The impact of objective and subjective measures of air quality and noise on house prices: a multilevel approach for downtown Madrid

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Abstract

*Air quality and urban noise are major concerns in big cities. This paper aims at evaluating how they impact transaction prices in downtown Madrid. For that purpose, we incorporate both objective and subjective measures for air quality and noise and we use multilevel models since our sample is hierarchically organized into 3 levels: 5080 houses (level 1) in 759 census tracts (level 2) and 43 neighborhoods (level 3). Variables are available for each level, individual characteristics for the first level and various socio-economic data for the other levels. First, we combine a set of noise and air pollutants measured at a number of monitoring stations available for each census tract. Second, we apply kriging to match the monitoring station records to the census data. We also use subjective measures of air quality and noise based on a survey. Third, we estimate hedonic models in order to measure the marginal willingness to pay for air quality and reduced noise in downtown Madrid. We exploit the hierarchical nature of our data by estimating multilevel models and we show that *** to be completed ****

Keywords: Air quality, noise, housing prices, multilevel model, spatial analysis

JEL codes: C21, C29, Q53, R21

1. Introduction

Road traffic, industry and construction operations can generate high levels of air pollution and noise in urban areas, reducing local environmental quality and even contributing to climate change. This is why both air and acoustic pollution stand at the top on the list of city dwellers' environmental concerns, constituting two of the European Commission's action fields, i.e.: "Air pollution" and "Urban problems, noise and odours" (EEA 2000). The figures are clear: on the one hand, according to the World Health Organization, almost 2.5 million people die each year from causes directly attributable to air pollution (WHO 2006). On the other hand, although several developed countries have implemented noise reduction policies in recent decades, it has been suggested that more than 20% of the population of the European Union (EU) are exposed to higher noise levels than considered acceptable (European Commission 1996). It is well-known that clean air and a certain degree of quietness are considered to be basic requirements for human health and well-being. For this reason, governments and other official institutions aim at monetizing the social value of changes in pollution levels. One of the non-market evaluation techniques is Rosen (1974)'s hedonic regression method.

In this study, we apply the hedonic regression technique to examine the effect of air and noise pollution on property prices on a data set of downtown Madrid (Spain). Although this method has been widely used in the literature, we propose two useful innovations in this paper: Firstly, we compare objective versus subjective measures of both air and noise pollution through Exploratory Spatial Data Analysis (ESDA) and econometric models. Secondly, we apply spatial multilevel modeling to a hedonic housing price equation.

First, we analyze both the effect of air and noise pollution on housing prices. This feature is not frequent in hedonic specifications that typically only include air pollutants. Indeed, since the seminal studies of Nourse (1967) and Ridker and Henning (1967) air pollution has been considered as an important determinant of house prices. Many authors have focused on hedonic property-value models in order to estimate the marginal willingness of people to pay for a reduction in the local concentration of diverse air pollutants (see Smith and Huang, 1993, 1995 for a first review and meta-analysis, respectively). Not so profusely and independently from air-pollution, noise has also captured the analysts' attention since the seventies (Mieszkowski and Saper 1978, Nelson 1979), mainly in order to measure the economic costs of airports, railroads and motorways. Nevertheless, the literature is scarce when it comes to analyzing the effects of both –air and noise- pollutants in hedonic models with the exception of Li and Brown (1980), Wardman and Bristow (2004), Baranzini and Ramírez (2005), Banfi et al (2007) and Hui et al (2008). Another important feature is that all the above-mentioned studies use "objective" air quality and noise variables, such as concentrations of pollutants level or decibels. The introduction of "subjective" measures, based on people's perceptions, of either air or noise pollution has been exceptionally considered in the hedonic specification for house prices, probably because they are more difficult to obtain (Murti et al 2003, Hartley et al 2005, Berezansky et al 2010), while to the best of our knowledge there is no valuation of objective versus subjective air and noise pollution, as a whole, in the same model. Baranzini et al. (2010) compare subjective and objective measures of noise but they do not consider air quality. It must be said that the combination of objective and subjective approaches is an idea that has been gaining ground in the literature. Our aim here is to compare the results provided by objective versus subjective measures of both air quality and noise.

From the methodological point of view, the second contribution of this paper is the application of spatial multilevel modeling to a hedonic housing price model. During the last two decades, hedonic models have incorporated several methodological innovations in order to introduce pollution into the utility function of potential house buyers, such as alternative specification functions (Graves et al 1988), neural networks (Shaaf and Erfani 1996), spatial econometrics (e.g. Kim et al. 2003, Anselin and Le Gallo 2006, Anselin and Lozano-Gracia, 2008) and spatio-temporal geostatitics (Beamonte et al. 2008), among others. Though multilevel models have also been applied to hedonic housing price models (Jones and Bullen 1994, Gelfand et al 2007, Djurdjevic et al 2008, Bonin 2009, Leishman 2009), only Beron et al (1999) and Orford (2000)'s papers use them to measure the role of air pollution on property prices. As we show in the next section, multilevel models are a very useful tool when considering neighborhood amenities effects (operating at upper-scaled spatial level), such as environmental quality, in households preferences.

To the best of our knowledge, it is the first time that all these aspects (evaluation of the impact of both noise and air quality in housing prices, comparison of objective and subjective measures, spatial multilevel modeling) are combined in a hedonic model.

The paper is structured as follows. First, we provide a short description of multilevel modeling applied to hedonic models. Second, we describe the database. Third, we analyze the differences between objective and subjective measures of air quality and noise using Exploratory Spatial Data Analysis. Then, we provide the econometric results. Finally, the last section concludes.

2. Multilevel hedonic housing models

In the empirical analysis, we employ multilevel modeling, since our data has a hierarchical structure, where a hierarchy refers to units clustered at different spatial levels. Indeed, as we detail below (section 3), the individual transactions are nested within census tracts, which themselves are nested within neighborhoods. While many applications of multilevel modeling can be found in education science, biology or geography, economic applications in general and hedonic housing applications in particular are scarcer.

However, employing multilevel modeling for hierarchical data presents advantages. Firstly, from an economic perspective, whenever the hierarchical structure is properly taken into account, it is possible to analyze more accurately the extent to which differences in housing prices come from differences in housing characteristics and/or from differences in the environment of the transactions, i.e. the characteristics of the census tracts or the neighborhoods. In our case, this is an appealing feature, as we integrate in the econometric specification various explanatory factors that operate at three spatial levels. It is also possible to capture cross-level effects. Secondly, from an econometric perspective, inference is more reliable. Indeed, most single-level models assume independent observations. However, it may be that units belonging to the same group (for instance houses in the same census tract) are associated with correlated residuals. More efficient estimates are obtained when relaxing this independence assumption and modeling explicitly this intra-group correlation.

Formally, in a nutshell, consider a transaction i, located in census tract j, which is itself located in neighborhood k. In the most general case, we can specify a 3-level model with transactions at level 1 located in census tracts at level 2 and neighborhoods at level 3. At level 1, we specify a linear relationship as follows:

(1) $$y_{ijk} = \beta_{0,jk} + \sum_{s=1}^{S} \beta_{s,jk} x_{s,ijk} + \varepsilon_{ijk}$$

where $i = 1,...,N$ refers to the transaction, $j = 1,...,M$ refers to the census tract and $k = 1,...,K$ refers to the neighborhood. y_{ijk} is the housing price (or its logarithm) of transaction i in census tract j and neighborhood k; $x_{s,ijk}$ (with $s = 1,...,S$) are the level 1 predictors; ε_{ijk} is a random term with $\varepsilon_{ijk} : Nid(0,\sigma_{\varepsilon}^{2})$. A multilevel model emerges from the fact that the intercept $\beta_{0,jk}$ and the slopes $\beta_{s,jk}$ are allowed to vary randomly at the census tract level such as (level 2):

(2) $$\beta_{s,jk} = \gamma_{s0,k} + \sum_{l=1}^{N_s} \gamma_{sl,k} x_{sl,jk} + w_{s,jk} \quad \text{for} \quad s = 0,...,S$$

where N_s is the total number of variables operating at the census tract level affecting each transaction-specific parameter $\beta_{s,jk}$; $x_{sl,jk}$ (with $l = 1,...,N_s$) are the level 2 predictors for the parameters $\beta_{s,jk}$; $w_{jk} = (w_{0,jk}...w_{s,jk}...w_{S,jk})'$ is a random term distributed as a multivariate normal with 0 mean and τ_{β} as a full variance-covariance matrix of dimension $(S+1)$. Finally, the intercept $\gamma_{s1,k}$ and the slopes $\gamma_{sl,k}$ of equation (2) are themselves allowed to vary randomly at the neighborhood level such as (level 3):

(3) $$\gamma_{sl,k} = \mu_{sl0} + \sum_{m=1}^{N_{sl}} \mu_{slm} x_{slm,k} + u_{sl,k} \quad \text{for} \quad s = 0,...,S \text{ and } l = 0,...,N_s$$

where N_{sl} is the total number of variables operating at the neighborhood level affecting each census tract-specific parameter $\gamma_{sl,k}$; $x_{slm,k}$ (with $m = 1,...,N_{sl}$) are the level 3 predictors for the parameters $\gamma_{sl,k}$; $u_k = (u_{00,k}..u_{0l}..u_{0N_s}...u_{S0,k}..u_{Sl}...u_{SN_s})'$ is a random term distributed as a multivariate normal with 0 mean and τ_{γ} as a full variance-covariance matrix of dimension $\sum_{s=0}^{S}(N_s+1)$. Note that the coefficients in equation (3) are not random but fixed. Finally, the errors terms (ε_{ijk}, $w_{s,jk}$ and $u_{sn,k}$) are assumed to be independent of each other.

Substituting equations (2) and (3) in the level 1 model (equation 1) yields a mixed specification where the dependent variable y_{ijk} is the sum of a fixed part and a random part. The former includes explanatory variables operating at the 3 different spatial levels ($x_{s,ijk}, x_{sl,jk}, x_{slm,k}$), together with interactions between these levels, while the latter is a complex combination of the random terms $\varepsilon_{ijk}, w_{s,jk}$ and $u_{sl,k}$. This model is usually estimated using restricted maximum likelihood, noted thereafter REML (see for instance Raudenbush and Bryk, 2002 or Goldstein, 2003 for more details on the estimation method).

The full multilevel model (1)-(3) is very general with potentially a high number of unknown parameters to estimate. In practice, simpler models are estimated. In particular, not all parameters at level 1 vary randomly at the census tract level and/or not all parameters at level 2 vary randomly at the neighborhood level. We specify in the empirical analysis our assumptions concerning the variability of each parameter.

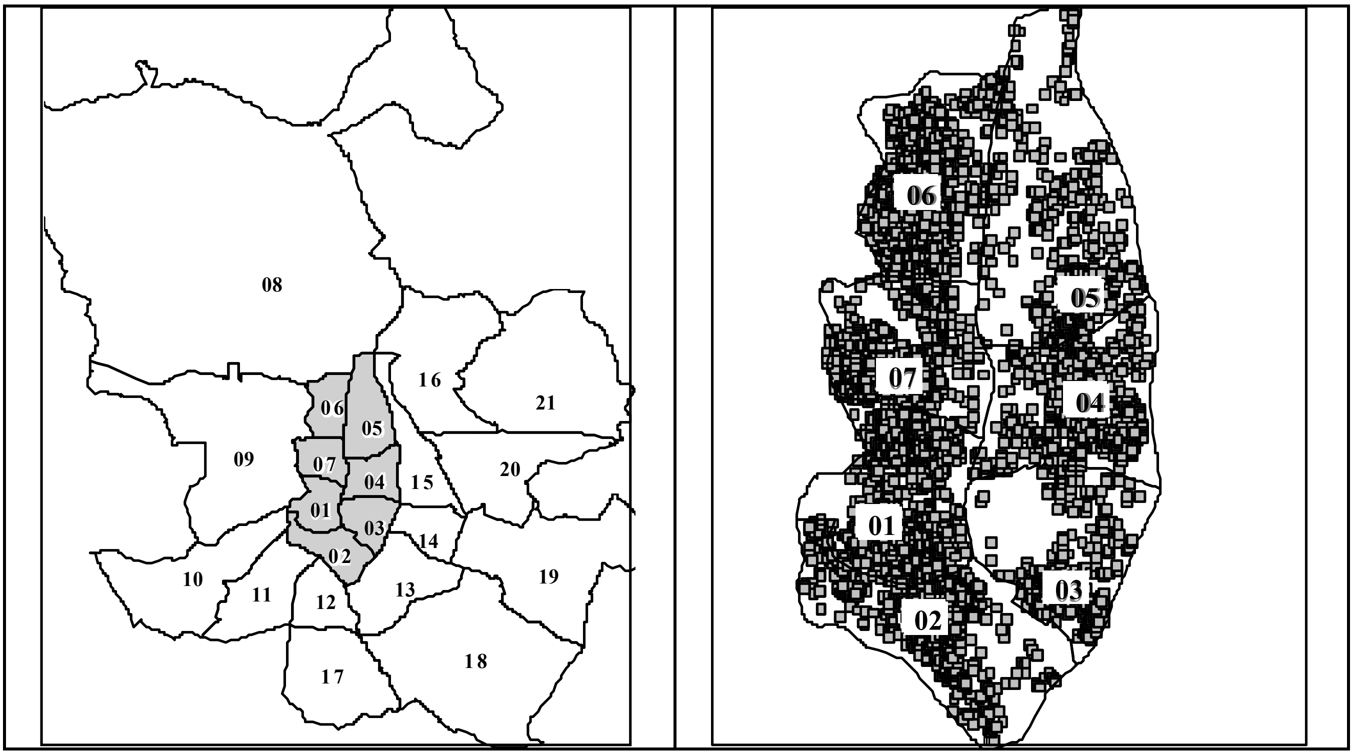
To analyze housing prices using hedonic models, multilevel modeling has been used by Beron *et al.* (1999). They apply a 3-level model to a sample of sales transaction in the South Coast Air Basin counties of Los Angeles, Orange, Riverside and San Bernardino in 1996 in order to evaluate the impact of an objective measure of air quality. Orford (2000) uses price data from Cardiff to show how a multilevel approach can explicitly incorporate the spatial structure of housing markets. Djurdjevic *et al.* (2008) use a 2-level model to analyze the Swiss rental market. Finally, Leishman (2009) argues that multilevel modeling can be used as a tool to identify sub-markets and to detect temporal change in the delimitation of sub-markets. We follow this strand of literature and use multilevel models to evaluate the differential impacts of objective and subjective measures of noise and air quality on housing prices in downtown Madrid.

3. Data

The city of Madrid is a municipality with a population of roughly 3.3 million inhabitants (as of January 2010). It comprises the city center or 'Central Almond' and a constellation of fourteen surrounding districts (Fig. 1a). Central Almond is the area formed by seven districts that are surrounded by the first metropolitan ring-road (the

M30). With more than 30% of the population and 50% of GDP of the city, Central Almond is clearly recognized as a unity with its own idiosyncrasy. Indeed, since 2004 to 2011, the Urbanism and Housing Area of the municipality government has launched two main “action plans” in order to restore and revitalize several areas of Central Almond (Ayuntamiento de Madrid 2009a, b, 2010). Our study therefore focuses on this area to contribute to shed light on an important issue, i.e. the people’s marginal willingness to pay for air quality and reduced noise in this core part of the city.

Fig. 1 (a) The city of Madrid and the Central Almond by districts. (b) Sample of houses.



Due to confidentiality constraints, it is not easy to obtain housing prices microdata from Spanish official institutions. For this reason, our records were drawn from a well-known on-line real-state database, ‘idealista.com’. Since this catalog immediately publishes the asking price of properties, we extracted the information during January 2008. The asking price has been used as a proxy for the selling price, as it is usual in many other cases (e.g. Cheshire and Sheppard 1998 or Orford 2000). In total, around 5,080 housing prices were finally recorded after the corresponding consolidation and geocoding processes[1]. The geographical distribution of houses is reported in Fig. 1b. ‘idealista.com’ also provides some property attribute data relating to dwelling type, living space, number of bedrooms, floor level and modernization and

[1] Geocoding has been tackled with the ‘Callejero del Censo Electoral’ (INE 2008).

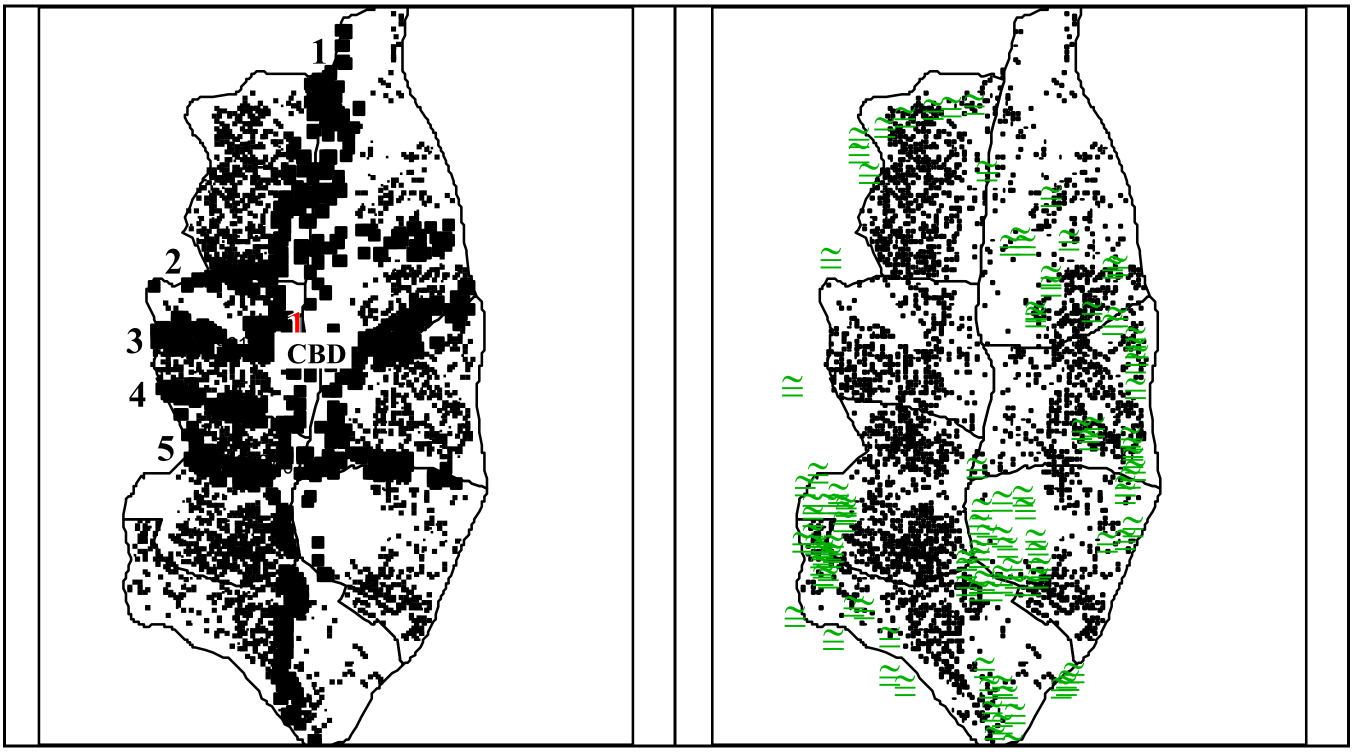
repair. In Table 1, we have only presented the definitions of the variables that were finally included in the model.

Table 1. The variables used in the model

Variable	Description	Source	Units	Period
LEVEL 1: HOUSES				
lprice	Housing price	Idealista	Euros (in logs)	Jan. 2008
A) Structural variables				
fl_1	First floor and upper	Idealista	0-1	Jan. 2008
attic	Attic	Idealista	0-1	Jan. 2008
house	House ('chalet')	Idealista	0-1	Jan. 2008
duplex	Duplex	Idealista	0-1	Jan. 2008
bedsit	Bedsit	Idealista	0-1	Jan. 2008
reform	Old house that must be reformed	Idealista	0-1	Jan. 2008
lm2	Living space	Idealista	Square meter (in logs)	Jan. 2008
B) Accessibility variables				
axis	Proximity to the main axis	Self-elab.	0-1	-
discen	Distance to the financial district	Self-elab	Km.	-
dispark	Distance to the nearest park	Self-elab.	Km.	-
C) Air and noise variables				
pollu	Objective air-pollution indicator	Munimadrid	100=average	2007
dBA	Objective noise indicator	Munimadrid	dB(A)	2008
cont	Subjective air-pollution indicator	Census	%	Nov. 2001
noise	Subjective noise indicator	Census	%	Nov. 2001
LEVEL 2: CENSUS TRACTS				
p65	Percent of population over 65 years	Padrón, INE	%	Jan. 2008
educ	Education level (secondary/university)	Census, INE	-	2001
unem	Unemployment rate	Census, INE	-	2001
ha90	House built after 1990	Census, INE	%	2001

Proximity of dwellings to enclaves like CBD, accessibility infrastructures (airports, motorways, and metro and rail stations), shopping facilities, parks, etc. is advertised by real estate agents and often capitalized in housing prices. For this reason, in order to capture these elements, we constructed the following accessibility measures: 1) distance to the airport terminals, 2) distance to the nearest metro or railway station, 3) distance to the M30 ring-road, 4) distance to the financial district, 5) distance to the main road-axis and commercial avenues and 6) distance to parks. From these, only the three last ones were statistically significant in the estimated model, with distance to the financial district the most determinant indicator. In effect, the new CBD, which is located at the geographical center of the Central Almond, is a huge block of modern office buildings with metro, railway and airport connections beside the government complex of *Nuevos Ministerios*. Another important variable is nearness to the main road-axis and commercial avenues. As depicted in Fig. 2a, we have selected those dwellings located at 250 meters (in average) along the main North-South axis (1) and four East-West avenues (2, 3, 4 y 5). Finally, distance to the nearest park is also an influential variable, especially in crowded and congested areas like the Central Almond. The parks are displayed in Fig. 2b.

Fig. 2 (a) Proximity to CBD and the main axis: 1 (*Castellana-Recoletos-Prado*), 2 (*Raimundo Fernández Villaverde-Concha Espina*), 3 (*José Abascal-María de Molina-América*), 4) (*Alberto Aguilera-Bilbao-Colón-Goya*), 5 (*Princesa-Gran Vía-Alcalá*). (b) Parks in the Central Almond.



The Central Almond is administratively divided into 7 districts, which are further subdivided into 43 neighborhoods and 780 census tracts. The 2001 Census provides a series of variables on socioeconomic and demographic characteristics relating to home-ownership at the level of census tracts. In Table 1, we present the most significant ones: percent of population over 65 years, percent of foreign population, percent of population with secondary and university degrees and percent of houses built after 1990. Though these variables are all referred to 2001, they are population averages which are very stable in time. This validates their inclusion in our model.

4. Noise and air pollution

In order to measure air-quality and noise effects on housing prices, we have elaborated some compound indicators.

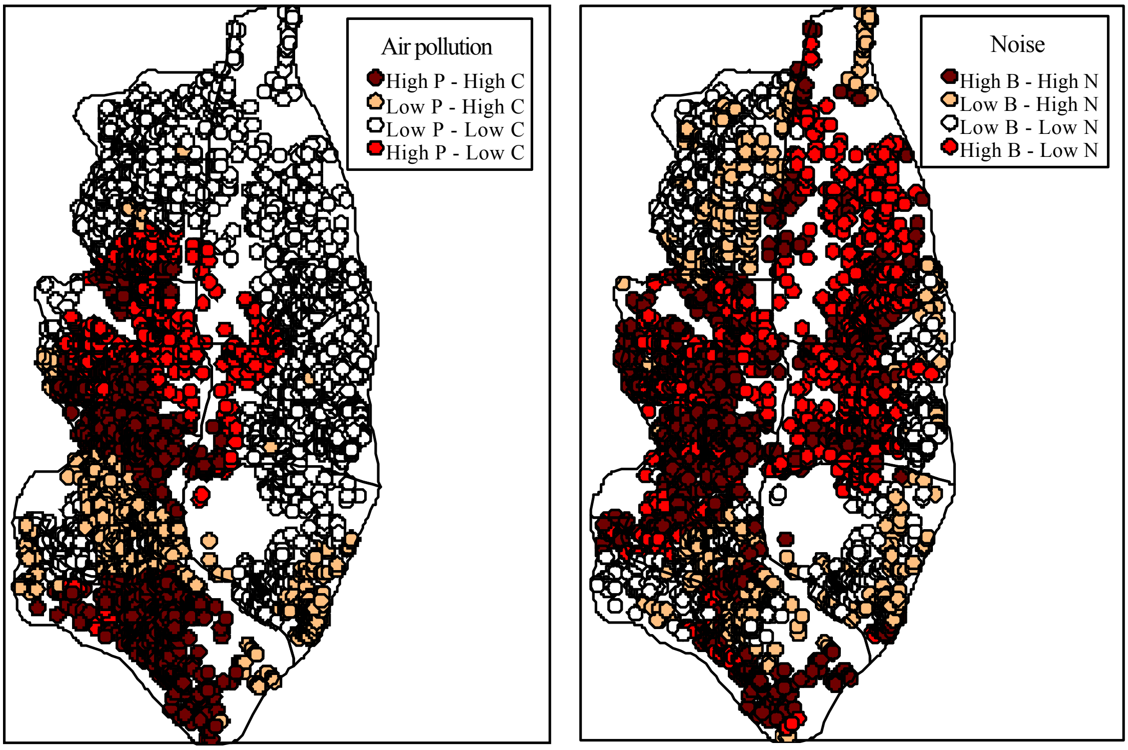
Regarding air-pollution, several types of air pollutants have been considered: five primary pollutants, which are the ones that cause most damage to ecosystems and human health (sulfur dioxide SO_2, oxides of nitrogen NO_x, nitrogen dioxide NO_2, carbon monoxide CO and particulate matter PM) and one secondary pollutant (ground-level ozone O_3), which is formed in the air when primary pollutants react or interact together to produce harmful chemicals. These variables were recorded at 27 fixed monitoring stations as annual averages of daily readings in 2007 and they are published by the Council of Madrid (http://www.munimadrid.es). As in Montero et al. (2010), we first interpolate these variables by ordinary kriging in order to combine them in a composite index with a distance indicator, the Pena Distance (DP2). It is an iterative procedure that weights partial indicators depending on their correlation with a global index. Its most attractive feature is that it uses all the valuable information contained in the partial indicators eliminating all the redundant variance present in these variables.

Regarding noise pollution, it is the name given to unwanted sound. The source of most acoustic pollution worldwide is transport systems (motor vehicles, aircraft, railways), as well as machinery and construction work. Our noise variable is a kriged estimation of traffic noise computed as an annual average of day, evening and night-time road traffic noise levels in A-weighted decibels (dBA) for 2008. These measures were recorded -for the whole city- from 1,797 fixed points as a daily average and then extrapolated for the most exposed façade of the buildings using noise curves and taking into account the distance to the road, reflection factors, hindrances, etc. (Ayuntamiento de Madrid 2008). The noise figures are transformed as an index, so as the “Central Almond” average is set to 100 and all the values are correspondingly re-scaled. This allows a direct comparison with the air-pollution index, which is accordingly measured.

Apart from these two ‘objective’ indicators, which are registered in specific monitoring stations, we compare them with two other ‘subjective’ indicators, which are based on the population’s perception of pollution and noise around their residences. They are measured by the 2001 Census for each census tract as the percentage of households that estimate that their homes’ surroundings are polluted or noisy.

Subjective data are not always correlated with the 'true' air quality or noise pollution. Even though some authors have pointed the limitations of subjective measures based on individuals' perceptions (e.g. Cummins 2000), the combination of both objective and subjective approaches seems to provide a better perspective for evaluating certain latent variables connected with quality of life (Delfim and Martins 2007). For example, prospective homebuyers most probably evaluate air quality based on whether or not the air 'appears' to be polluted or based on what other people and the media say about local air pollution (Delucchi et al. 2002). The same goes for noise (Miedema and Oudshoorn 2001, Nelson 2004, Palmquist 2005).

Fig. 3 (a) Scatterplot map of objetive air-pollution (P) and subjective air-pollution (C). (b) Scatterplot map of objective noise (B) and subjective noise (N).



In order to analyze these differences for our sample, we represent on a map the values of the four quadrants of a scatterplot of objective versus subjective pollutants in the Central Almond, so that it is possible to identify some peculiar non-coincidences between these variables (Fig. 3). In general, people living in contaminated places with some relevant value added (such as accessibility to the financial district or to main road-axis), do not have the perception of living in a so air/noise polluted area, probably because these location advantages mitigate the drawbacks of 'real' pollution. There are also non-coincidences in which subjective perceptions about contamination are worse than what is objectively registered in the monitoring stations. For instance, people living in the old CBD (historical center) think that air-pollution in this area is higher than it really is, maybe because it is the main tourist and commercial area, in which most of its streets are crowded (though progressively pedestrian, with traffic restrictions, since a decade ago). This is also the case of wealthier -and perhaps more exigent- people living in exclusive neighborhoods, such as *El Viso* or *Niño Jesús*, who think that their homes are noisier than they objectively are. Another similar non-coincidence takes place in some south-eastern and south-western edges of the Central Almond, along the M30. When asked in 2001, their inhabitants declared they lived in a highly air and/or noise-polluted area due to the presence of the M30 in front of their houses. However, the existent situation (represented by the objective measure, which is dated in 2008) is very different since the M30 ring was tunneled in 2007 along this part of the city.[2]

5. Results

5.1. Grand mean model

We first specify the grand mean model, which is fully unconditional: no predictor variables are specified at any level. This model allows determining how variations in housing prices are allocated across each spatial level. Formally, it is represented as the following log-linear model:

$$(4) \qquad \begin{cases} lprice_{ijk} = \beta_{0,jk} + \varepsilon_{ijk} \\ \beta_{0,jk} = \gamma_{00,k} + w_{0,jk} \\ \gamma_{00,k} = \mu_{000} + u_{00,k} \end{cases} \Rightarrow lprice_{ijk} = \mu_{000} + u_{00,k} + w_{0,jk} + \varepsilon_{ijk}$$

where $lprice_{ijk}$ is the log of price of transaction i in census tract j and neighborhood k; $\beta_{0,jk}$ is the mean log of price of census tract j in neighborhood k; $\gamma_{00,k}$ is the mean log of price in neighborhood k; μ_{000} is the grand mean; $\varepsilon_{ijk} : Nid\left(0,\sigma_{\varepsilon}^{2}\right)$ is the random term measuring the deviation of transaction ijk's log of price from the mean log of price in census tract j; $w_{0,jk} : Nid\left(0,\sigma_{w}^{2}\right)$ is the random term measuring the deviation of census tract jk's mean log of price from the mean log of price in neighborhood k;

[2] We built a dummy variable in order to capture this mismatch between the Census and the objective measures moment of time, but it was not significant at all.

$u_{00,k} : Nid\left(0,\sigma_u^2\right)$ is the random term measuring the deviation of neighborhood k's mean log of price from the grand mean.

Table 2. The Grand Mean model and Model 1

Variables			Grand Mean model	Benchmark model
Fixed				
		Const.	12.971190***	8.910863***
	Structural	*floor*	-	0.115840***
		attic	-	0.045662***
		house	-	0.257412***
		duplex	-	0.046847***
		bedsit	-	0.071195***
		lm2	-	2.037960***
		reform	-	-0.085792***
Random:	Variance (standard error)			
		Neighb.	0.084216 (0.01980)	0.021991 (0.00499)
		Census	0.044347 (0.00432)	0.005490 (0.00058)
		Houses	0.179351 (0.00385)	0.027577 (0.00059)
Intra-class (neighb.)			27%	40%
Intra-class (census)			14%	10%
LR			-3,237.93	1,526.38
Deviance (H_0: Grand Mean model)			-	9,528.63***
LR vs linear model			1,550.03***	2,059.12***

* significant at 0.10, ** significant at 0.05, *** significant at 0.01

The REML estimation results are displayed in Table 2 (third column). The average house price for the whole of 'Central Almond' in Madrid amounts to 429,849 € (Table 2).[3] The model further allows decomposing the variation around this grand mean into variation at the level of the individual transaction, census tract and neighborhoods.[4] The greatest variation occurs between individual transactions (almost 60%) although more than one-fourth of the variation takes place between neighborhoods (27%). This means that housing prices vary significantly between neighborhoods, which could be indicative of sub-markets. The LR test of absence of random effects strongly rejects the null, hence suggesting that a multilevel approach with random effects is relevant.

[3] This figure is the result of calculating the exp(12.971190), since we use a log-linear model.

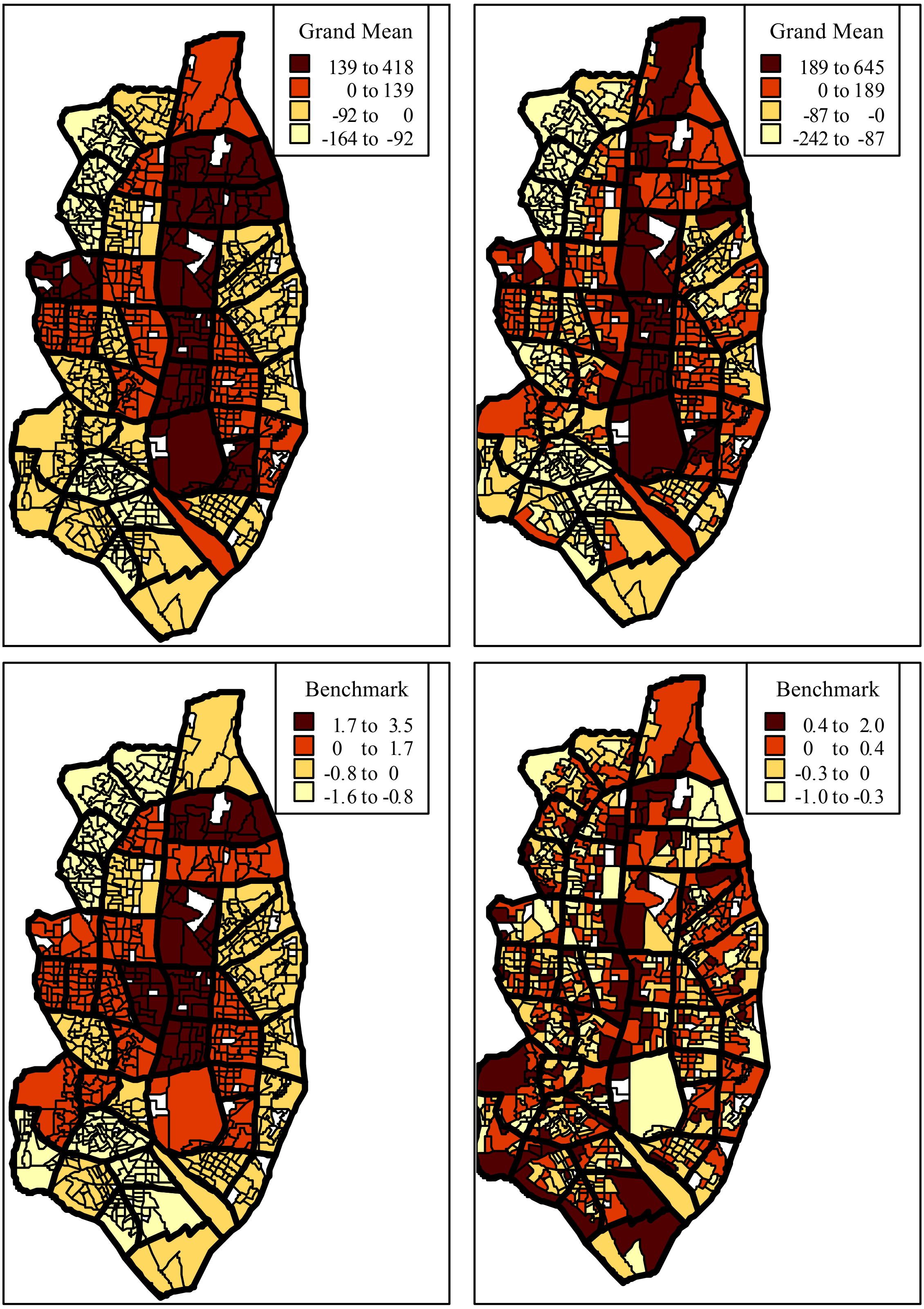
[4] They are computed respectively as follows: $\sigma_\varepsilon^2/\left(\sigma_\varepsilon^2+\sigma_w^2+\sigma_u^2\right)$; $\sigma_w^2/\left(\sigma_\varepsilon^2+\sigma_w^2+\sigma_u^2\right)$ and $\sigma_u^2/\left(\sigma_\varepsilon^2+\sigma_w^2+\sigma_u^2\right)$. The last two equations correspond respectively to the intra-class correlation for neighborhoods and census tracts that are reported in Table 2.

Table 3. Neighborhood level premiums for the Grand Mean and Models (1) and (2)

Grand Mean model		Benchmark model		Model 2P (*pollu*)		Model 2C (*cont*)	
Rank order	Price (€)	Rank order	Price (€)	Rank order	Price (€)	Rank order	Price (€)
Recoletos	417,781	Recoletos	3,468	Recoletos	2,828	Nueva España	2,559
Castellana	320,662	Castellana	2,671	Castellana	2,132	Recoletos	2,532
Jerónimos	289,276	El Viso	2,177	El Viso	1,754	El Viso	1,573
El Viso	276,144	Almagro	1,673	Nueva España	1,646	Castellana	1,561
Niño Jesús	200,482	Nueva España	1,660	Hispanoamérica	1,171	Hispanoamérica	1,345
Nueva España	188,464	Hispanoamérica	1,109	Goya	1,051	Castilla	1,218
Hispanoamérica	140,989	Goya	1,052	Almagro	952	Vallehermoso	973
Vallehermoso	139,746	Vallehermoso	1,003	Vallehermoso	823	Jerónimos	743
Almagro	95,517	Jerónimos	930	Jerónimos	812	Niño Jesús	741
Castilla	79,389	Trafalgar	730	Niño Jesús	740	Castillejos	671
Goya	65,070	Lista	675	Lista	673	Almagro	625
Estrella	60,881	Justicia	647	Gaztambide	545	Gaztambide	572
Ibiza	53,909	Rios Rosas	646	Trafalgar	421	Legazpi	551
Gaztambide	53,232	Gaztambide	613	Arapiles	400	Atocha	533
Lista	40,933	Niño Jesús	498	Rios Rosas	377	Adelfas	434
Rios Rosas	27,042	Arapiles	493	Sol	337	Goya	400
Justicia	16,363	Castillejos	252	Ibiza	322	Arapiles	237
Castillejos	9,364	Ibiza	170	Justicia	259	Rios Rosas	213
Arapiles	3,072	Sol	115	Castillejos	242	Trafalgar	190
Atocha	736	Palacio	66	Palacio	191	Palacio	170
Guindalera	-11,229	Cortes	-4	Cortes	54	Sol	158
Palacio	-22,555	Atocha	-138	Castilla	-68	Justicia	-70
Legazpi	-24,364	Castilla	-173	Atocha	-75	Acacias	-74
Cortes	-26,305	Universidad	-252	Ciudad Jardín	-141	Cortes	-131
Ciudad Jardín	-35,181	Ciudad Jardín	-319	Adelfas	-219	Lista	-193
Sol	-35,260	Guindalera	-382	Universidad	-266	Pacífico	-271
Adelfas	-41,243	Cuatro Caminos	-413	Estrella	-303	Delicias	-407
Cuatro Caminos	-42,322	Estrella	-480	Cuatro Caminos	-312	Ibiza	-466
Fuente del Berro	-45,445	Pacífico	-556	Pacífico	-317	Cuatro Caminos	-519
Trafalgar	-48,855	Adelfas	-569	Guindalera	-322	Estrella	-550
Prosperidad	-49,395	Fuente del Berro	-587	Prosperidad	-514	Almenara	-668
Pacífico	-49,528	Prosperidad	-600	Fuente del Berro	-532	Imperial	-729
Imperial	-70,374	Acacias	-706	Embajadores	-735	Universidad	-747
Almenara	-77,425	Legazpi	-774	Acacias	-757	Ciudad Jardín	-815
Universidad	-84,721	Embajadores	-987	Legazpi	-830	Valdeacederas	-886
Delicias	-84,880	Imperial	-1,020	Imperial	-881	Chopera	-927
Acacias	-91,068	Delicias	-1,106	Berruguete	-1,121	Embajadores	-952
Chopera	-129,383	Almenara	-1,219	Almenara	-1,142	Palos de Moguer	-1,046
Palos de Moguer	-139,174	Palos de Moguer	-1,263	Valdeacederas	-1,151	Guindalera	-1,074
Valdeacederas	-146,189	Berruguete	-1,357	Bellas Vistas	-1,211	Fuente del Berro	-1,153
Berruguete	-150,829	Valdeacederas	-1,368	Delicias	-1,218	Berruguete	-1,255
Embajadores	-161,740	Bellas Vistas	-1,433	Palos de Moguer	-1,253	Prosperidad	-1,322
Bellas Vistas	-163,389	Chopera	-1,557	Chopera	-1,561	Bellas Vistas	-1,730

The first column of Table 3 describes the price variations around the grand mean (429,849 €) at the neighborhood level. For instance, transactions in *Recoletos* and *Castellana* are more than 300,000 € more expensive than the average 'Central Almond' price in Madrid, while transactions in *Berruguete*, *Embajadores* and *Bellas Vistas* are more than 150,000 € cheaper.

Figure 4 Neighbourhood (left) and census tract-level (right) premiums (mile €)



We illustrate graphically these results in the upper left part of Figure 4. The cheapest neighborhoods are concentrated in the southern and northern part of the city whereas the neighborhoods with the highest premiums are located around the central axis along *Castellana-Recoletos-Prado* Avenues. The deviations of prices in census tracts compared to the grand mean (upper right part of Figure 4) follow a similar pattern but displaying some variations in more heterogeneous neighborhoods like *Castilla*, *Ciudad Jardín* or *Castillejos*.

5.2. The benchmark model

We label as Model 1 the benchmark model, which is the grand mean model to which only structural attributes of each transaction are included in the level 1 equation:

$$(5) \qquad \begin{cases} lprice_{ijk} = \beta_{0,jk} + \sum_{s=1}^{S} \beta_s x_{s,ijk} + \varepsilon_{ijk} \\ \beta_{0,jk} = \gamma_{00,k} + w_{0,jk} \\ \gamma_{00,k} = \mu_{000} + u_{00,k} \end{cases} \qquad (\textit{Model 1})$$

where S is the number of structural attributes. We assume that the associated coefficients are fixed: they do no vary randomly across census tracts and/or neighbourhoods.[5] The REML results are reported in Table 2 (fourth column). Among all structural variables considered, only the coefficients that are significant at the 5% level have been included. All the structural attributes coefficients estimates show the expected sign. They are strongly statistically significant at 1% with the exception of the number of bedrooms, which is not significant even at the 5% level. This can be explained by a strong correlation with the floor area variable. The difference in the likelihood ratio statistic of this model and the grand mean model (the deviance or likelihood ratio test) is 9,528.63. Under the null hypothesis, it follows a chi-squared distribution with degrees of freedom equal to 7, i.e. the number of new parameters (Woodhouse *et al*., 1996). The p-value is less than 0.001: the structural attributes therefore have a significant effect in explaining house price variation in the model.

Turning to the analysis of intra-class correlations, the inclusion of structural attributes implies a strong decline of the transaction-level variance. This means that a large part of price differences between individual transactions is a result of differences in these attributes. In contrast, 40% of the total variation now occurs between neighbourhoods, compared to 27% in the grand mean model. This result is reflected by

[5] This assumption will be relaxed below for some variables.

the analysis of the neighbourhood-level differences (second column of Table 2) as both the rank of neighbourhoods and the size of their contextual effects are modified. For instance, two of the previous most expensive neighbourhoods, *Castilla* and *Estrella* are now closer to the "Central Almond" average, while a previously below-average neighbourhood, *Trafalgar*, is now significantly above average. Much more evident are the modifications in the rank of the census tracts (lower right part of Figure 4). There still exists some concentration of higher premiums in part of the census tracts of the central axis (mainly along *Castellana* and *Recoletos* Av.), with the rest of the values more or less scattered all over the "Central Almond". Also, the size of the neighbourhood and census tract premiums has declined substantially, meaning that they were previously mainly capturing the effects of structural attributes. Furthermore, buyers are getting much less for their money in neighbourhoods like *Recoletos* and *Castellana* than in areas like *Chopera* and *Bellas Vistas*.

5.3. Model with structural and accessibility variables

Model 2 includes the same random and transaction-level fixed terms than the Benchmark model (Model 1), together with additional accessibility indicators and pollution variables (noise or air pollution). Formally, it can be expressed as in equation (5), with $x_{s,ijk}$ now including structural attributes, accessibility variables and pollution variables. In most models, among all the accessibility variables that we tried, only three accessibility indicators are significant at 5%: distance to the CBD (*discen*), distance to the main city axis (*axis*) and distance to parks (*dispark*). Multicolinearity might be an explanation for the absence of significance of the other accessibility variables: since they are confined to a plan, these variables are too highly intercorrelated to allow a precise analysis of their individual effects. Concerning the analysis of the impact of noise and air pollution on housing prices, we have specified four different models depending on the selected pollution variable[6]:

- model 2B includes the objective measure of noise (*dbA*)
- model 2N includes the subjective measure of noise (*noise*)
- model 2P includes the objective measure air pollution (*pollu*)
- model 2C includes the subjective measure of air pollution (*cont*)

[6] Due to the high correlation between air and noise pollution levels (Li and Brown 1980), it is necessary to sort out these separate effects in order to measure their marginal effect on housing prices.

The REML estimation results are displayed in Table 4. The inclusion of these accessibility and pollution variables does not alter either the values or the sign of the structural attributes, which are all significant at 5%. Concerning the accessibility variables, distance to the CBD (*discen*), in model 2P, and distance to parks (*dispark*), in models 2B and 2N, are not significant.

Table 4. Model 2 with noise and air pollution variables

		Noise and air pollution			
Variables		Objective (2B)	Subjective (2N)	Objective (2P)	Subjective (2C)
	Const.	7.592241***	9.074196***	8.814853***	9.199207***
Structural	*floor*	0.113775***	0.114698***	0.115070***	0.116381***
	attic	0.042192***	0.042535***	0.047338***	0.046579***
	house	0.235992***	0.236597***	0.248072***	0.249259***
	duplex	0.040473**	0.039686**	0.047840***	0.047413***
	bedsit	0.074080***	0.075041***	0.068839***	0.068988***
	lm2	2.058950***	2.058055***	2.034649***	2.035260***
	reform	-0.085394***	-0.083671***	-0.085233***	-0.086402***
Accessibility	*axis*	0.059998***	0.067511***	0.046982***	0.045414***
	discen	-0.070257***	-0.088085***	-	-0.076879***
	dispark	-	-	-0.041832**	-0.044492***
Air and noise variables	*dbA*	0.014200***	-	-	-
	noise	-	-0.000390	-	-
	pollu	-	-	0.001021***	-
	cont	-	-	-	-0.002519**
Variance (standard error)	*Neighb.*	-	-	0.020410 (0.004656)	0.010480 (0.00252)
	Census	0.013424 (0.00104)	0.014519 (0.00109)	0.005097 (0.00055)	0.005172 (0.00055)
	Houses	0.027591 (0.00059)	0.027525 (0.00059)	0.027492 (0.00059)	0.027357 (0.00059)
Intra-class (neighbourhood)		0%	0%	39%	24%
Intra-class (census)		33%	35%	10%	12%
LR		1,386.49	1,370.06	1,535.53	1,555.62
Deviance (H_0: Benchmark)		-	-	18.28***	58.48***
LR vs linear model		822.76***	931.76***	1,850.34***	1,246.92***

The coefficients for noise and air pollution across the four models are significant at 5% with the exception of subjective noise (*noise*), which does not seem to have any impact on housing prices. However, this result may be due to omitted higher-level interactions and will be reassessed with further models. Globally, the deviance statistic (with Model 1 as the null hypothesis) indicates that the addition of accessibility and pollution attributes has a significant effect on housing prices. For objective measures (*dbA* and *pollu*), we obtain a positive sign whereas the sign is negative for the subjective variables (*noise* and *cont*). In other words, noise and air pollution seem to have a negative influence on housing prices -as expected- but only when they are measured as people's perceptions. On the contrary, when noise and air pollution are recorded from a group of fixed locations and subsequently kriged to the level of houses, their impact on prices turns out to be positive. Following the exploratory analysis in section 4, this counter-intuitive sign confirms that the households' perceptions of noise and air pollution differ from objective measures, pleading for the use of subjective measures to assess the impact of noise and air pollution on prices.

We also find that in models 2B and 2N for objective and subjective noise, the neighbourhood-level random effect is no longer significant[7] resulting in the census tract level now explaining 33% (*dbA*) and 35% (*noise*) of house price variations. This result means that noise seems to be a more "local" phenomenon than air quality so that random variations at the census tract level are enough to capture price variability.

Finally, looking at the neighbourhood premiums, it appears that the addition of accessibility and pollution variables has resulted in some changes (third and fourth column of Table 2). First, the effects of area are now smaller. In models 2P and 2C (for air pollution variables), the reduction in the size of the neighbourhood premiums had declined substantially, suggesting that they were capturing the compositional effects of the housing stock (Table 3). In the case of models 2B and 2N (for noise variables), there is no neighbourhood-level variation. However, for the air pollution specifications, there are interesting changes in rank, notably in model 2C, as the promotion of *Legazpi*, *Castilla* and *Adelfas*. These neighbourhoods command a higher premium, given the accessibility and subjective air-pollution attributes of the areas, which may be caused by other features, such as social class.

5.4. Model with structural, accessibility and census tract variables

As a first robustness check, we now estimate a model with the same random and transaction level fixed terms as in the previous model, but which further incorporates some attributes available at the census tract level (Model 3):

[7] This is why the deviance statistic has not been computed in cases 2B and 2N as Model 1 is not nested in models 2B and 2N.

$$(6) \quad \begin{cases} lprice_{ijk} = \beta_{0,jk} + \sum_{s=1}^{S} \beta_s x_{s,ijk} + \varepsilon_{ijk} \\ \beta_{0,jk} = \gamma_{00,k} + \sum_{l=1}^{N_0} \gamma_{0l} x_{0l,jk} + w_{0,jk} \\ \gamma_{00,k} = \mu_{000} + u_{00,k} \end{cases} \qquad (Model\ 3)$$

These N_0 variables only affect the intercept of the level 1 model ($\beta_{0,jk}$) and we assume that they remain fixed across census tracts, i.e. they do not vary randomly at the neighborhood level. They are the census tracts variables shown in Table 1: *P65*, *educ*, *unem* and *ha90*.

Table 5. Model 3 with structural attributes, accessibility variables and census tract level variables

Variables		Noise		Air-pollution	
		Objective (3B)	Subjective (3N)	Objective (3P)	Subjective (3C)
	Constant	7.501044***	8.439646***	8.559091***	8.939796***
Structural	*floor*	0.112362***	0.113003***	0.113932***	0.115302***
	attic	0.046013***	0.046658***	0.047519***	0.046852***
	house	0.244359***	0.242348***	0.254909***	0.253879***
	duplex	0.047028***	0.046716***	0.047753***	0.047318***
	bedsit	0.072480***	0.072548***	0.066805***	0.067300***
	lm2	2.035985***	2.035257***	2.023457***	2.025078***
	reform	-0.087484***	-0.082655***	-0.088674***	-0.089084***
Accesibility	*axis*	0.049330***	0.058374***	0.041556***	0.042230***
	discen	-0.050929***	-0.062792***	-	-0.062438***
	dispark	-	-	-0.033920**	-0.032945**
Census tracts	*P65*	-	-	-0.005315***	-0.005475***
	educ	0.007697***	0.008941***	0.006325***	0.005863***
	unem	-0.007390***	-	-0.005962***	-0.005883***
	ha90	0.001157**	0.001152**	-	-
Pollution variables	*dbA*	0.010698***	-	-	-
	noise	-	-0.000457	-	-
	pollu	-	-	0.001034***	-
	cont	-	-	-	-0.002616***
Variance (standard error)	*Neighbour.*	-	-	0.013733 (0.00325)	0.007333 (0.00182)
	Census	0.009957 (0.00083)	0.010753 (0.00087)	0.004038 (0.00048)	0.004207 (0.00049)
	Houses	0.027530 (0.00059)	0.027494 (0.00059)	0.027451 (0.00059)	0.027323 (0.00058)
Intra-class (neighbourh.)		0%	0%	30%	19%
Intra-class (census tracts)		27%	28%	9%	11%
LR		1,448.03	1,435.88	1,568.47	1,583.15
Deviance (H_0: Model 2)		123.08***	131.65***	65.90***	55.06***
LR vs linear model		607.15***	668.85***	1,141.40***	880.16***

The REML estimation results are displayed in Table 5. Compared to model 2, since the census tract variables do not vary at the level of houses, the fixed and random estimates for the transaction-level attributes remain more or less unchanged, mainly for the structural attributes. However, the census tract-level and neighbourhood-level random effects have decreased, so that the transaction level now explains approximately one third of house price variations (between 27%-40%, depending on the specification). Again, the neighbourhood random effect is not significant for models 3B and 3N. The census tract variables act as a proxy for social class and, as expected, they have a significant effect upon house price differentials with the expected sign, a result confirmed by the computation of the deviance statistic with Model 2 as the null hypothesis. The results concerning the differential impacts of objective and subjective measures of noise and air pollution on house prices remain unchanged.

5.5. Model with varying slopes for lm2 and, in case, decib/noise and cont/pollu

In all the previous models, we have assumed that the structural attributes and the pollution variables are constant across downtown Madrid. Therefore, all differences were captured by a single variance term (σ_{ε}^{2}). However, we have shown that in Model 3, approximately one third of house price variation occurs between census tracts and/or neighborhoods. These unexplained variations might in fact be caused by variation in the implicit prices of structural attributes and/or pollution variables at both spatial levels. In other words, if sub-markets exist, then we would expect significant variations of the implicit prices of some attributes across census tracts and neighborhoods. Therefore, our second robustness test consists in estimating models in which some level 1 coefficients are allowed to vary randomly at higher spatial levels.

More specifically, since floor area (*lm2*) is the main structural attribute, it is allowed to vary randomly at the census tract level. The objective and subjective measures of noise are also allowed to vary randomly at the census tract level. However, after several tries, we found that the objective and subjective measures of air pollution only vary randomly at the neighborhood levels, further confirming the local nature of noise with respect to air-pollution[8]. Formally, for noise measures, our final specification is as follows (Models 4B and 4N):

[8] Often transitory and seldom catastrophic, noise is considered as an environmental intrusion with a very local effect, which depends –among others- on the time of the day or the distribution and distance of exposed persons from the source (Falzone 1999. Bickel et al 2003).

$$
(7) \quad \begin{cases} lprice_{ijk} = \beta_{0,j} + \beta_{1,j} lm2_{ijk} + \beta_{2,j} dBA/noise_{ijk} + \sum_{s=3}^{S} \beta_s x_{s,ijk} + \varepsilon_{ijk} \\ \beta_{0,j} = \gamma_{00} + \sum_{l=1}^{N_0} \gamma_{0l} x_{0l,jk} + w_{0,jk} \\ \beta_{1,j} = \gamma_{10} + w_{1,jk} \\ \beta_{2,j} = \gamma_{20} + w_{2,jk} \end{cases}
$$

where *dBA/noise* is either *dbA* or *noise*. For air pollution measures, our final specification is as follows (Models 4P and 4C):

$$
(8) \quad \begin{cases} lprice_{ijk} = \beta_{0,jk} + \beta_{1,j} lm2_{ijk} + \beta_{2,k} pollu/cont_{ijk} + \sum_{s=3}^{S} \beta_s x_{s,ijk} + \varepsilon_{ijk} \\ \beta_{0,jk} = \gamma_{00,k} + \sum_{l=1}^{N_0} \gamma_{0l} x_{0l,jk} + w_{0,jk} \\ \beta_{1,j} = \gamma_{10} + w_{1,jk} \\ \gamma_{00,k} = \mu_{000} + u_{00,k} \\ \beta_{2,k} = \mu_{200} + u_{20,k} \end{cases}
$$

where *pollu/cont* is either *pollu* or *cont*.

The REML estimation results are displayed in Table 6. Looking at the significance of the coefficients, all the structural, locational and pollution variables are strongly significant. Interestingly, Model 4N is the only model in which the coefficient associated to the subjective measure of noise (*noise*) is statistically significant once higher-level interactions at the level of census tracts are explicitly considered. We find again the difference in sign between objective and subjective measures of noise and air pollution. We now examine the geographical variation of pollution variables.

Table 6. Model 4 with varying slopes for *lm2* and pollution variables.

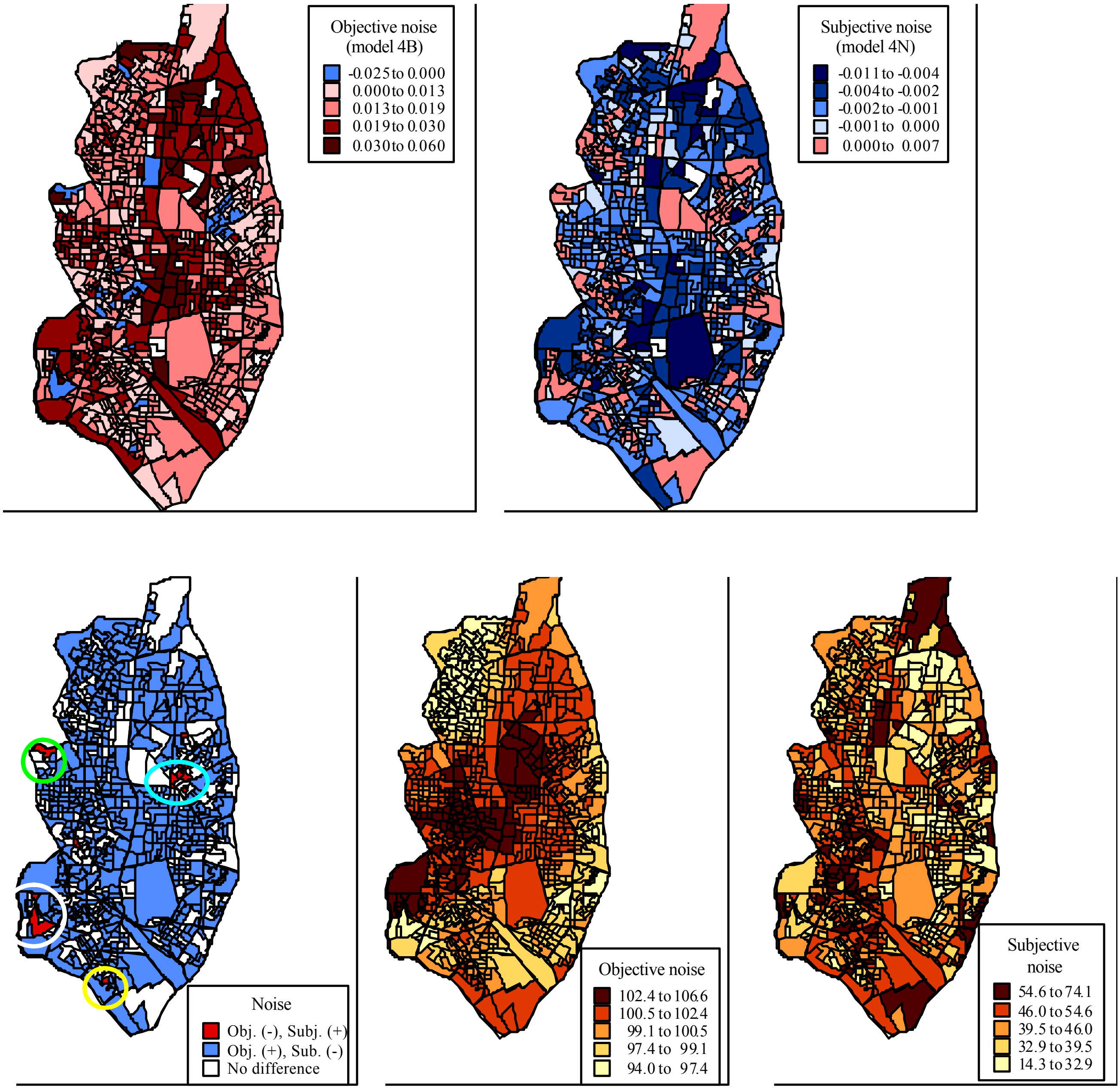
		Noise		Air-pollution	
		Objective (4B)	Subjective (4N)	Objective (4P)	Subjective (4C)
	constant	7.398895***	8.548232***	8.618724***	8.986422***
Structural	*floor*	0.115604***	0.117164***	0.118561***	0.120687***
	attic	0.054317***	0.053105***	0.053707***	0.053056***
	house	0.240507***	0.252558***	0.269246***	0.260919***
	duplex	0.048548***	0.047880***	0.049714***	0.050435***
	bedsit	0.065889***	0.064153***	0.059074***	0.061206***
	lm2	2.020611***	2.018975***	2.005984***	2.006315***

	reform		-0.089329***	-0.086753***	-0.098837***	-0.097490***
Accesibility	*axis*		0.042233***	0.049610***	0.036976***	0.036167***
	discen		-0.044203***	-0.055806***	-	-0.055079***
	dispark		-	-	-0.027532*	-0.032120**
Census tracts	*p65*		-	-	-0.004244***	-0.004669***
	educ		0.007316***	0.007688***	0.005890***	0.005579***
	unem		-	-	-0.005424***	-0.005304***
	ha90		0.001580***	0.001245***	-	-
Pollution variables	*dba07*		0.011041***	-	-	-
	noise		-	-0.000889**	-	-
	pollu		-	-	0.000704**	-
	cont		-	-	-	-0.004151***
Variance and covariance (standard error)	*Neighb.*	*constant*	-	-	0.004428 (0.00340)	0.030530 (0.01272)
		air-pollut.	-	-	5.11e-07 (2.73e-07)	0.000016 (9.71e-06)
		air-pollut-constant	-	-	-	-0.000678 (0.00035)
	Census	*constant*	3.044929 (1.40356)	0.224907 (0.04147)	0.210474 (0.02954)	0.203808 (0.02907)
		lm2	0.069669 (0.00932)	0.071518 (0.00902)	0.066424 (0.00858)	0.065018 (0.00846)
		noise var.	0.000276 (0.00013)	0.000019 (0.00001)	-	-
		lm2-constant	-0.178069 (-)	-0.113460 (0.01781)	-0.117534 (0.01586)	-0.114391 (0.01562)
		noise var-const	-0.028019 (0.01347)	-0.000694 (0.00041)	-	-
		noise var-lm2	0.000616 (0.00043)	-0.000116 (0.00018)	-	-
	Houses		0.024631 (0.00055)	0.024290 (0.00056)	0.024775 (0.00055)	0.024681 (0.00055)
LR			1,585.51	1,580.20	1,669.31	1,682.12
LR vs linear model			902.07***	957.49***	1,343.08***	1,091.32***

Indeed, Model 4 enables exploring the importance of noise and air pollution in house price variation further by allowing these variables to vary at the neighborhood (for air pollution) or the census tract level (for noise). The effect of noise per se only varies quite significantly between census tracts, though with a different sign (Figure 5).

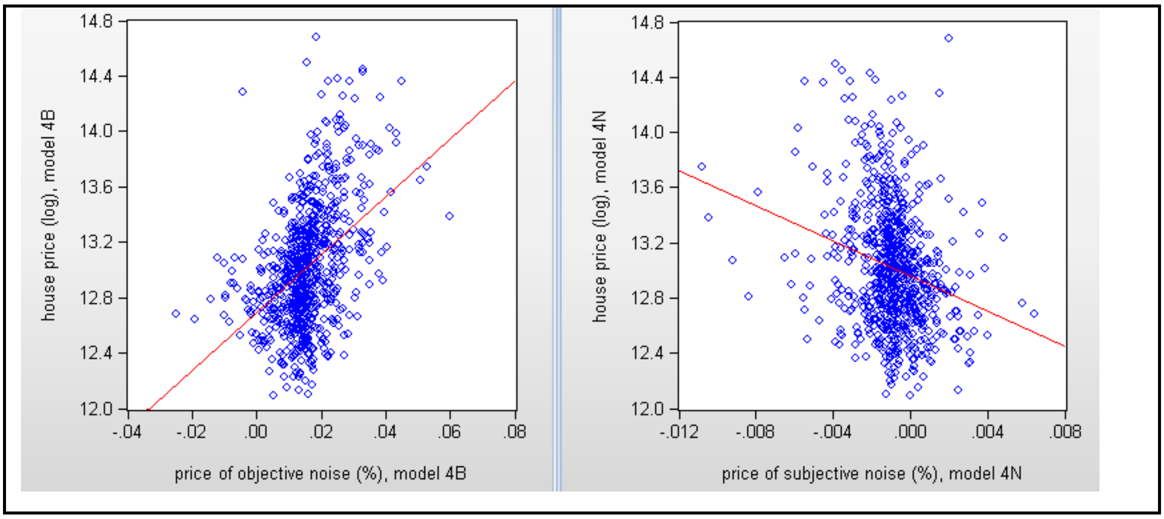
The relationship between noise and average census-tract level house price is a linear relationship, with a positive slope for marginal price of objective noise and a negative slope for marginal price of subjective noise (Figure 6). Consequently, the neighborhoods with more expensive houses are those in which marginal price-noise is higher for measured noise but lower for perceived noise, and vice versa….

Figure 5 Changes in census-tract-level prices due to noise



In addition, the corresponding covariance values in Table 6 point to a poor functional relation between noise variables at this higher level with floor area. Only objective noise and average census-tract-level house price exhibit a strong exponential and negative interrelation. Consequently the marginal price-objective noise relationship is negatively steeper in areas of higher house prices, and vice versa.

Figure 6. Price of noise by average census tract-level house price.



6. Conclusion

--- TO BE DONE ---

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