	1
Order Categorical variables						
matPisos	Floors predominant material					
matParedes	Walls predominant material					
ubiAgua	Water source in the house					
dondCocina	Cooking area					
combCocina	Cooking combustible					
viaEstado	Quality of dwellings' roads of access					

Table 12. Variables Aggregated by Block

Variable	Description	N	Mean	SD	Min.	Max.
areaConstruida	Dwellings' constructed area (mean by block m2)	11,643	135.2	86.94	34	3,262
areaTerreno	Dwellings' land area (mean by block m2)	11,643	83.49	52.99	1.9	497
valorM2Terren	Land's price per area (mean by block US$)	11,643	274.3	215.2	1.8	1,923
vetustez	Buildings' year of construction (mean by block)	11,643	1,985	13.28	1,944	2,010
puntaje	Distance to tourist attractions (m)	11,643	41.32	15.03	10	91
distAtraTuris	Distance to fix sources of pollution (m)	11,643	1,140	836.5	0	6,346
distFuenCont	Distance to public transportation stops (m)	11,643	751.5	571.5	0	3,365
distSITP	Distance to principal roads (m)	11,643	308.2	266.8	0	1,847
distMallaVial	Distance to RMCAB's stations (m)	11,643	145.2	171.9	0	1,202
distRMCAB	Distance to rivers and canals (m)	11,643	2,688	1,679	149	9,937
distRiosCanales	Distance to health attention centers (m)	11,643	1,325	797.7	0	4,757
distIPS	Mean number of murders during last ten years in the block	11,643	330.8	239.4	0	1,900
homicidios	2011 mean rainfall (mm/month)	11,643	.3341	.8821	0	14
precipitacion	Dwellings' constructed area (mean by block m2)	11,643	69.35	27.42	33	155

Table 13. Air Quality Data

Variable	Description	N	Mean	SD	Min.	Max.
meanStock	PM10 Annual Concentration (ug/m3)	11,643	52.84	9.294	38	84
meanEnc	PM10 mean dailly Concentration while EMB (ug/m3)	11,643	59.3	9.724	40	88
maxStock	PM10 Max Concentration (ug/m3)	11,643	255.4	39.48	176	376
inter2meanPM	PM10 concentration by VNA (ug/m3)	6,077	48.64	7.718	38	84

Table 14. Hedonic Price Function Estimation

	(1) All	(2) Apart.	(3) House in Condos	(4) House no Condos
PM10	-.0044232***	-.004801***	-.005864***	-.0032885***
	(0.0006)	(0.0008)	(0.0021)	(0.0010)
meanStock_arr	.0021758**	.0018384	.0041532	.0024991
	(0.0009)	(0.0011)	(0.0051)	(0.0019)
arriendo	.14348	-.32157	13.735	5.7744*
	(1.5398)	(1.8342)	(13.2059)	(3.2158)
ascensor	.25352***	.2039***		
	(0.0205)	(0.0209)		
numCuartos	.051728***	.059019***	.01175	.059237***
	(0.0043)	(0.0066)	(0.0170)	(0.0065)
garaje	.14267***	.082951***	.15947***	.20698***
	(0.0112)	(0.0143)	(0.0398)	(0.0202)
terraza	.016502	.053411***	-.0027788	-.022291
	(0.0113)	(0.0152)	(0.0515)	(0.0187)
zonVerdes	.043364***	.04116***	.013993	.062796**
	(0.0129)	(0.0152)	(0.0394)	(0.0291)
banios	.22063***	.24252***	.31054***	.15977***
	(0.0074)	(0.0100)	(0.0269)	(0.0128)
numTelFijo	.072368***	.092437***	-.011275	.057438***
	(0.0116)	(0.0151)	(0.0477)	(0.0196)
internet	.080549***	.074326***	.07907**	.084939***
	(0.0106)	(0.0138)	(0.0388)	(0.0184)
conjunCerr	.033214**	.021566		
	(0.0140)	(0.0162)		
jardin	.011869	-.023303	.088645**	.050323***
	(0.0104)	(0.0145)	(0.0361)	(0.0182)
pisos	-.0012566	-.0025856	.0045486	-.0048535
	(0.0024)	(0.0023)	(0.0243)	(0.0150)
plancha	.028076**	.026538	.0018322	.055805**
	(0.0138)	(0.0209)	(0.0488)	(0.0228)
humedad	-.020329**	-.038685***	.0013925	-.011586
	(0.0101)	(0.0136)	(0.0379)	(0.0169)
matPisos	-.035357***	-.032657***	-.029966*	-.035474***
	(0.0041)	(0.0056)	(0.0154)	(0.0070)
matParedes	-.012912***	-.015035**	-.0032751	-.0096505
	(0.0046)	(0.0062)	(0.0192)	(0.0077)
ubiAgua	-.02053	-.038534	.065523	-.0013319
	(0.0202)	(0.0249)	(0.0755)	(0.0373)
dondCocina	.0008017	.03541	-.077904	.017266
	(0.0185)	(0.0360)	(0.0481)	(0.0260)
combCocina	-.024391**	-.010418	.065872	-.053252***
	(0.0114)	(0.0140)	(0.0554)	(0.0206)
homicidios	-.025746***	-.017869***	-.067032**	-.033037***
	(0.0058)	(0.0068)	(0.0309)	(0.0115)

inseguridad	-.055064***	-.064808***	.013614	-.026999
	(0.0117)	(0.0144)	(0.0369)	(0.0233)
distMallaVial	-.0000944***	-.000112***	-.000302***	-.0000685
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
distRiosCanales	.0000297***	.0000457***	-.0000641**	.000011
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
distIPS	-.0000322	-.0000575*	.0001061	-.0000449
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
distAtraTuris	-.0000466***	-.0000314***	-.0001***	-.0000489***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
distFuenCont	2.71e-06	.0000422***	.0000786**	-.0000535***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
areaTerreno	.0005949***	.0003257**	.0020001***	.0007889***
	(0.0001)	(0.0001)	(0.0005)	(0.0002)
lnValorM2Ter	.29089***	.32454***	.20779***	.23416***
	(0.0094)	(0.0130)	(0.0372)	(0.0163)
vetustez	.0009134*	.00134**	.0041894	.0009746
	(0.0005)	(0.0006)	(0.0026)	(0.0008)
viaEstado	-.022364***	-.016711*	-.043281	-.02841***
	(0.0061)	(0.0086)	(0.0279)	(0.0094)
ruido	.002148	-.019173	.023205	.025346
	(0.0101)	(0.0129)	(0.0375)	(0.0178)
malOlor	-.0033555	.0041268	-.055176	.0032058
	(0.0104)	(0.0138)	(0.0356)	(0.0177)
indComSer	-.026506***	-.027453**	-.060293	-.010795
	(0.0101)	(0.0130)	(0.0415)	(0.0178)
anunciosExc	-.011673	-.003631	.059302	-.029591
	(0.0179)	(0.0229)	(0.0611)	(0.0320)
invasionAndenes	.019643	-.0014221	.029012	.054976**
	(0.0131)	(0.0164)	(0.0478)	(0.0242)
ascensor_arr	.049651	.084254**		
	(0.0366)	(0.0363)		
numCuartos_arr	.047657***	.046064***	.067393	.046608***
	(0.0076)	(0.0098)	(0.0458)	(0.0148)
garaje_arr	.0012089	.03858*	.011933	-.022558
	(0.0196)	(0.0226)	(0.1044)	(0.0443)
terraza_arr	-.073989***	-.10491***	-.091427	-.067449*
	(0.0181)	(0.0217)	(0.1184)	(0.0384)
zonVerdes_arr	-.018088	-.012797	.043339	-.096473
	(0.0229)	(0.0249)	(0.0947)	(0.0689)
banios_arr	-.015573	-.030192*	-.076027	.0067594
	(0.0146)	(0.0175)	(0.0685)	(0.0305)
numTelFijo_arr	-.080708***	-.094412***	-.058761	-.065093*
	(0.0174)	(0.0209)	(0.0939)	(0.0353)
internet_arr	.018396	.022272	-.005312	-.020698
	(0.0182)	(0.0211)	(0.0961)	(0.0413)
conjunCerr_arr	.0081444	.0005016		
	(0.0244)	(0.0265)		

jardin_arr	-.053897***	-.012766	-.15074	-.05968*
	(0.0167)	(0.0208)	(0.0948)	(0.0350)
pisos_arr	-.0004896	-.0012723	-.016761	.01479
	(0.0043)	(0.0042)	(0.0619)	(0.0286)
plancha_arr	-.019379	-.034586	.015239	-.016781
	(0.0226)	(0.0298)	(0.1151)	(0.0464)
humedad_arr	-.03022*	-.0012967	.015471	-.072948**
	(0.0162)	(0.0194)	(0.1001)	(0.0342)
matPisos_arr	-.0056248	-.0006787	.028709	-.018745
	(0.0069)	(0.0084)	(0.0432)	(0.0140)
matParedes_arr	.012542	.0090294	-.003297	.027177*
	(0.0077)	(0.0093)	(0.0456)	(0.0159)
ubiAgua_arr	-.039338	-.031588	-.25543	-.034372
	(0.0319)	(0.0380)	(0.3163)	(0.0605)
dondCocina_arr	-.032321	-.04433	-.051287	-.054144
	(0.0265)	(0.0441)	(0.1013)	(0.0406)
combCocina_arr	-.021076	-.050852***	.015034	.051957
	(0.0167)	(0.0194)	(0.1029)	(0.0354)
homicidios_arr	.015651*	.0074694	.042222	.032735*
	(0.0085)	(0.0094)	(0.0671)	(0.0196)
inseguridad_arr	.014535	.022262	-.1158	.018074
	(0.0184)	(0.0209)	(0.0958)	(0.0431)
distMallaVial_arr	.0000452	.0001272**	.0003792	-.0000102
	(0.0000)	(0.0001)	(0.0003)	(0.0001)
distRiosCanales_arr	.0000152	5.37e-06	.0001033	-9.24e-06
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
distIPS_arr	1.91e-06	.0000415	.0001469	-.000029
	(0.0000)	(0.0000)	(0.0002)	(0.0001)
distAtraTuris_arr	-4.70e-07	-.0000235*	.0000268	.0000426*
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
distFuenCont_arr	-4.87e-06	-.0000326	.0000814	-4.93e-06
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
areaTerreno_arr	-.0003448*	-.0002147	-.0004987	-.0001303
	(0.0002)	(0.0002)	(0.0015)	(0.0004)
lnValorM2Ter_arr	-.03852**	-.06623***	.22946*	-.035421
	(0.0154)	(0.0187)	(0.1203)	(0.0328)
vetustez_arr	-.0000613	.0003138	-.0076848	-.003041*
	(0.0008)	(0.0009)	(0.0066)	(0.0016)
viaEstado_arr	.017092*	.0016187	-.012388	.059944***
	(0.0098)	(0.0123)	(0.0544)	(0.0189)
ruido_arr	-.0086088	.0099277	.059631	-.039344
	(0.0164)	(0.0190)	(0.0944)	(0.0360)
malOlor_arr	-.0027534	-.010517	.013058	-.0050262
	(0.0168)	(0.0200)	(0.0917)	(0.0355)
indComSer_arr	.042771***	.055461***	-.0091785	-.0078607
	(0.0161)	(0.0188)	(0.0935)	(0.0353)
anunciosExc_arr	.0056752	-.0071663	-.11066	.056647
	(0.0289)	(0.0335)	(0.1451)	(0.0642)

invasionAndenes_arr	-.014858	.0040824	-.11612	-.054801
	(0.0221)	(0.0251)	(0.1365)	(0.0506)
Constant	1.9643**	.86349	-4.1785	2.1229
	(0.9497)	(1.2596)	(5.3193)	(1.6024)
R-Square	.71078	.7496	.70758	.62982
N	11,492	7,160	684	3,648
Var. Est.	ols	ols	ols	ols

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15. Hedonic Price Function Correcting Variance Estimator

	(1) All	(2) Apart.	(3) House in Condos	(4) House no Condos
PM10	-.0044232***	-.004801***	-.005864**	-.0032885***
	(0.0008)	(0.0010)	(0.0023)	(0.0012)
meanStock_arr	.0021758**	.0018384	.0041532	.0024991
	(0.0009)	(0.0012)	(0.0035)	(0.0016)
arriendo	.14348	-.32157	13.735	5.7744*
	(1.8958)	(2.3661)	(11.1985)	(2.9439)
ascensor	.25352***	.2039***		
	(0.0264)	(0.0264)		
numCuartos	.051728***	.059019***	.01175	.059237***
	(0.0054)	(0.0079)	(0.0203)	(0.0077)
garaje	.14267***	.082951***	.15947***	.20698***
	(0.0144)	(0.0163)	(0.0477)	(0.0241)
terraza	.016502	.053411***	-.0027788	-.022291
	(0.0136)	(0.0192)	(0.0526)	(0.0194)
zonVerdes	.043364***	.04116***	.013993	.062796**
	(0.0139)	(0.0159)	(0.0435)	(0.0317)
banios	.22063***	.24252***	.31054***	.15977***
	(0.0118)	(0.0155)	(0.0359)	(0.0158)
numTelFijo	.072368***	.092437***	-.011275	.057438**
	(0.0147)	(0.0182)	(0.0523)	(0.0231)
internet	.080549***	.074326***	.07907*	.084939***
	(0.0110)	(0.0140)	(0.0405)	(0.0191)
conjunCerr	.033214*	.021566		
	(0.0185)	(0.0210)		
jardin	.011869	-.023303	.088645**	.050323***
	(0.0129)	(0.0178)	(0.0423)	(0.0191)
pisos	-.0012566	-.0025856	.0045486	-.0048535
	(0.0028)	(0.0026)	(0.0281)	(0.0165)
plancha	.028076*	.026538	.0018322	.055805**
	(0.0164)	(0.0245)	(0.0628)	(0.0258)
humedad	-.020329*	-.038685***	.0013925	-.011586
	(0.0115)	(0.0144)	(0.0412)	(0.0182)
matPisos	-.035357***	-.032657***	-.029966	-.035474***

	(0.0052)	(0.0070)	(0.0185)	(0.0081)
matParedes	-.012912**	-.015035**	-.0032751	-.0096505
	(0.0057)	(0.0073)	(0.0214)	(0.0086)
ubiAgua	-.02053	-.038534	.065523	-.0013319
	(0.0204)	(0.0238)	(0.0574)	(0.0367)
dondCocina	.0008017	.03541	-.077904	.017266
	(0.0232)	(0.0341)	(0.0962)	(0.0254)
combCocina	-.024391*	-.010418	.065872	-.053252**
	(0.0135)	(0.0153)	(0.0601)	(0.0255)
homicidios	-.025746***	-.017869**	-.067032*	-.033037**
	(0.0066)	(0.0076)	(0.0381)	(0.0130)
inseguridad	-.055064***	-.064808***	.013614	-.026999
	(0.0127)	(0.0153)	(0.0400)	(0.0229)
distMallaVial	-.0000944*	-.000112	-.000302*	-.0000685
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
distRiosCanales	.0000297***	.0000457***	-.0000641	.000011
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
distIPS	-.0000322	-.0000575	.0001061	-.0000449
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
distAtraTuris	-.0000466***	-.0000314**	-.0001**	-.0000489***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
distFuenCont	2.71e-06	.0000422**	.0000786*	-.0000535***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
areaTerreno	.0005949*	.0003257	.0020001**	.0007889***
	(0.0003)	(0.0005)	(0.0009)	(0.0003)
lnValorM2Ter	.29089***	.32454***	.20779**	.23416***
	(0.0322)	(0.0411)	(0.0875)	(0.0299)
vetustez	.0009134	.00134	.0041894	.0009746
	(0.0008)	(0.0010)	(0.0038)	(0.0010)
viaEstado	-.022364***	-.016711	-.043281	-.02841**
	(0.0080)	(0.0102)	(0.0273)	(0.0112)
ruido	.002148	-.019173	.023205	.025346
	(0.0114)	(0.0142)	(0.0350)	(0.0187)
malOlor	-.0033555	.0041268	-.055176	.0032058
	(0.0111)	(0.0144)	(0.0408)	(0.0184)
indComSer	-.026506**	-.027453*	-.060293	-.010795
	(0.0124)	(0.0154)	(0.0509)	(0.0204)
anunciosExc	-.011673	-.003631	.059302	-.029591
	(0.0184)	(0.0208)	(0.0623)	(0.0356)
invasionAndenes	.019643	-.0014221	.029012	.054976**
	(0.0142)	(0.0164)	(0.0553)	(0.0274)
ascensor_arr	.049651	.084254**		
	(0.0347)	(0.0364)		
numCuartos_arr	.047657***	.046064***	.067393*	.046608***
	(0.0086)	(0.0108)	(0.0379)	(0.0158)
garaje_arr	.0012089	.03858	.011933	-.022558
	(0.0213)	(0.0248)	(0.0891)	(0.0419)
terraza_arr	-.073989***	-.10491***	-.091427	-.067449**

	(0.0193)	(0.0247)	(0.0948)	(0.0336)
zonVerdes_arr	-.018088	-.012797	.043339	-.096473
	(0.0219)	(0.0242)	(0.0690)	(0.0650)
banios_arr	-.015573	-.030192	-.076027	.0067594
	(0.0171)	(0.0214)	(0.0490)	(0.0314)
numTelFijo_arr	-.080708***	-.094412***	-.058761	-.065093*
	(0.0194)	(0.0234)	(0.0792)	(0.0365)
internet_arr	.018396	.022272	-.005312	-.020698
	(0.0180)	(0.0213)	(0.0682)	(0.0393)
conjunCerr_arr	.0081444	.0005016		
	(0.0252)	(0.0284)		
jardin_arr	-.053897***	-.012766	-.15074*	-.05968*
	(0.0176)	(0.0224)	(0.0821)	(0.0317)
pisos_arr	-.0004896	-.0012723	-.016761	.01479
	(0.0038)	(0.0038)	(0.0512)	(0.0259)
plancha_arr	-.019379	-.034586	.015239	-.016781
	(0.0236)	(0.0328)	(0.0931)	(0.0448)
humedad_arr	-.03022*	-.0012967	.015471	-.072948**
	(0.0158)	(0.0191)	(0.0716)	(0.0310)
matPisos_arr	-.0056248	-.0006787	.028709	-.018745
	(0.0071)	(0.0094)	(0.0326)	(0.0134)
matParedes_arr	.012542	.0090294	-.003297	.027177*
	(0.0083)	(0.0099)	(0.0335)	(0.0163)
ubiAgua_arr	-.039338	-.031588	-.25543	-.034372
	(0.0298)	(0.0313)	(0.2573)	(0.0616)
dondCocina_arr	-.032321	-.04433	-.051287	-.054144
	(0.0327)	(0.0408)	(0.1150)	(0.0464)
combCocina_arr	-.021076	-.050852**	.015034	.051957
	(0.0181)	(0.0201)	(0.0953)	(0.0386)
homicidios_arr	.015651*	.0074694	.042222	.032735*
	(0.0080)	(0.0089)	(0.0471)	(0.0180)
inseguridad_arr	.014535	.022262	-.1158	.018074
	(0.0172)	(0.0200)	(0.0821)	(0.0381)
distMallaVial_arr	.0000452	.0001272	.0003792	-.0000102
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
distRiosCanales_arr	.0000152	5.37e-06	.0001033	-9.24e-06
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
distIPS_arr	1.91e-06	.0000415	.0001469	-.000029
	(0.0000)	(0.0001)	(0.0002)	(0.0001)
distAtraTuris_arr	-4.70e-07	-.0000235	.0000268	.0000426**
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
distFuenCont_arr	-4.87e-06	-.0000326	.0000814	-4.93e-06
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
areaTerreno_arr	-.0003448	-.0002147	-.0004987	-.0001303
	(0.0003)	(0.0005)	(0.0012)	(0.0004)
lnValorM2Ter_arr	-.03852	-.06623*	.22946*	-.035421
	(0.0248)	(0.0354)	(0.1178)	(0.0331)
vetustez_arr	-.0000613	.0003138	-.0076848	-.003041**

	(0.0009)	(0.0012)	(0.0056)	(0.0015)
viaEstado_arr	.017092	.0016187	-.012388	.059944***
	(0.0107)	(0.0139)	(0.0433)	(0.0168)
ruido_arr	-.0086088	.0099277	.059631	-.039344
	(0.0170)	(0.0201)	(0.0733)	(0.0321)
malOlor_arr	-.0027534	-.010517	.013058	-.0050262
	(0.0162)	(0.0195)	(0.0787)	(0.0325)
indComSer_arr	.042771**	.055461***	-.0091785	-.0078607
	(0.0173)	(0.0210)	(0.0715)	(0.0324)
anunciosExc_arr	.0056752	-.0071663	-.11066	.056647
	(0.0279)	(0.0314)	(0.1131)	(0.0595)
invasionAndenes_arr	-.014858	.0040824	-.11612	-.054801
	(0.0219)	(0.0244)	(0.0866)	(0.0543)
Constant	1.9643	.86349	-4.1785	2.1229
	(1.5550)	(2.0375)	(7.5555)	(1.9335)
R-Square	.71078	.7496	.70758	.62982
N	11,492	7,160	684	3,648
Var. Est.	cluster	cluster	cluster	cluster

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 16. Hedonic Price Function Correcting Variance Estimator

	(1) All	(2) Apart.	(3) House in Condos	(4) House no Condos
PM10	-.0044232***	-.004801***	-.005864***	-.0032885***
	(0.0006)	(0.0008)	(0.0018)	(0.0010)
meanStock_arr	.0021758**	.0018384*	.0041532	.0024991
	(0.0009)	(0.0011)	(0.0037)	(0.0016)
arriendo	.14348	-.32157	13.735	5.7744**
	(1.5091)	(1.8296)	(11.2954)	(2.9383)
ascensor	.25352***	.2039***		
	(0.0198)	(0.0208)		
numCuartos	.051728***	.059019***	.01175	.059237***
	(0.0053)	(0.0076)	(0.0184)	(0.0077)
garaje	.14267***	.082951***	.15947***	.20698***
	(0.0119)	(0.0145)	(0.0430)	(0.0220)
terraza	.016502	.053411***	-.0027788	-.022291
	(0.0125)	(0.0172)	(0.0519)	(0.0196)
zonVerdes	.043364***	.04116***	.013993	.062796*
	(0.0132)	(0.0149)	(0.0387)	(0.0335)
banios	.22063***	.24252***	.31054***	.15977***
	(0.0090)	(0.0116)	(0.0287)	(0.0150)
numTelFijo	.072368***	.092437***	-.011275	.057438**
	(0.0137)	(0.0169)	(0.0540)	(0.0227)
internet	.080549***	.074326***	.07907*	.084939***
	(0.0111)	(0.0138)	(0.0439)	(0.0195)

conjunCerr	.033214**	.021566		
	(0.0144)	(0.0170)		
jardin	.011869	-.023303	.088645**	.050323***
	(0.0109)	(0.0156)	(0.0370)	(0.0188)
pisos	-.0012566	-.0025856	.0045486	-.0048535
	(0.0021)	(0.0022)	(0.0237)	(0.0168)
plancha	.028076*	.026538	.0018322	.055805**
	(0.0151)	(0.0211)	(0.0598)	(0.0246)
humedad	-.020329*	-.038685***	.0013925	-.011586
	(0.0106)	(0.0139)	(0.0383)	(0.0175)
matPisos	-.035357***	-.032657***	-.029966*	-.035474***
	(0.0048)	(0.0066)	(0.0163)	(0.0077)
matParedes	-.012912***	-.015035**	-.0032751	-.0096505
	(0.0050)	(0.0065)	(0.0191)	(0.0082)
ubiAgua	-.02053	-.038534*	.065523	-.0013319
	(0.0205)	(0.0226)	(0.0606)	(0.0417)
dondCocina	.0008017	.03541	-.077904	.017266
	(0.0214)	(0.0328)	(0.0915)	(0.0254)
combCocina	-.024391*	-.010418	.065872	-.053252**
	(0.0134)	(0.0152)	(0.0619)	(0.0260)
homicidios	-.025746***	-.017869***	-.067032**	-.033037**
	(0.0057)	(0.0058)	(0.0305)	(0.0141)
inseguridad	-.055064***	-.064808***	.013614	-.026999
	(0.0120)	(0.0145)	(0.0394)	(0.0236)
distMallaVial	-.0000944***	-.000112**	-.000302***	-.0000685
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
distRiosCanales	.0000297***	.0000457***	-.0000641*	.000011
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
distIPS	-.0000322	-.0000575*	.0001061	-.0000449
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
distAtraTuris	-.0000466***	-.0000314***	-.0001***	-.0000489***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
distFuenCont	2.71e-06	.0000422***	.0000786**	-.0000535***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
areaTerreno	.0005949***	.0003257	.0020001**	.0007889***
	(0.0002)	(0.0002)	(0.0010)	(0.0002)
lnValorM2Ter	.29089***	.32454***	.20779***	.23416***
	(0.0148)	(0.0227)	(0.0446)	(0.0215)
vetustez	.0009134*	.00134**	.0041894	.0009746
	(0.0005)	(0.0007)	(0.0030)	(0.0009)
viaEstado	-.022364***	-.016711*	-.043281*	-.02841***
	(0.0065)	(0.0089)	(0.0254)	(0.0100)
ruido	.002148	-.019173	.023205	.025346
	(0.0106)	(0.0135)	(0.0355)	(0.0184)
malOlor	-.0033555	.0041268	-.055176	.0032058
	(0.0107)	(0.0139)	(0.0377)	(0.0183)
indComSer	-.026506**	-.027453**	-.060293	-.010795
	(0.0106)	(0.0133)	(0.0405)	(0.0186)

anunciosExc	-.011673	-.003631	.059302	-.029591
	(0.0187)	(0.0218)	(0.0640)	(0.0360)
invasionAndenes	.019643	-.0014221	.029012	.054976**
	(0.0136)	(0.0158)	(0.0604)	(0.0265)
ascensor_arr	.049651	.084254**		
	(0.0331)	(0.0345)		
numCuartos_arr	.047657***	.046064***	.067393*	.046608***
	(0.0083)	(0.0107)	(0.0372)	(0.0153)
garaje_arr	.0012089	.03858*	.011933	-.022558
	(0.0192)	(0.0222)	(0.0976)	(0.0420)
terraza_arr	-.073989***	-.10491***	-.091427	-.067449*
	(0.0184)	(0.0231)	(0.0940)	(0.0346)
zonVerdes_arr	-.018088	-.012797	.043339	-.096473
	(0.0216)	(0.0241)	(0.0696)	(0.0643)
banios_arr	-.015573	-.030192	-.076027	.0067594
	(0.0160)	(0.0199)	(0.0573)	(0.0306)
numTelFijo_arr	-.080708***	-.094412***	-.058761	-.065093*
	(0.0185)	(0.0220)	(0.0805)	(0.0363)
internet_arr	.018396	.022272	-.005312	-.020698
	(0.0177)	(0.0207)	(0.0758)	(0.0383)
conjunCerr_arr	.0081444	.0005016		
	(0.0234)	(0.0269)		
jardin_arr	-.053897***	-.012766	-.15074*	-.05968*
	(0.0163)	(0.0212)	(0.0776)	(0.0319)
pisos_arr	-.0004896	-.0012723	-.016761	.01479
	(0.0038)	(0.0038)	(0.0500)	(0.0258)
plancha_arr	-.019379	-.034586	.015239	-.016781
	(0.0231)	(0.0304)	(0.0981)	(0.0438)
humedad_arr	-.03022*	-.0012967	.015471	-.072948**
	(0.0155)	(0.0188)	(0.0820)	(0.0315)
matPisos_arr	-.0056248	-.0006787	.028709	-.018745
	(0.0074)	(0.0094)	(0.0364)	(0.0136)
matParedes_arr	.012542	.0090294	-.003297	.027177*
	(0.0077)	(0.0093)	(0.0367)	(0.0156)
ubiAgua_arr	-.039338	-.031588	-.25543	-.034372
	(0.0303)	(0.0328)	(0.3731)	(0.0642)
dondCocina_arr	-.032321	-.04433	-.051287	-.054144
	(0.0302)	(0.0399)	(0.1075)	(0.0442)
combCocina_arr	-.021076	-.050852**	.015034	.051957
	(0.0179)	(0.0202)	(0.1022)	(0.0380)
homicidios_arr	.015651**	.0074694	.042222	.032735
	(0.0078)	(0.0081)	(0.0475)	(0.0207)
inseguridad_arr	.014535	.022262	-.1158	.018074
	(0.0174)	(0.0203)	(0.0866)	(0.0377)
distMallaVial_arr	.0000452	.0001272**	.0003792	-.0000102
	(0.0001)	(0.0001)	(0.0003)	(0.0001)
distRiosCanales_arr	.0000152	5.37e-06	.0001033	-9.24e-06
	(0.0000)	(0.0000)	(0.0001)	(0.0000)

distIPS_arr	1.91e-06	.0000415	.0001469	-.000029
	(0.0000)	(0.0000)	(0.0002)	(0.0001)
distAtraTuris_arr	-4.70e-07	-.0000235	.0000268	.0000426**
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
distFuenCont_arr	-4.87e-06	-.0000326	.0000814	-4.93e-06
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
areaTerreno_arr	-.0003448	-.0002147	-.0004987	-.0001303
	(0.0002)	(0.0003)	(0.0014)	(0.0004)
lnValorM2Ter_arr	-.03852*	-.06623**	.22946*	-.035421
	(0.0220)	(0.0297)	(0.1173)	(0.0384)
vetustez_arr	-.0000613	.0003138	-.0076848	-.003041**
	(0.0008)	(0.0009)	(0.0057)	(0.0015)
viaEstado_arr	.017092*	.0016187	-.012388	.059944***
	(0.0095)	(0.0121)	(0.0437)	(0.0169)
ruido_arr	-.0086088	.0099277	.059631	-.039344
	(0.0158)	(0.0188)	(0.0724)	(0.0329)
malOlor_arr	-.0027534	-.010517	.013058	-.0050262
	(0.0159)	(0.0192)	(0.0758)	(0.0327)
indComSer_arr	.042771***	.055461***	-.0091785	-.0078607
	(0.0155)	(0.0186)	(0.0746)	(0.0315)
anunciosExc_arr	.0056752	-.0071663	-.11066	.056647
	(0.0279)	(0.0322)	(0.1148)	(0.0587)
invasionAndenes_arr	-.014858	.0040824	-.11612	-.054801
	(0.0210)	(0.0233)	(0.0948)	(0.0508)
Constant	1.9643*	.86349	-4.1785	2.1229
	(1.0412)	(1.3406)	(6.0947)	(1.7200)
R-Square	.71078	.7496	.70758	.62982
N	11,492	7,160	684	3,648
Var. Est.	robust	robust	robust	robust

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17. Demand for Air Quality Estimation

	(1) First Stage PM10	(2) Second Stage
PM10		-.019147***
		(0.0040)
Rainfall	-.14822***	
	(0.0081)	
RMCAB dist.	-.0002314	
	(0.0002)	
Income	-.0001018**	.0002206***
	(0.0000)	(0.0000)
educMasAlta	-.49102***	.12441***
	(0.0720)	(0.0131)
sexoJH	.64129***	-.063219***

	(0.1677)	(0.0233)
edadJH	-.0009901	.0049661***
	(0.0082)	(0.0012)
tiemBogJH	-.022468***	-.0051147***
	(0.0057)	(0.0009)
hog_hijos	.040759	.011488
	(0.1024)	(0.0147)
hog_orgAmb	-.85449**	.1048
	(0.4192)	(0.0790)
menores_5	-.27783	.12154***
	(0.2022)	(0.0463)
men5Tos	.48817	-.062458*
	(0.3065)	(0.0364)
men5DifRes	-.36422	-.0001149
	(0.4584)	(0.0649)
perHog	.018225	-.072895***
	(0.0803)	(0.0133)
arriendo	-.48439**	-.10482***
	(0.2048)	(0.0259)
numCuartos	.085968	-.0033312
	(0.0970)	(0.0144)
garaje	-1.6871***	.20443***
	(0.2802)	(0.0288)
banios	-1.2134***	.80598***
	(0.1666)	(0.0628)
distAtraTuris	.0019802***	-.0001104***
	(0.0003)	(0.0000)
ruido	.0077454	-.032506
	(0.1998)	(0.0246)
distFuenCont	-.0012007***	.0001676***
	(0.0004)	(0.0000)
distSITP	.000542	7.92e-06
	(0.0008)	(0.0001)
distMallaVial	-.0003288	-.0000136
	(0.0013)	(0.0002)
Constant	67.6***	.64451**
	(1.0719)	(0.2811)
R-Square	0.367	0.513
N	10,981	10,981
Hausman pValue		0.013
Relevance pValue		0.000
Hansen pValue		0.509
Var. Est.	robust cluster	robust cluster

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 18 A. Two Step Clustering results

Cluster	1	2	3
Size	40.7%	12.3%	47.0%
Entries	Apartments 0 (100%) Build Area 160.94 Land Area 104.65 Horizontal property 0 (100%) Year 1984.10	Apartments 0 (100%) Build Area 72.27 Land Area 69.80 Horizontal property 1 (100%) Year 1999.58	Apartments 1 (100%) Build Area 71.31 Land Area 35.96 Horizontal property 1 (100%) Year 1995.59

*Table 18. First Stage Models with Different Functional Forms**

	Log-Lin	Log-Log	Lin-Lin	Lin-Log
General	-0.00442	-0.26849	-0.99435	-68.60079
	(0.00000)	(0.00000)	(0.02392)	(0.00718)
	[0.71078]	[0.71104]	[0.58967]	[0.58985]
Apartment	-0.00480	-0.27884	0.18504	3.99060
	(0.00000)	(0.00000)	(0.76296)	(0.91092)
	[0.74960]	[0.74972]	[0.64045]	[0.64044]
Condos	-0.00586	-0.34559	-1.29877	-84.86062
	(0.01282)	(0.01224)	(0.50470)	(0.44813)
	[0.70758]	[0.70797]	[0.55942]	[0.55972]
No-condos	-0.00329	-0.20799	-1.82440	-113.29564
	(0.00490)	(0.00229)	(0.00005)	(0.00003)
	[0.62982]	[0.63011]	[0.52091]	[0.52150]

Relevance test p-value in parentheses
Regression’s R2 in square brackets
*Coefficients for PM10 variable

Table 19. First Stage with different pollution measures

	β	IC-	IC+	β – During Survey	β - Annual Max	β - EPA
General	-0.00442	-0.00596	-0.00289	-0.00593	-0.00193	-0.00600
				0.00000	0.00000	0.00000
Apartment	-0.00480	-0.00677	-0.00284	-0.00606	-0.00190	-0.00641
			.	0.00000	0.00000	0.00001
Condos	-0.00586	-0.01046	-0.00126	-0.00635	-0.00215	-0.00626
				0.01224	0.00131	0.19151
No-condos	-0.00329	-0.00558	-0.00100	-0.00524	-0.00177	-0.00360
				0.00001	0.00000	0.08318

Relevance test p-value in parentheses

Table 20. Demand for Air Quality Estimation using Voronoi Neighborhood Averaging Methodology for air Quality Interpolation

	(1) First Stage PM10	(2) Second Stage
PM10		$-.031665^{***}$
		(0.0075)
Rainfall	$-.15167^{***}$	
	(0.0085)	
RMCAB dist.	.0002162	
	(0.0002)	
Income	$-.0001169^{**}$	$.0002082^{***}$
	(0.0000)	(0.0000)
educMasAlta	$-.4358^{***}$	$.10925^{***}$
	(0.0691)	(0.0174)
sexoJH	$.79051^{***}$	$-.067484^{*}$
	(0.1974)	(0.0392)
edadJH	-.0070145	$.0040839^{**}$
	(0.0087)	(0.0019)
tiemBogJH	.0031437	$-.0048475^{***}$
	(0.0064)	(0.0013)
hog_hijos	.13608	$.050179^{**}$
	(0.1298)	(0.0247)
hog_orgAmb	-.58679	-.008124
	(0.4050)	(0.1303)
menores_5	-.058902	$.18928^{**}$
	(0.2511)	(0.0782)
men5Tos	-.0091032	-.086776

	(0.3839)	(0.0975)
men5DifRes	-.24612	.036377
	(0.5816)	(0.1229)
perHog	.078021	-.094872***
	(0.0971)	(0.0208)
arriendo	-.1439	-1.2317***
	(0.2273)	(0.0488)
numCuartos	.16738	-.039553
	(0.1114)	(0.0256)
garaje	-1.6564***	.11335**
	(0.2933)	(0.0472)
banios	-1.0738***	.72509***
	(0.1667)	(0.0557)
distAtraTuris	.0005389	-.0001262*
	(0.0005)	(0.0001)
ruido	-.26651	-.027326
	(0.2231)	(0.0409)
distFuenCont	-.0036405***	.0004671***
	(0.0006)	(0.0001)
distSITP	-.0006808	-.0001276
	(0.0011)	(0.0001)
distMallaVial	-.0007108	-.0003792*
	(0.0018)	(0.0002)
Constant	65.026***	2.1812***
	(1.1947)	(0.4270)
R-Square	0.398	0.500
N	5,691	5,691
Hausman pValue		0.159
Relevance pValue		0.000
Hansen pValue		0.164
Var. Est.	robust cluster	robust cluster

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 21. Demand for Air Quality Estimation using Log-Lin Function

	(1) First Stage PM10	(2) Second Stage
PM10		-.012123***
		(0.0019)
Rainfall	-.14822***	
	(0.0081)	
RMCAB dist.	-.0002314	
	(0.0002)	
Income	-.0001018**	.0000624***
	(0.0000)	(0.0000)
educMasAlta	-.49102***	.10305***
	(0.0720)	(0.0048)

sexoJH	.64129***	-.027592***
	(0.1677)	(0.0104)
edadJH	-.0009901	.0026156***
	(0.0082)	(0.0005)
tiemBogJH	-.022468***	-.0026426***
	(0.0057)	(0.0003)
hog_hijos	.040759	-.0051659
	(0.1024)	(0.0068)
hog_orgAmb	-.85449**	.047103
	(0.4192)	(0.0296)
menores_5	-.27783	.017573
	(0.2022)	(0.0133)
men5Tos	.48817	-.018001
	(0.3065)	(0.0184)
men5DifRes	-.36422	.0068573
	(0.4584)	(0.0295)
perHog	.018225	-.032064***
	(0.0803)	(0.0055)
arriendo	-.48439**	-.074922***
	(0.2048)	(0.0125)
numCuartos	.085968	.062829***
	(0.0970)	(0.0063)
garaje	-1.6871***	.21771***
	(0.2802)	(0.0135)
banios	-1.2134***	.24625***
	(0.1666)	(0.0133)
distAtraTuris	.0019802***	-.0001057***
	(0.0003)	(0.0000)
ruido	.0077454	.001568
	(0.1998)	(0.0106)
distFuenCont	-.0012007***	-.0000626***
	(0.0004)	(0.0000)
distSITP	.000542	-.0001316***
	(0.0008)	(0.0000)
distMallaVial	-.0003288	-.0002421***
	(0.0013)	(0.0001)
Constant	67.6***	-.14014
	(1.0719)	(0.1227)
R-Square	0.367	0.605
N	10,981	10,981
Hausman pValue		0.004
Relevance pValue		0.000
Hansen pValue		0.001
Var. Est.	robust cluster	robust cluster

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 22. Demand for Air Quality Estimation using Log-Log Function

	(1) First Stage PM10	(2) Second Stage
log(PM10)		-.73335***
		(0.1117)
Rainfall	-.0027762***	
	(0.0001)	
Log RMCAB dist.	.013576*	
	(0.0077)	
Income	-2.24e-06***	.0000621***
	(0.0000)	(0.0000)
educMasAlta	-.0089133***	.1019***
	(0.0013)	(0.0048)
sexoJH	.011933***	-.026545**
	(0.0029)	(0.0104)
edadJH	-.0000874	.0025445***
	(0.0001)	(0.0005)
tiemBogJH	-.0003537***	-.0026485***
	(0.0001)	(0.0003)
hog_hijos	.0004681	-.0048248
	(0.0018)	(0.0068)
hog_orgAmb	-.015248**	.047091
	(0.0075)	(0.0297)
menores_5	-.0049757	.017777
	(0.0035)	(0.0133)
men5Tos	.0087444*	-.01775
	(0.0053)	(0.0184)
men5DifRes	-.0067652	.0058906
	(0.0080)	(0.0295)
perHog	.0002461	-.032109***
	(0.0014)	(0.0055)
arriendo	-.0088669**	-.076084***
	(0.0036)	(0.0125)
numCuartos	.0015662	.063277***
	(0.0017)	(0.0064)
garaje	-.030402***	.21584***
	(0.0049)	(0.0135)
banios	-.02404***	.24288***
	(0.0030)	(0.0134)
distAtraTuris	.0000266***	-.0001029***
	(0.0000)	(0.0000)
ruido	.0014355	.0026643
	(0.0035)	(0.0106)
distFuenCont	-.0000273***	-.0000645***
	(0.0000)	(0.0000)
distSITP	.0000128	-.0001352***
	(0.0000)	(0.0000)
distMallaVial	-.0000127	-.0002462***

	(0.0000)	(0.0001)
Constant	4.1307***	2.1313***
	(0.0572)	(0.4552)
R-Square	0.384	0.606
N	10,981	10,981
Hausman pValue		0.002
Relevance pValue		0.000
Hansen pValue		0.141
Var. Est.	robust cluster	robust cluster

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$