Housing market analysis using a hierarchical–spatial approach: the case of Belo Horizonte, Minas Gerais, Brazil

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The paper analyzes the determinants of apartments’ prices in Belo Horizonte, MG, Brazil, with the use of hierarchical models, spatial models and a hierarchical-spatial approach. Besides the apartments’ characteristics, such as area, age and building standard, prices were determined by local urban amenities. The hierarchical models indicated that local variables, such as urban violence, infrastructure and services, explained over 75% of prices’ remaining variability. The spatial models analyzed if, after controlling for price variability with the explanatory variables in the second level of the hierarchical models, spatial correlations still existed in price determination. The positive and significant spatial coefficient in spatial autoregressive models (SAR) indicated spatial dependency. The hierarchical-spatial approach showed that over 70% of apartment prices’ remaining variability could be explained by local variables and that the lagged urban services variable explained another 12% of this variability.

Keywords: real estate market; hedonic price models; hierarchical models; spatial econometrics; Belo Horizonte; Brazil

Introduction

Brazilian cities display a remarkable spatial heterogeneity, similar to many others in developing countries. In particular, urban services and infrastructure are spatially concentrated in specific areas, while sizable proportions of the cities lack basic public and private goods. This local variability affects real estate prices in ways that might greatly differ from developed countries.

Hedonic price models are commonly used to analyse the determinants of prices in real estate markets (Krause & Bitter, 2012), and some previous studies have analysed Brazilian data using this approach (e.g. Maciel & Biderman, 2010; Moraes & Cruz, 2003; Paixão, 2010; Rondon & Andrade, 2005; Sousa Filho & Arraes, 2004; Teixeira & Serra, 2006). However, most estimated the hedonic models by the method of ordinary least squares (OLS), which might present some limitations.

Prices depend on the real estates’ characteristics, which are defined for each house, apartment or commercial property. Besides these individually identified attributes, features associated with location also determine prices, and some limitations are intrinsically present in the definition of a locality. For example, a common procedure while defining a locality is arbitrarily to divide a region into geographical units of analysis. Then locality is represented by mean values of selected variables for each of these units of analysis. Therefore, following this procedure, mean values of a set of variables,
which poorly and imperfectly characterize regions, are taken to represent non-homoge-

Due to these properties, in general, databases used to analyse real estate prices tend
to be naturally hierarchical with a first level represented by the real estate characteristics,
which are individually defined for each observation, and a second level related to the
areas’ attributes (Goodman & Thibodeau, 1998). In addition, in a similar vein, Quigley
(1985) emphasizes that choice strategy of where to live is also hierarchical, as individu-
als first choose a city, then a neighbourhood, and finally a particular property in the cho-

Even though the use of hierarchical models can overcome some of the limitations
imposed by the structure of the database, other types of shortcomings may occur if the
models exhibit spatial correlation. For instance, when an econometric model is specified,
there might be omitted variables that are spatially correlated (Kalenkoski & Lacombe,
2008), which is what happens in many studies of real estate markets (Dubin, 1998).
Moreover, interactions and externalities between observations and regions may also
exist. These features create spatial dependency and/or spatial heterogeneity (Anselin,
1988; Dubin, 1998), and a hierarchical–spatial approach can be applied in order to over-
come some of these drawbacks. Empirical applications of this method are yet not
numerous in economics in general or in real estate market analyses in particular.

As described above, similar to this paper, some authors have discussed the determi-
nants of real estate prices in Brazil using hedonic models. Nevertheless, this paper
applies a rather different approach, which includes the use of hierarchical models and a
hierarchical–spatial approach. Thus, using this methodology, we could overcome many
of the empirical limitations of hedonic models estimated by OLS techniques.

Moreover, it uses two complementary databases in the empirical analysis: one with
data for real estate and another for areas. The first one is the Real Estate Transference
Taxes database of the municipality of Belo Horizonte (RETT-BH). This database has
data for prices and attributes of all real estate units (commercial and housing) sold in a
particular period. In our analysis, we selected the data between January 2004 and July
2010. The second database has data for the 81 Planning Units (PU) of Belo Horizonte.
The data include the Quality of Urban Life Index (QULI) and three of its nine indica-
tors: urban infrastructure, urban services and security. Those indicators were considered
the ones with greater propensity to impact real estate prices. We use data from 2006, as
it is representative of the discussed period.

To the best of our knowledge, this paper is the first to attempt to use the above-
mentioned methodology and these two databases, which might enable a more insightful
perspective of housing price determinants.

The paper is structured as follows. The next section presents an overview of Belo
Horizonte to contextualize the following discussions. The third section presents a litera-
ture review of studies that empirically analysed the determinants of real estate prices in
Brazil and other countries. The fourth section details the two mentioned databases and
presents the empirical strategy applied in the paper in three separate presentations, respectively for the hedonic model, for the hierarchical model, and for the hierarchical–spatial approach. The fifth section shows the empirical results. The sixth section concludes.

An overview of Belo Horizonte

Belo Horizonte is the capital of Minas Gerais state, and has approximately 2.3 million inhabitants. It is currently the sixth most highly populated among the Brazilian municipalities. Its metropolitan region is the third largest urban agglomeration in Brazil, with around 5 million people, representing 2.6% of the Brazilian population (Instituto Brasileiro de Geografia e Estatística (IBGE), 2010). In addition, the municipality of Belo Horizonte had the fifth largest municipal gross domestic product (GDP) among the more than 5000 municipalities in Brazil in 2011. Belo Horizonte was founded in 1897 and was the first planned city in Brazil. At that time, the elites who idealized the flourishing urban centre had among their objectives the creation of organized, clean and

Figure 1. Brazil, Minas Gerais and Belo Horizonte.
segregated areas, which would be detached from the lower class neighbourhoods (Costa, 1994). This planning created a centre–periphery radial model for the city, which concentrated urban services and urban infrastructure in particular areas, and reinforced social disparities. Figure 1 shows that most main avenues in the city connect the urban (and planned) centre with the outskirts of the city.

Since the 1940s some urban innovations tried to diminish this spatial heterogeneity by enforcing the development of different areas in the municipality, but with little success (Gough, 1994), specially from the military period (1964–84) to the end of hyperinflation in 1994 (Santos, 1999). The most recent urban interventions were a set of public actions implemented by the state government since 2003, which brought some dynamism to the north of the metropolitan region, an area that is traditionally the least developed of Belo Horizonte (Brito & Souza, 2008; Gomes, 2008). Amongst these actions, the following can be emphasized: a revitalization of avenues leading to the north of the city; the enlargement of the international airport; and the construction of the Administrative Center of the state government of Minas Gerais, also shown in Figure 1. All these urban actions have relatively increased real estate prices in the north of Belo Horizonte, and thus there has been a homogenization of real estate prices in the capital since 2004 (Aguiar & Simões, 2010).

Although different urban policies were recently implemented in order to overcome some of the most appalling social problems in Belo Horizonte (Simões, Goldner, & Campolina, 2008), some problems still decisively affect real estate prices, such as those related to urban mobility or to security. Moreover, urban services and infrastructure are still heterogeneously distributed among the municipal areas, feature that also affects real estate prices.

Brief literature review

This paper analyses the determinants of housing market prices in a city located in a developing country using hierarchical models and a hierarchical–spatial approach. This section presents a literature review emphasizing some studies that addressed similar methodological and theoretical questions. Concerning methods, the application of hierarchical models in real estate market analyses is relatively recent (Chasco & Le Gallo, 2013; Gelfand, Banerjee, Sirmans, Tu, & Ong, 2007; Habib & Miller, 2008; Huang & Clark, 2002; Leishman, 2009; Orford, 2000, 2002), and is becoming more popular as these models effectively consider the natural hierarchical structure of most real estate market databases.

According to Vanoutrive & Parenti (2009), besides the hierarchical methodology, spatial models are increasingly being used in real estate market analyses, however each approach is conducted separately. Nonetheless, the authors emphasized that, depending on how the geographical units of analysis are defined and how the second levels of the hierarchical models are specified, spatial autocorrelation is not eliminated. In contrast to the approach used in this paper, the authors suggest the use of more levels in the hierarchical models in order to overcome the limitations of the existence of spatial correlation. These authors discussed extensively many studies that addressed questions associated with real estate markets and the use of hierarchical and spatial models and none applied a similar methodology to the one used in this paper.

Some authors, however, did apply a similar hierarchical–spatial approach to the one used in this paper in other settings, such as in birth weight analyses (Morenoff, 2003), in schooling enrolment studies (Riani, Rios-Neto, & Moro, 2007) and in neighbourhood
contextual social organization analysis (Swaroop & Morenoff, 2006). Therefore, to the best of our knowledge, this paper is the first to use this methodological approach while discussing the determinants of real estate prices.

Regarding the analyses of real estate markets in developing countries, although there was a recent increase in the number of studies, they are still not nearly as numerous as in developed countries (Malpezzi, 1999; Malpezzi & Mayo, 1985; Wu, 2003). The lack of databases, or the inaccessibility of existing data, in part explains this smaller number of studies (Wu, 2003). For instance, Malpezzi & Mayo (1985) stated that there was little information on real estate market behaviour available for policy-makers in developing countries. They argue that the literature in developed countries has grown because, in order to intervene efficiently in housing markets, governments demand detailed knowledge about them. These authors emphasized that the literature associated with housing markets would advance in developing countries if there were a greater concern of local governments in more effectively coordinate real estate markets.

Although not numerous, some studies were performed in developing countries in order to gather information on real estate markets the better to design public policies, such as those that analysed the effect of the bus rapid transit (BRT) on real estate prices in Bogotá, Colombia (Rodríguez & Targa, 2004); the impacts of urban environmental on housing prices in Guangzhou, China (Jim & Chen, 2006); water services valuation in Bangalore, India (Anselin, Lozano-Garcia, Deichmann, & Lall, 2010); and the small importance given to land ownership regularization in Tijuana, Mexico (Monkkonen, 2012).

According to Malpezzi (1999), housing market behaviour is remarkably similar in different areas, but institutions and constraints, in particularly the amount of income available for housing and other goods and services, can vary dramatically from place to place. Having as background this local variability of institutions and constraints, Daniere (1994) analysed Cairo, Egypt and Manila, Philippines, and observed that low-income households conferred greater value on locations that were close to their jobs or to the central business district (CBD), had a regular source of potable water, and were well connected to public transportation. Ozus, Dokmeci, Kiroglu, & and Egdemir (2007) analysed Istanbul, Turkey, and verified that planned districts had higher housing prices. Ahmad (2014) showed that owners and renters in Bangladesh valued having a living room and a dining room/kitchen as well as the structural quality of the building, and the existence of proper sanitation facilities and electricity access.

In Brazil, as in many other developing countries, a sizable proportion of real estate transactions are performed informally, and therefore lack proper registration (Abramo, 2003). Thus, given this unavailability and unreliability of information, the majority of real estate analyses with Brazilian data discuss only formal markets (Fundação João Pinheiro (FJP), 2009). We present an overview of these studies below.

Since the 1990s, most studies with Brazilian data applied hedonic models estimated with OLS techniques (Aguirre & Faria, 1997; Aguirre & Macedo, 1997; Moraes & Cruz, 2003; Paixão, 2009, 2010; Rondon & Andrade, 2005; Sousa Filho & Arraes, 2004; Teixeira & Serra, 2006). Many only analysed the influence of the real estate characteristics and of location on prices in different municipalities and metropolitan regions in Brazil. Others papers discussed the effect of particular local characteristics on real estate prices, such as sanitation projects in São Paulo (Aguirre & Faria, 1997); air pollution in Brasília (Batalhone, Nogueira, & Mueller, 2002); and the metropolitan beltway in São Paulo (Maciel & Biderman, 2010). Moreover, a point emphasized in the Brazilian literature is the influence of crime and security on
By 2000, an increase in the use of other types of methods could be observed, such as spatial methods and microeconometric models. Among the first group, there are studies that analysed the cities of São Paulo (Hermann & Haddad, 2005; Nadalin, 2010), Belo Horizonte (Furtado, 2009) and Recife (Dantas, Magalhães, & Vergolino, 2010). The second group applied different techniques to study different localities, such as instrumental variables to analyse the city of São Paulo (Biderman, 2001), two-stage least squares models to study São Paulo Metropolitan Region (Fávero, Belfiore, & Lima, 2008) and hierarchical models to analyse the city of Belo Horizonte (Aguiar & Simões, 2010). These last studies could overcome some of the limitations of the hedonic models estimated by OLS techniques, however, with a rather different approach than the one used in this paper.

Databases and methodology
The section describes the aforementioned databases in two subsections. It then presents the applied methodology in another three subsections. To the best of our knowledge, this paper is the first to attempt to use these databases and this methodology to analyse the Brazilian housing market.

The Real Estate Transference Tax (RETT) database
RETT is a municipal tax disbursed in all real estate transferences in Brazil. Since 2000, in Belo Horizonte, it is 2.5% of the estimated value of the good (Belo Horizonte City Hall (PBH), 2011). The municipality registers the value of the transaction, type of the building and localization. That is, this database has data for prices and for the building attributes for all real estate sold in a particular period. In our analysis, we selected the data between January 2004 and July 2010.

This database is increasingly being used in Brazil in studies associated with real estate markets (Aguiar & Simões, 2010; Cunha, 2000; Paixão, 2010), and urban structure (Abramo, 1989; González, 1997; Smolka & Furtado, 1996). Among the advantages of this database are the high reliability (for a discussion on the theme, see Gonzalez, 1997) and the possibility of using spatial methods (FJP, 2009). Although the transference values might be underestimated due to the auto-declaratory nature of the data with fiscal purposes, the relative variability of prices are less biased. Another limitation of the data is that the date of reference is not the day of transaction, but rather the day of registration of the transaction. Fortunately, this seems not to be a problem for data of the municipality of Belo Horizonte. The time span between the day of transaction and the day of registration do not vary remarkably and systematically within apartments (FJP, 2009). Finally, because the database includes only formal information, there exists a clear undercount of the number of transactions, especially among the low-income population, as is observed in slums in Belo Horizonte. This problem is minimized in our study because we only analysed apartments, which tend to be formally registered due to financing procedures. For detailed description of this database, see FJP (2009).

The paper does not address the price determinants for houses or commercial real estates. Considering houses, as price determinants differ from those of apartments, the analysis should be done separately. However, the sample size for houses was considered not enough to perform a reliable analysis. For apartments, for instance, there were...
nearly 127 000 observations, a sizable enough sample. Moreover, the database variables were considered insufficient to perform a consistent analysis of the highly heterogeneous commercial real estates. For instance, particular features, as being located in a corner, might increase tremendously the price of commercial real estates and the database is incapable of differentiating locality in such a detail. We selected among the available variables in this database some that might influence the price of apartments. These are the built area, the age of the building, and five dummies indicating the quality of the building finishing materials. Table 1 shows some descriptive statistics for these variables.

The mean value of the transactions was around 130 000 reais (approximately US $60 000) and the standard deviation had a similar value, indicating a high dispersion of prices. The mean age of the apartments was reasonably low (13.8 years) also with a standard deviation of similar magnitude. The mean size of the apartments was 117 m², and most classified as normal quality.

The Quality of Urban Life Index (QULI)
The variables described above are only part of the needed variables to determine housing estate prices, as they do not include features associated with location, which also affect transaction values. In order to include in the model attributes related to locality, we used QULI and related data of 2006, as this year is representative of the discussed period.

The index indicates the local availability and accessibility of goods and services, and varies between 0 and 1, respectively for the worst and the best situations. It is composed of 34 indicators that were grouped into nine sub-indexes, which also vary from 0 to 1. These sub-indexes are weighted as follows to give the final value for the index: (1) food supply, 8%; (2) culture, 3%; (3) education, 13%; (4) habitation, 19%; (5) infrastructure, 17%; (6) environment, 7%; (7) health, 14%; (8) urban services, 11%; and (9) security, 8%. We also used in the analysis the sub-indexes of the QULI that might influence more directly on housing market prices, such as infrastructure, urban services and security.

Initially designed to be used as a basis for public policy evaluations, the index is easily updated, being an instrument to quantify the impact of specific municipal and private interventions. It also assists the municipal administration in the spatial

| Variables                                      | Mean   | Standard deviation |
|------------------------------------------------|--------|--------------------|
| Value (reais)                                  | 130.318| 132.934            |
| Age (years)                                    | 13.8   | 12.4               |
| Area (m²)                                      | 117.1  | 66                 |
| Quality of building finishing materials        |        |                    |
| Popular                                        | 0.01   | 0.09               |
| Low                                            | 0.21   | 0.4                |
| Normal                                         | 0.59   | 0.49               |
| High                                           | 0.17   | 0.37               |
| Luxury                                         | 0.03   | 0.16               |

Note: Number of observations = 126 716.
Source: Prodabel/PBH (via Fund. IPEAD) and Prodabel/PBH.
The index was estimated for the 81 PUs of Belo Horizonte, which are approximately homogenous neighbourhoods. Because of administrative purposes, the municipal administration divided the city into these planning units (PUs), separating nearby heterogeneous areas, such as some of the slums surrounded by higher income regions. Figure 2 shows the municipality of Belo Horizonte and its PUs.

This index has a decisive advantage for empirical studies that analyse the determinants of housing market prices. It does not include variables related to the population of each region, a common procedure in many studies presented in the previous section, poor proxies for the quality of life of an area. Differently, the QULI contains information, such as the number of supermarkets, quality and quantity of public transportation, healthcare centres and crime rates, which are directly related to the population’s well-being. Hence, the use of this database as a complement to the real estate transfers tax database allows the analyses of spatial features related to housing price determination in more insightful ways.

Figure 2. Predicted values for the PUs of Belo Horizonte – Model 2.
Hedonic price models

Hedonic price models differ in perspective from most econometric models, because they do not define a particular estimation method. In fact, this class of models defines a methodology that is used to analyse how different characteristics affect the price of complex goods, such as cars, apartments and houses (Hermann & Haddad, 2005; Rosen, 1974).

Generally, while comparing two bundles of goods, it is possible to explain price differences based on their diverse compositions. However, for complex goods, which are composed of many inseparable features, the price for each characteristic is estimated by shadow prices or marginal values. For instance, how much is a bathroom, a living room or a nearby park worth? It is not reasonable to separate any of these features from the rest of the real estate in order to determine the values of an extra bathroom or a better localization.

The hedonic models associate real estate prices with its characteristics in order to find their marginal value. The most common estimation method for hedonic models is the log-linear regression (Sheppard, 1999):

\[
\ln P_i = X_{ij}\beta + e_i
\]

where \(P_i\) is the real estate price; \(X_{ij}\) is a matrix with the covariates, i.e. the quantities of each attribute of the complex good; \(\beta\) is the coefficients of the model; and \(e_i\) is the errors.

Hierarchical models

Most databases used in studies of housing market prices determination are naturally hierarchical, as prices depend on the characteristics of the apartment, and on features of the locality shared by a group of apartments. That is, the database has a first level with data for apartments, and a second level with data for regions, which are commonly presented as mean values of particular variables in a specific region.

The standard linear model (SLM) assumes that observations are independent from each other, and this assumption might not hold for a database hierarchically constructed. Thus, the use of hierarchical models (Hox, 2002; Queiroz, 2001) seems more appropriate, as they differ from the SLM, and assume that the intra-group variance is different between groups, although the assumption of independency between groups continues to be valid.

Fontes, Simões, & Hermeto (2010) present the equations of a hierarchical model with two levels, which is similar to the one applied here:

\[
Y_{ij} = \beta_{0j} + \beta_{kj}X_{kj} + u_{ij}
\]

\[
\beta_{0j} = \gamma_{00} + \gamma_{0m}Z_{mj} + u_{0j}
\]

\[
\beta_{kj} = \gamma_{k0} + \gamma_{km}Z_{mj} + u_{kj}
\]

where \(i\) represents the first level, here apartments; \(j\) represents the second level, here PU; \(Y_{ij}\) is the dependent variable, which here is the logarithm of prices; \(X_{kj}\) is a vector with \(k\) variables related to apartment \(i\) in PU \(j\), the variables from the RETT database; \(Z_{mj}\) is a vector with \(m\) second level variables, which here are the variables from the
QULI database for the PU; $\beta$’s and $\gamma$’s are the coefficients estimated by the model; and the other terms are errors.

The error term in equation (2), the one for the first level, is normally distributed, $r_{ij} \sim N(0, \sigma^2)$. The errors terms $u_{0j}$ and $u_{1j}$ in equations (3) and (4) of level 2 are also normally distributed, $u_{0j} \sim N(0, \sigma_{0j}^2)$ and $u_{1j} \sim N(0, \sigma_{1j}^2)$. These last two errors are independent of the first, and covariance between them, $\text{COV}(u_{0j}, u_{1j})$, in general, is not equal to zero.

In order to apply this model, the paper follows the strategy proposed by Hox (2002). First, we tested the validity of the hierarchical approach with the use of a simple model, the ANOVA model with random effects, also known as the unique intercept model. The model does not include the explanatory variables in any level. The model estimates the intra- and intergroup variances, respectively $\sigma^2$ and $\sigma_{0j}^2$, and the proportion of the variance explained by the second level:

$$\rho = \frac{\sigma_{0j}^2}{\sigma_{0j}^2 + \sigma^2}$$

In the second step, the analysis of covariance (ANCOVA) model, which includes the independent variables of the first level, was estimated. After controlling for these variables, it is expected that the first level will increase its explanatory power, because part of the variability of the data is explained by differences in the vector $X_{kij}$. Hence, the variance associated with the second level might decrease, as less variability is left for intergroup comparisons (Fontes, Simões, & Hermeto, 2010). This model is similar to an OLS with clustered data.

Finally, we estimated a complete hierarchical model, which also included the independent variables in the second level, $Z_{mj}$. Therefore, this model considers that these variables may influence both the intercept and the slopes of the first level.

Stata 9.0 software was used to estimate the hierarchical models via maximum likelihood estimators. This method gives consistent and asymptotically efficient estimates (Hox, 2002).

**Spatial models and the hierarchical–spatial approach**

Hierarchical models incorporate a regional perspective, as they take into account that data are spatially clustered. However, this type of model does not consider that possibly the data present spatial dependence and/or spatial heterogeneity (Anselin, 1988). This is expected in the real estate market:

Housing prices are a prime example: clearly the location of the house will have an effect on its selling price. If the location of the house influences its price, then the possibility arises that nearby houses will be affected by the same location factors. Any error in measuring these factors will cause their error terms to be correlated. (Dubin, 1998, p. 304)

Moreover, if prices of nearby apartments and/or if characteristics of nearby areas influence the housing market, as is expected, there might be endogenous and/or exogenous interactions. Therefore, the use of spatial models in a housing market analysis, such as the one discussed here, is advisable. Other researchers have also applied spatial econometric techniques to examine hedonic house price equations, as in Brasington (2004), and this approach is commonly used in studies of regional and urban economy (Anselin, 2010).
In the hierarchical models, data in the first level are analysed in clusters, represented by the second level of the model. Therefore, these models can be considered as being a specific type of spatial model, because they enable a certain level of spatial correlation corrections. These models have as one of the assumptions that the groups in the second level are independent. However, this might not occur, for instance, if the error terms of this level are spatially correlated (Le Sage & Pace, 2009). In order to overcome this possible limitation, we applied a hierarchical–spatial approach in order to verify if there was a non-controlled spatial correlation on prices among the PUs.

The paper followed the empirical strategy proposed in Riani et al. (2007). First, the ANCOVA model was estimated and the residues of this model were used as the dependent variable of the spatial models. The independent variables of these models were the same used in the second level of the complete hierarchical model.

The empirical procedure for model selection was set similarly as the specific to general strategy proposed by Elhorst (2010). The methodological presentation begins with the Manski model, which is a general one:

\[ y = \rho Wy + X\beta WX\theta + u \]
\[ u = \lambda Wu + \varepsilon, \varepsilon \sim N(0, \sigma^2 I_n) \]

where \( y \) is the dependent variable; \( W \) is the weight matrix; \( X \) is a vector with covariates; \( \beta \) are the coefficients estimated by the model; and \( \rho, \theta, \lambda \neq 0 \) are respectively the coefficients of the spatial correlations for the endogenous interactions, for the exogenous interactions, and for the errors.

In a specific to general approach, the first step is the estimation of the SLM, which is the most specific model in the above framework, with \( \theta = \lambda = \rho = 0 \). Then, the classical and robust Lagrange multiplier (LM) tests were applied to verify if the SLM residues showed spatial correlation. Based on the results of these tests, we rejected the SLM and estimated the spatial lag model \( \theta = \lambda = 0, \rho \neq 0 \), and compared it with the spatial Durbin model \( \lambda = 0, \theta \neq 0, \rho \neq 0 \) using a maximum likelihood ratio test.

The empirical strategy for the spatial models was implemented with the use of standard procedures of R packages. The weight matrix was the contiguity one with row normalization.

The results of the spatial models indicated that prices are possibly influenced by endogenous and exogenous interactions, which tend to mingle their effects (Manski, 1993). Based on these results, in order to take into account these interactions, we created four lagged variables using the weight matrix. The lagged variables are for price logarithm, QULI, urban services and infrastructure. These variables were then used as explanatory in the second level of hierarchical models, similar to those discussed in the fifth section, characterizing a spatial–hierarchical approach.

**Empirical results**

This section presents the empirical results in two subsections, the first with the hierarchical models and the second with the hierarchical–spatial approach.
| Variable  | ANOVA | ANCOVA | Model 1 | Model 2 | Model 3 | Model 4 | OLS |
|-----------|-------|--------|---------|---------|---------|---------|-----|
| Fixed effects (first level) | | | | | | | |
| Intercept | 11.14*** | 9.86*** | 9.79*** | 9.79*** | 9.79*** | 9.85*** | 9.07*** |
| (0.0633) | (0.0326) | (0.0290) | (0.0145*** | (3.46e-05) | (3.46e-05) | (3.46e-05) | (0.0142*** |
| Time trend | 0.0145*** | 0.0145*** | 0.0145*** | 0.0145*** | 0.0145*** | 0.0145*** | 0.0110*** |
| (3.46e-05) | (3.46e-05) | (3.46e-05) | (3.46e-05) | (3.46e-05) | (3.46e-05) | (3.46e-05) | (3.70e-05) |
| Area | 0.0065** | 0.0065** | 0.0065** | 0.0065** | 0.0065** | 0.0065** | 0.0065** |
| (1.63e-05) | (1.63e-05) | (1.63e-05) | (1.63e-05) | (1.63e-05) | (1.63e-05) | (1.63e-05) | (1.69e-05) |
| Age | 0.106*** | 0.106*** | 0.106*** | 0.106*** | 0.106*** | 0.106*** | 0.106*** |
| (8.47e-05) | (8.47e-05) | (8.47e-05) | (8.47e-05) | (8.47e-05) | (8.47e-05) | (8.47e-05) | (8.47e-05) |
| Luxury | 0.489*** | 0.489*** | 0.489*** | 0.489*** | 0.489*** | 0.489*** | 0.489*** |
| (0.0132) | (0.012) | (0.0112) | (0.0112) | (0.0112) | (0.0112) | (0.0112) | (0.0112) |
| High | 0.412*** | 0.412*** | 0.412*** | 0.412*** | 0.412*** | 0.412*** | 0.412*** |
| (2.16e-05) | (2.16e-05) | (2.16e-05) | (2.16e-05) | (2.16e-05) | (2.16e-05) | (2.16e-05) | (2.16e-05) |
| Normal | 0.413*** | 0.413*** | 0.413*** | 0.413*** | 0.413*** | 0.413*** | 0.413*** |
| (0.0112) | (0.0112) | (0.0112) | (0.0112) | (0.0112) | (0.0112) | (0.0112) | (0.0112) |
| Low | 0.414*** | 0.414*** | 0.414*** | 0.414*** | 0.414*** | 0.414*** | 0.414*** |
| (2.16e-05) | (2.16e-05) | (2.16e-05) | (2.16e-05) | (2.16e-05) | (2.16e-05) | (2.16e-05) | (2.16e-05) |
| Popular Ref. | 0.413*** | 0.413*** | 0.413*** | 0.413*** | 0.413*** | 0.413*** | 0.413*** |
| QULI | 0.413*** | 0.413*** | 0.413*** | 0.413*** | 0.413*** | 0.413*** | 0.413*** |
| Random effects (second level) — estimates as variances | | | | | | | |
| Intercept | 0.273*** | 0.184*** | 0.045** | 0.059*** | 0.019** | 0.176*** | 0.176*** |
| (0.0471) | (0.0471) | (0.0471) | (0.0471) | (0.0471) | (0.0471) | (0.0471) | (0.0471) |
| QULI | 0.423*** | 0.184*** | 0.045** | 0.059*** | 0.019** | 0.176*** | 0.176*** |
| (0.0471) | (0.0471) | (0.0471) | (0.0471) | (0.0471) | (0.0471) | (0.0471) | (0.0471) |
| Urban services | 0.045** | 0.059*** | 0.019** | 0.176*** | 0.176*** | 0.176*** | 0.176*** |
| (0.051) | (0.051) | (0.051) | (0.051) | (0.051) | (0.051) | (0.051) | (0.051) |
| Infrastructure | 0.273*** | 0.184*** | 0.045** | 0.059*** | 0.019** | 0.176*** | 0.176*** |
| (0.0471) | (0.0471) | (0.0471) | (0.0471) | (0.0471) | (0.0471) | (0.0471) | (0.0471) |

**Table 2. Hierarchical linear models.**
Table 2. (Continued).

| Variable            | ANOVA   | ANCOVA  | Model 1 | Model 2 | Model 3 | Model 4 | OLS     |
|---------------------|---------|---------|---------|---------|---------|---------|---------|
| Security            | 0.077***| 0.467***| 0.077***| 0.077***| (0.043) | (0.109) | (0.043) |
| Unexplained Residue | 0.395***| 0.0757***| 0.0757***| 0.0755***| 0.0755***| 0.0755***|         |
| Residue             | (0.00157)| (0.0003)| (0.0003)| (0.0003)| (0.0003)| (0.0003)|         |

**Variance component (second level)**

| Variable      | ANOVA   | ANCOVA  | Model 1 | Model 2 | Model 3 | Model 4 | OLS     |
|---------------|---------|---------|---------|---------|---------|---------|---------|
| Intercept     | 38.30%  | 36.40%  | 15.80%  | 5.70%   | 0.83%   | 5.70%   |         |
| QUILI         | 59.70%  | 90.70%  |         |         |         |         |         |
| Urban services|         |         |         | 50.60%  | 50.60%  |         |         |
| Infrastructure|         |         |         | 0.00%   | 0.00%   |         |         |
| Security      |         |         | 22.1%   | 78.2%   | 22.1%   |         |         |
| Total explained| 38.30%  | 36.40%  | 75.50%  | 78.40%  | 87.40%  | 78.40%  |         |
| Unexplained residue | 61.70%  | 63.60%  | 24.50%  | 21.60%  | 12.60%  | 21.60%  |         |

| Number of observations | 126 716 | 126 640 | 126 640 | 126 640 | 126 640 | 126 640 | 126 640 |
|------------------------|---------|---------|---------|---------|---------|---------|---------|
| $R^2$                  |         |         |         |         |         |         |         |
| Number of groups       | 69      | 69      | 69      | 69      | 69      | 69      | 69      |

Notes: Standard errors are given in parentheses.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Source: Prodabel/PBH (via Fund. IPEAD) and Prodabel/PBH.
Hierarchical models
The hierarchical models analysed the determinants of apartment prices following the strategy proposed by Hox (2002). The dependent variable was the logarithm of the apartments’ price. The independent variables for the first level are the ones presented in Table 1: area, age and quality of the building finishing materials. The models also include a temporal tendency as prices increased approximately uniformly in the period.

Regarding the second level, besides ANOVA and ANCOVA, there are four different models: model 1 uses the QULI as the explanatory variable; model 2 utilizes the sub-indexes related to urban services and security; model 3 uses urban infrastructure and security; and model 4 utilizes urban services, infrastructure and security. Moreover, we describe an OLS model that is similar to model 1 as a benchmark for comparisons.

Table 2 presents the results. The first column shows the results for the ANOVA model. As discussed, this model has no explanatory variables in any level, is a benchmark for comparisons with other models, and is useful to estimate the distribution of total variance between the two levels: intra- and intergroup. Notice that when none of the explanatory variables was included in the models, the majority of the variance observed for the logarithm of apartment prices was due to intra-group variability, 61.7% (0.395/(0.245 + 0.395)), while a sizable proportion was related to intergroup variations, 38.3%.

The second column shows the results for the ANCOVA model, which includes the explanatory variable only in the first level. All coefficients in the first level were significant at 5%. The positive coefficient for the temporal tendency indicates, as anticipated, that there was a general increase in prices for apartments in Belo Horizonte during the period. Concerning the size of the apartment, as expected, the larger the apartment the more valued. The coefficient for age was negative, indicating that older apartments were cheaper. For the dummies associated with the quality of the building finishing materials, the category named popular was the reference. Notice that all dummies were positive, indicating, not surprisingly, that higher quality buildings cost more. All these results discussed for the first level were expected and these variables are included in the model as controls in order to discuss the geographical variables of the second level more insightfully.

Comparing the variance in the ANOVA and ANCOVA models, the second model shows smaller values, as the apartments’ mean characteristics vary between the PUs, and the explanatory variables in the first level explain a sizable proportion of price variability. Nonetheless, a large proportion of the variance, 36.4%, was still explained by random differences in the intercept, which is related to omitted or non-observable geographical variables.

The next four columns in Table 2 show the results for the other four hierarchical models, which also included the explanatory variables in the second level. The coefficients in the first level are rather similar in all four models. The table also presents the proportion of variance explained by each variable of the second level and the variance distribution between levels.

In model 1 we included the QULI as explanatory variable in the second level. The second level explained more than 75% of the remaining variance in prices. That is, it remarkably increased the variance explained locally when compared to the ANCOVA model. As already discussed in Aguiar & Simões (2010), this indicator captures at a large extent features related to urban amenities, which influence real estate prices.
large proportion of the variance, 59.7% of the total, was explained by this index, and
the intercept loses in explanatory power from 36.4% to 15.8%. This indicates that only
one variable can explain a large proportion of the second level variability, which is
associated with location. That is, the QULI captures in one index many features associ-
ated with local characteristics that affect prices.

We compared this first hierarchical model with a similar non-hierarchical OLS
model in order to compare the methodology with more conventional methods. The
results of the OLS model overestimated the coefficients for age and for the dummies for
the quality of building finishing materials. As results differed and the database presents
a natural hierarchical nature, the use of the hierarchical models seems justi-
fied.

Therefore, we continue the presentation with model 2, which includes two sub-
indexes of the QULI, urban services and security in the second level. Notice that the
second level explains an even larger proportion of the remaining variance than model 1,
showing the effectiveness of these two sub-indexes of the QULI as explanatory vari-
ables on housing market price analysis. The variables infrastructure and security were
included in the second level in model 3. The first variable had a small explanatory
power, while the second had a greater one. Model 4 confirms this when the three
explanatory variables were included in the same model. Probably, the variable infra-
structure has a smaller effect on prices, because it is more evenly distributed among the
PU.

Concluding this section, we observed that only one explanatory variable in the
second level, the QULI, or two simpler variables, urban services and security,
remarkably increased the explanatory power of the models. That is, the QULI and its
sub-indexes explain a sizable proportion of the influence of location in housing price
determination. Nonetheless, differently than the initially expected according to Brazilian
literature, infrastructure had a small explanatory power. For instance, Moraes & Cruz
(2003) observed a significant positive correlation between infrastructure and prices when
they analysed different Brazilian metropolitan regions. The municipality of Belo
Horizonte, however, is more homogenous considering this aspect, what partially
explains our finding.

In this section, we described the use of hierarchical models to determine housing
market prices. Still, omitted spatially correlated variables, and endogenous and/or exoge-
nous interactions might influence housing prices. The next section analyses these fea-
tures with the use of spatial models and of the hierarchical–spatial approach.
Hierarchical–spatial approach

This section describes the results of the hierarchical–spatial approach. Our empirical strategy is similar to the one applied by Riani et al. (2007). The residues of the ANCOVA model presented in Table 2 were used as the dependent variable in the spatial models. We used the set of variables of the second level of models 1, 2 and 3 of Table 2 as independent variables in respectively models 1, 2 and 3 presented in Table 3. The main objective of this analysis is to verify if there was a remaining spatial correlation in the residues after controlling by the explanatory variables of both levels of the hierarchical models. Moreover, we wanted to choose between a spatial model with correlation in the errors or with endogenous and/or exogenous variables.

Following a specific to general strategy of model selection (Elhorst, 2010), we initially estimated the SLM and applied the LM tests to its residues. The results suggested the use of the SAR models for all three groups of explanatory variables. Then, this model was compared to the spatial Durbin model, and the results again indicated the use of the spatial lag model. Table 3 presents the results.

Table 4. Hierarchical–spatial approach models.

| Variable               | Model 1      | Model 2      | Model 3      | Model 4      |
|------------------------|--------------|--------------|--------------|--------------|
| **Fixed effects (first level)** |              |              |              |              |
| Omitted                |              |              |              |              |
| **Random effects (second level) – estimates as variances** |              |              |              |              |
| Intercept              | 0.021***     | 0.0165***    | 0.005***     | 0.0165***    |
|                        | (0.029)      | (0.017)      | (0.007)      | (0.017)      |
| Lagged price           | 0.00023**    | 0.0002***    | 1.03e–11***  | 0.0002***    |
|                        | (0.00025)    | (0.0001)     | (4.96e–11)   | (0.0001)     |
| QUILI                  | 0.183***     |              |              |              |
|                        | (0.051)      |              |              |              |
| Urban services         |              | 0.176***     |              | 0.176***     |
|                        |              | (0.055)      |              | (0.055)      |
| Infrastructure         |              |              | 0.049***     | 2.91e–13***  |
|                        |              |              | (0.017)      | (1.83e–12)   |
| Security               | 0.077***     | 0.467***     |              | 0.077***     |
|                        | (0.043)      | (0.109)      |              | (0.043)      |
| Unexplained            | 0.076***     | 0.075***     | 0.075***     | 0.075***     |
|                        | (0.0003)     | (0.0003)     | (0.0003)     | (0.0003)     |
| **Variance component (second level)** |              |              |              |              |
| Intercept              | 7.56%        | 4.81%        | 0.83%        | 4.80%        |
| Lagged price           | 0.08%        | 0.01%        | 0.00%        | 0.01%        |
| QUILI                  | 65.41%       |              |              |              |
| Urban services         |              | 50.98%       |              | 50.98%       |
| Infrastructure         |              |              | 8.33%        | 0.00%        |
| Security               |              |              | 22.29%       | 78.20%       |
| Total explained        | 73.05%       | 78.08%       | 87.36%       | 78.08%       |
| Unexplained residue    | 26.95%       | 21.92%       | 12.64%       | 21.92%       |
| Number of observations | 126 640      | 126 640      | 126 640      | 126 640      |
| Number of groups       | 69           | 69           | 69           | 69           |

Notes: Standard errors are given in parentheses.

***p < 0.01, **p < 0.05, *p < 0.1.

Source: Prodabel/PBH (via Fund. IPEAD) and Prodabel/PBH.
Model 1 includes the QULI as explanatory variable. The coefficient was positive and significant as expected. In model 2, the coefficient for urban services was positive and significant, and for security was non-significant. We obtained a similar result for model 3 with a positive coefficient for infrastructure, which includes data on sewage, electricity, telephone and urban transport, and a non-significant for security. However, although the coefficient for security was non-significant, this variable should not be considered irrelevant in price determination (Rondon & Andrade, 2005) due to direct and indirect effects.

Table 5. Hierarchical–spatial approach models.

|                | Model 1   | Model 2   | Model 3   | Model 4   |
|----------------|-----------|-----------|-----------|-----------|
| **Fixed effects (first level)**                       |           |           |           |           |
| Omitted                                                |           |           |           |           |
| **Random effects (second level) – estimates as variances** |           |           |           |           |
| Intercept                                              | 0.025***  | 0.011***  | 0.005***  | 0.011***  |
|                                                        | (0.029)   | (0.009)   | (0.007)   | (0.017)   |
| QULI                                                    | 0.178***  |           |           |           |
|                                                        | (0.051)   |           |           |           |
| Urban services                                         | 0.172***  | 0.172***  |           |           |
|                                                        | (0.053)   | (0.053)   |           |           |
| Infrastructure                                          | 0.049***  | 6.65e–13*** | 3.15e–12 |
|                                                        | (0.017)   |           |           |           |
| Security                                                | 0.074***  | 0.467***  | 0.074***  |           |
|                                                        | (0.039)   | (0.109)   | (0.039)   |           |
| Lagged QULI                                             | 0.059***  |           |           |           |
|                                                        | (0.087)   |           |           |           |
| Lagged urban services                                   | 0.048***  | 0.484***  |           |           |
|                                                        | (0.053)   | (0.053)   |           |           |
| Lagged infrastructure                                   |           | 1.28e–11*** | (7.48e–09)|           |
| Unexplained                                             | 0.076***  | 0.075***  | 0.075***  |           |
|                                                        | (0.0003)  | (0.0003)  | (0.0003)  |           |
| Residue                                                 |           |           |           |           |

**Variance component (second level)**

|                |           |           |           |           |
|----------------|-----------|-----------|-----------|-----------|
| Intercept                                               | 7.27%     | 2.95%     | 0.83%     |           |
| QULI                                                     | 52.61%    |           |           |           |
| Urban services                                           | 45.27%    | 45.27%    |           |           |
| Infrastructure                                            | 8.33%     | 78.20%    | 19.36%    |           |
| Security                                                  | 19.36%    | 78.20%    | 19.36%    |           |
| Lagged QULI                                               | 17.74%    | 12.57%    | 12.57%    |           |
| Lagged urban services                                    |           | 12.57%    |           |           |
| Lagged infrastructure                                    |           |           | 0.00%     |           |
| Total explained                                          | 77.61%    | 80.15%    | 87.36%    | 77.20%    |
| Unexplained residue                                      | 22.39%    | 19.85%    | 12.64%    | 19.85%    |

| Number of observations                                   | 126 640   | 126 640   | 126 640   | 126 640   |
| Number of groups                                         | 69         | 69         | 69         | 69         |

Notes: Standard errors are given in parentheses.

***p < 0.01, **p < 0.05, *p < 0.1.

Source: Prodabel/PBH (via Fund. IPEAD) and Prodabel/PBH.
Most importantly in this analysis with the spatial lag model, the spatial correlations for the endogenous interactions are positive, relatively strong and significant for all models. That is, even after controlling for the explanatory variables in the first and second levels of the hierarchical model, the residues of the ANCOVA model still presented positive spatial correlation.

The spatial coefficients were of high magnitude, suggesting that there might be interactions between observations. The results indicate that apartment prices possibly are influenced by nearby apartment prices and/or by nearby regional characteristics. Besides, local attributes, measured by the mean value aggregated by PU may be limited to explain price variability (Le Sage & Pace, 2009; Anselin, 1988). The QULI index and its sub-index, although extremely powerful urban indicators, does present this limitation, as other indices estimated for areas that are necessarily presented as a mean for a whole region.

The results of the spatial models suggested the existence of possible endogenous or and exogenous interactions. In order to take them into account in the hierarchical models, lagged values for price logarithm, QULI, services and infrastructure were included in the second level of the models as described in the next two tables.

The first group of models presented in Table 4 includes in all specifications the lagged price in addition to the explanatory variables already used in the models of Table 2. Notice that the models analyse if prices in a particular locality are influenced or correlated to prices in a contiguous PU. The coefficients were positive and significant in all models, indicating that prices are positively spatially correlated, however, the magnitudes of the spatial coefficient were small, and explained very little of the remaining price variance. These results suggest that even if positive endogenous interactions occur, the magnitude is small, possibly due to the large size of the PU. That is, apartment prices might interact with each other in a short range; however, given the size of a PU, prices in a particular region are very weakly correlated with prices in nearby areas. A database with distances between apartments should be used to further analyse this topic, probably applying a weight matrix defined by a function of the distance.

Table 5 shows the results for the second group of models. Model 1 includes the QULI and its lagged value in the second level. Notice that the lagged variable explained a sizable proportion of the remaining variance, indicating that the QULI of nearby areas were positively correlated to and/or influenced prices. Similar results were observed for urban services in model 2. Differently, infrastructure explained very little of the remaining variance in model 3. These results suggest that prices are partially determined not only by the apartments’ characteristics and by local attributes, but also due to features associated with urban services and quality of life in nearby regions, which tend to be easily accessible by private or public transportation.

Based on the results of model 2 in Table 5, Figure 2 shows for each PU of Belo Horizonte the predicted prices in April 2007 for a 10-year-old apartment with 100 m² and a normal quality for the building finishing materials. Some general tendencies are observed. The regions in the south and central parts of the city are the most valued, while further north and further southwest, prices are the lowest. It is observed a concentric logic of price determination around the most valued areas with a few exceptions, mostly slums and the area located in the middle of the municipality.
Conclusions

The paper analysed the determinants of housing market prices in Belo Horizonte, MG, Brazil, with the use of hedonic price hierarchical models, and of a hierarchical–spatial approach. We used two databases, one with data for each apartment sold in this city during a particular period, and another with QULI and related data, which were estimated for the 81 PUs of Belo Horizonte. This index was shown to be extremely rich in addressing house price determination, increasing the explanatory power of the econometric models. By using the aforementioned empirical strategy and these two databases, the paper could overcome some of the limitations that normally plague housing market analysis.

The hierarchical models showed that, besides the apartments’ characteristics, such as area, age and building standard, prices were determined by local urban amenities. The models indicated that second level local variables, such as urban violence and services, explained over 75% of prices’ remaining variability.

We used spatial models to analyse if there were remaining spatial correlations and/or externalities in price determination after controlling for price variability with the explanatory variables of both levels of the hierarchical models. The results indicated the use of the hierarchical–spatial approach, which suggested that prices were partially determined by some of the characteristics of the nearby areas.

To coordinate real estate markets more effectively, local governments could apply the results of this paper. In order to intervene efficiently in housing markets, governments might profit from a more detailed knowledge about how these markets work. Moreover, the results described here can better inform public authorities of how particular public interventions may affect real estate prices. In this vein, policies that promote the gentrification or improvement of specific areas might influence prices in adjoining regions. In addition, public authorities might more effectively determine real estate tax rates, which are based on the potential sales prices, taking into account the characteristics of nearby neighbourhoods. These tax rates could more effective reflect the property’s value, implicating in a more progressive and just real estate tax rates.

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