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Urban House Prices: A Tale of 48 Cities

Konstantin A. Kholodilin and Dirk Ulbricht

Abstract
In this paper, the authors construct a unique data set of Internet offer prices for flats in 48 large European cities across 24 countries. The data collected between January and May 2012 from 33 websites, are drawn from Internet advertisements of dwellings. Using the resulting sample of more than 1,000,000 announcements, the authors compute the quality-adjusted city-specific house prices. Based on this information, they investigate the determinants of the apartment prices. Four factors are found to be relevant for the dwelling price level using Bayesian Model Averaging: Population density, mortgage per capita, income inequality, and unemployment rate. The results are robust to applying two alternative estimation techniques: OLS and quantile regression. Based on the auhors´ estimation results they are able to identify cities where the prices are overvalued. This is a useful indication of a build-up of house price bubbles.

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Keywords Internet advertisements; housing prices; large European cities; fundamental prices

Authors
Konstantin A. Kholodilin, ✉ DIW, Berlin, Germany, kkholodilin@diw.de
Dirk Ulbricht, DIW, Berlin, Germany

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Wir sind zwar arm, aber trotzdem sexy.

Klaus Wowereit,
Former mayor of Berlin

1 Introduction

The housing market is one of the most important markets, since it affects the life of virtually every person. In view of this one would expect that statistical data on dwelling prices abound. In fact, it is not the case.

Consider the example of Berlin. After stagnating through the first decade of the 2000s, Berlin housing prices started rising in the late 2010. While some warn about the build-up of a bubble, many investors hold that Berlin is still a bargain when compared to other European metropolises. Some anecdotal evidence of house prices in Paris, London, or Moscow appear to support this view. However, is this really the case when looking at representative data? And, does that still hold when considering market characteristics (fundamentals)?

Surprisingly, there are no official statistics available. In particular, what is lacking is the information on price levels that would allow international or intercity comparisons. The official bodies (e.g., Bank for International Settlements) typically publish only price indices expressed in percentages. In addition, there are few if any studies on the determinants of the home price levels or fundamental price levels. By contrast, there are many papers dealing with the determinants of the price dynamics: Abraham and Hendershott (1996), Blackley and Follain (1991), Borowiecki (2009), Clapp and Giaccotto (1994), Ebru and Eban (2011), Égert and Mihaljek (2007), Follain and Velz (1995), Glindro et al. (2011), Hlaváček and Komárek (2009), Hort (1998), Hua and Craig (2011), Iacoviello (2002), Lee (2009), Mahalik and Mallick (2011), Ozanne and Thibodeau (1983), Özsoy and Şahin (2009), Poterba (1991), Stepanyan et al. (2010), and Sutton (2002) to name just a few.

Here we focus on large metropolitan areas. When estimating fundamental house prices, this can only be done in a meaningful way using a panel of comparable markets. In his theory of a hierarchy of central places, Christaller (1933) pointed at the different functionalities of urban agglomerations of different sizes, the larger settlements providing a wider spectrum of services. Furthermore, huge metropolitan areas have more liquid markets that are more accessible to foreign capital investors. Thus, prices can be expected to be subject to different influences than in smaller cities or rural areas. As typically there are only very few huge metropolitan areas within one country, we analyze a set of large European cities.

Focusing on large cities is advantageous insofar as data availability on potential explanatory factors on a regional level is better than on smaller cities or towns. This is particularly important for economic data such as regional GDP or unemployment. However, again, the analysis is limited by the availability of official data. In particular, most regional statistics are published with a considerable time delay of several years. Thus, the most recent estimate of fundamental house prices will necessarily come with corresponding time lag, as well. This limits its practical value to some special situations.[1] Still, this is the best one can get.

We follow a two-step procedure. First, representative square meter hedonic prices that take account of the dwelling-specific characteristics are derived for each city. Simply taking average prices as representative prices for each city would imply treating large luxury and simple small apartments as if they were the same. Thereby, hedonic prices are estimated using separate city-specific regressions instead of using all variables in one regression. This is done because dwelling-specific information is not homogeneously available across countries. For example, for some cities variables describing types of dwellings (maisonette, loft, etc.) or type of building (concrete, bricks, etc.) are available. In contrast, for other cities only dwelling size (area and number of rooms) and location (city districts) are available. If we restrict the list of variables employed to the smallest common set, then we would lose valuable information.

Second, once the 48 city-specific hedonic prices are obtained, these are regressed on city-specific variables like unemployment rate or population density. While the city-specific hedonic prices are treated as representative actual prices,

[1] For example, a bargain is likely to be struck where an undervaluation has been identified and the actual prices have been constant or even decreasing since.

the fitted values are interpreted as fundamental prices and differences between the former and the latter are identified as over- and undervaluations.

This paper aims at answering two research questions: First, we want to determine which variables are relevant for the determination of the fundamental price level. Second, based on this model, we want to identify markets that are over- or undervalued.

We make several contributions to the literature. Firstly, we construct a unique data set of offer prices for flats in 48 large European cities from various Internet sites. Apart from Western European cities, East European cities and Istanbul are also considered. Secondly, we create a database of fundamental variables that is internationally comparable and includes official statistics, particularly macroeconomic ones, at a regional level. Thirdly, we select the relevant explanatory variables using a state-of-the-art technique, the Bayesian Model Averaging. Fourthly, we estimate the effect of fundamentals across the whole dwelling price distribution using a quantile regression.

We find that, in concordance with the literature, population density, mortgage per capita, and income inequality exert positive effect upon the dwelling prices. In contrast, higher unemployment leads to lower prices for dwellings. Moreover, we find that actual housing prices in 7 cities are overvalued, while those in 11 cities are undervalued by more than 20% respectively when compared to the fundamental prices.

The paper is structured as follows: Section 2 describes the data used in the study. In Section 3, the determinants of housing prices are discussed. In Section 4, the methodology of estimating quality-adjusted prices and fundamental prices is explained and estimation results are presented. Finally, Section 5 concludes.

2 Housing price data

In order to construct the estimates of prices for flats in 48 large European cities, the advertisements offering dwellings for sale on different Internet sites were downloaded. The list of the corresponding sites can be found in Table 1 (all tables and figures can be found in Appendix). The choice of Internet sites, from which to download the data, was dictated by three criteria: 1) the size of the site—ideally, the site should contain the largest number of ads compared to its competitors; 2) the availability of data on both price and area (e.g., most British sites do not report information on area); and 3) the possibility to download data—the websites have different designs, for some of which the downloading of data is problematic.

The codes for data downloading are written in the free software environment for statistical computing and graphics **R**.[2] The data were downloaded at monthly frequency in the period stretching from January through May 2012.

It should be stressed that what we use here are offer prices and not the final transaction prices. There are several studies comparing both prices: e.g., Faller et al. (2009) and Henger and Voigtländer (2014) for Germany. The findings of these studies indicate that on average the offer prices are 6–8% above the real transaction prices. Significantly smaller gaps are found for urban locations. The differences may also systematically vary across the phases of business cycle. That said, we still have to make use of the offer prices as proxies for the transaction prices, which are simply not available for all the cities in question.

The original data contained in the Internet ads are quite noisy. Sometimes the ads of not yet constructed housing units are placed among the ads of the secondary market. This problem is particularly acute in case of houses for sale. The detailed examination of the information contained in the ads, including the textual analysis as in Kholodilin and Mense (2011), could permit alleviating the problem. It is, however, a very time-consuming exercise and is not carried out here.

Moreover, the quality of advertised flats can vary substantially both across cities and time. Usually, it is correlated with the welfare level, culture, and availability of the free space in each city. For example, flats in Central and Eastern Europe (CEE) are typically smaller (50–60 m^2 and 2 rooms), whereas in Western Europe they are much larger (70–90 m^2 and 3 rooms), see Table 1 and Figure 1, where the CEE cities are denoted by red color. One notable exception is Paris, where a typical flat is about 60 m^2 large and has 2 rooms. One can even find the ads of flats as small as 9 m^2, which are offered for exorbitant prices in Paris. It is difficult to imagine something like this in Berlin. The flats in cities of non-continental and Nordic countries are also relatively small. The largest flats (about 110 m^2 and more than 3 rooms) can be found in Lisbon and Istanbul.

[2] http://www.r-project.org/, see also R Development Core Team (2012).

We do not dispose of the most detailed information published in the advertisements. We record only several most important characteristics of flats, whose list differs from one Internet site to another. This has to do both with our downloading techniques and with the amount of information published online. In some countries, for example, Germany or Russia, the Internet sites contain very detailed information on dwellings, explicitly classified into separate fields. In other countries, like the United Kingdom, the information is very poorly structured and is presented in a much more implicit way: It is to be found not in separate fields, but is dispersed over the informal text of announcement. The British sites most often do not even report the area of the dwellings offered for sale. Counting of the rooms is another major difference in the way the flat's characteristics are reported. While in most continental countries, the announcements contain the total number of rooms in the dwellings, the Belgian, British, Greek, and Turkish sites publish only the number of bedrooms. The French people, by contrast, sometimes report the number of all the premises of a dwelling, which possibly include the kitchen and bathroom.

Therefore, the data processing we undertake here is rather limited. It amounts basically to two types of corrections. Firstly, we consider the price per square meter and not the total value of flat. To some extent this permits adjusting the prices for the size of flats. It should be noted, however, that even the price for m^2 can vary depending on the size of the dwelling. Sometimes the larger the flat the lower the price per m^2, which can be explained by the diminishing marginal utility of the flat's size. Secondly, the outliers for three key characteristics (price, area, and number of rooms) are removed. If an observation is higher (lower) than the median by 1.5 time interquartile range, then it is treated as an outlier and dropped from the sample. These corrections are, of course, far from being perfect, but can still deliver reasonable results.

Another challenge is that in some countries the offer prices include the transactions costs. For example, in France the price is expressed as *FAI* (*frais d'agence inclus*), that is, including the realtor's fee. The fee can vary between 5% and 10% of the dwelling's value. To make the things more complicated, it is subject to changes depending on the economic situation. In the middle of a speculative bubble, the realtors have a stronger bargaining power and can charge even higher fees. When the housing market is in downturn, the fees decline. In the Netherlands, almost 90% of ads are *k.k.* (*kosten koper*), i.e., they contain the transaction costs, which can make up to 7.5% of the original dwelling's value and include property tax, realtor's fee, and land registry payment. The rest of dwellings—usually the new ones—are *v.o.n.* (*vrij op naam*), that is, include the loan-related costs, which represent 3% of the flat's value.[3] In most other countries, the transaction costs are not mentioned at all in the ads. We corrected the French and Dutch prices by subtracting from them the corresponding fees: 7.5% from French prices and 7.5% from Dutch k.k. prices and 3% from Dutch v.o.n. prices.

Yet another complication arises due to heterogeneous typology of flats in different countries. As Table 2 shows, in some countries, like France, Germany, Italy, or Spain, the market participants differentiate between numerous types of dwellings. Whereas in other countries the market distinguishes normally only one type of flat. In the former Soviet Union countries, by contrast, more weight is put on the type of building—in what period and of what material (concrete, bricks, etc.) it was built and to what construction series it belongs,—in which the flat is located.

Finally, in some cases the webpages still contain ads that were placed several years ago. In cases when the date of publishing an adv is known, advertisements placed prior to July 2011 are removed.

As seen in Table 2, in most cases, the currency, in which the prices for flats are expressed, is euro. To a large extent this has to do with the fact that most cities in our sample are located in the Euro area countries. Nevertheless, some non-Euro area states (Bulgaria, Latvia, and Romania) also quote their prices in euros. Ukrainians instead of using hryvnia, quote their housing prices in US dollars, sometimes euphemistically calling them "conditional units". Thus, the property prices are anchored to a more stable currency than the national one. Therefore, to render the house prices comparable we converted them in the so-called international dollars using purchasing power parities.

The distribution of Internet offer prices for dwellings in 48 European cities are shown in Figure 2. For each city a boxplot of the asking prices for flats is displayed. The width of boxplot is proportional to the number of ads. The notches represent an estimated confidence interval for each median estimate. The total number of downloaded and processed ads in all 35 webpages exceeds 1,000,000.

[3] The transaction costs in that case are paid by the seller.

The biggest number of ads is available for Warsaw (more than 114,000), whilst the fewest advertisements are available for Oslo (805).

3 Determinants of housing prices

The literature suggests a wide range of the determinants of the housing prices. Table 3 contains a list of the determinants with corresponding signs in regressions ("+" or "–"), which are grouped in broad categories. This list is far from being exhaustive and is based on the results of 18 papers in this area, namely: Abraham and Hendershott (1996), Blackley and Follain (1991), Borowiecki (2009), Clapp and Giaccotto (1994), Égert and Mihaljek (2007), Follain and Velz (1995), Glindro et al. (2011), Hlaváček and Komárek (2009), Hort (1998), Hua and Craig (2011), Iacoviello (2002), Lee (2009), Mahalik and Mallick (2011), Ozanne and Thibodeau (1983), Özsoy and Şahin (2009), Poterba (1991), Stepanyan et al. (2010), and Sutton (2002). It shows both the total number of uses of a determinant (columns 2 through 4) and the proportion of the uses (columns 5 through 7). The most frequently used determinants are income variables (15.4%, exerting predominantly positive effect), demographic variables (13.2%, exerting predominantly positive effect), and interest rates (13.2%, exerting exclusively negative effect). Other groups of determinants ordered according to the frequency of their use include: 1) Credit (6.6%) and Housing supply (6.6%); 2) Labor market (6.6%); 3) Land supply (6.6%); 4) Overall prices (4.4%); and 5) Institutions (4.4%). In addition, equity prices and construction cost are frequently used in the home price regressions.

Due to data limitations, land supply and institutions are the only determinants not covered in this study. We examine the following determinants of dwelling prices:

- Per-capita income is a measure of welfare of a particular city and, thus, a good indicator of the demand for housing. It is expected that income has a positive effect upon the price level. As a proxy for the income we take GDP per capita in the city. In cases, where such information is not available for the city, per-capita GDP for region, to which the city belongs, is taken. The data are made comparable using purchasing power parities.

- Housing is a very expensive good. Therefore, in the majority of the cases, its purchase by households implies borrowing money. Hence, the variables of the credit market are of utmost importance to explain the variations in housing prices. Often, interest rates are cited in the literature as such an indicator. Indeed, the long-term interest rate on housing loans represents the cost of borrowing, which is extremely relevant when acquiring a dwelling. Therefore, a negative impact of the interest rate upon property prices is expected. We included national mortgage interest rates and 10 year government bond rates.

- However, since we dispose of static price data only, it is barely possible to observe the effect of the interest rate upon the prices for flats. In addition, the data on mortgage interest rates are too heterogeneous. They refer to different maturities and can be variable or fixed, which precludes their meaningful use in regression. Moreover, to a large extent the effect is determined by the institutional structure of the financial market and national preferences towards the risk taking. The restrictions on providing housing loans to the individuals, as well as the willingness of the credit institutions to grant such loans, are quite different in different countries. In addition, the risk aversion is very different across countries. In Germany, for example, the people are more risk-averse and, therefore, prefer to have housing loans with the interest rates fixed for a relatively long period of time, say, 10 to 20 years. Therefore, additionally to considering interest rates, we opted for using an amount of mortgage loans per capita, as well. The indicator refers to 2010 and stems from the European Mortgage Federation. This variable reflects both the demand for housing credit and the restrictions on the supply side of the credit market. It is expected to have a positive impact upon the flats' price. A big disadvantage is that the variable is only available at the country level. However, the same problem is faced in case of the interest rate.

- Population is a measure of size of the city. Thus, it also should represent the demand pressure on the housing market.

- As an alternative, population growth from 2011 to 2012 is also included. Prices are expected to be higher if population is growing faster. Where these numbers are not available, population growth from 2010 to 2011 was included.[4]

- Population density is at the same time a measure of demand pressure and an indirect measure of supply shortage. When the population density is high, it may imply that the land endowment is very limited and, thus, the possibilities to increase the supply of housing are restrained. This should lead to higher real estate prices.

- Unemployment rate measures a share of people who cannot afford buying dwellings and, thus, whose demand is excluded from the housing market. Moreover, it is an indicator of the stability of income. Higher unemployment rate signals that it is easier to lose a job but more difficult to find a new one. Therefore, a higher unemployment rate should imply lower housing prices.

- Income inequality can be an important determinant of the property prices. In case of high income inequality, the existence of a handful of very rich people can imply that they will be looking for investment opportunities and invest part of their excessive capital into property, thus, driving prices up, especially in the luxury segment. Therefore, inequality might lead to extremes, so the average house price might actually be positively affected. We use the Gini index as an income inequality measure.

- Population per dwelling measures the degree of pressure in the housing market. Therefore, a larger number of persons per dwelling should drive up housing prices.

- Homeownership rate (HOR) and flat prices can be in a reciprocal relationship. On the one hand, a low homeownership rate means that smaller number of people are eager to buy a dwelling. This can happen even if dwelling prices are low. A nice example of such a situation is Post-World War II Germany. The HOR can be to a large extent affected by institutional factors (see, e.g., Voigtländer (2006)) and, thus, reflect the lack of attractiveness

[4] For Athens, Dublin, and Istanbul growth rates are interpolated as the respective years are not available.

of possessing an own dwelling that is explained by other factors than the price. This, of course, pushes the property prices down. An opposite example is found in the Central and East European countries, as well as in South European countries, where the homeownership is considered to be an important attribute that virtually everybody strives to attain as it is a of symbol of success as well as an old-age provision replacing an insufficient state welfare system. Therefore, in these countries, even despite high and growing property prices, people dream of their own home. It should be noticed also that in many CEE countries the high homeownership rate is explained by a free privatization of the dwellings, which was carried out in favor of the tenants who used to live in them. On the other hand, even in the homeownership-friendly countries, the high property prices can deter people from buying a dwelling. Therefore, there is a certain endogeneity problem in case of the HOR. Hence, in order to avoid the problem we take the historic HOR values.

- Capital city is a dummy variable indicating the respective city's function as a national capital. Due to their importance capitals tend to offer more highly paid jobs that should increase prices.
- Inflation is considered, as the overall price level should also influence housing prices.
- Finally, a dummy for the Euro area (EA) is included to account for the fact that the EA countries have a common monetary policy. In addition, for each explanatory variable an interaction term with the EA dummy is created.

The sources of data and their definitions are reported in Table 4.

4 Estimation results

The estimation is conducted in two steps. In the first step, the dependent variable—square meter price for an urban dwelling—is estimated using hedonic approach and dwelling-specific data from the Internet sites. Thus, we obtain an estimate of the actual price for a representative dwelling in each city. This price is adjusted for structural and locational characteristics of dwellings.

In the second step, the resulting quality-adjusted price at city level is regressed on a set of city-specific explanatory variables in order to determine fundamental price. The deviation between actual (quality-adjusted) price and fundamental (fitted) price is treated as over- or undervaluation due to cyclical fluctuations of the housing market.

4.1 Hedonic price

The dwellings offered for sale on the Internet sites are very diverse. Therefore, in order to make their prices comparable across cities, we need to compute quality-adjusted prices. The quality adjustment is conducted using hedonic regression of the following form:

$$\log(P_{ij}) = S'_{ij}\beta_j + L'_{ij}\gamma_j + u_{ij} \tag{1}$$

where P_{ij} is the total asking price for i-th dwelling from j-th city; S_{ij} and L_{ij} are the vectors of structural and locational characteristics of the dwelling, respectively; and u_{ij} is the error term.

The advertisements contain data on characteristics of individual dwellings. The structural characteristics refer to the size and equipment of apartment as well as to the features of the building. The locational characteristics refer to the geographical location of the dwelling. Here, it is approximated by the city district or postcode region, in which the dwelling is located.

As outlined in the introduction, the information provided in the advertisements is very heterogeneous across the cities so that the hedonic regression defined in equation (1) is estimated for each city individually. In order to capture non-linearities and for ease of interpretation the dependent variable and the dependent variables area and number of rooms are specified in logs. Outliers are detected using the Bonferroni p-values for studentized residuals in linear and generalized linear models, see Fox (2008).

The city-specific regression results are reported in Tables 5 through 18. The dependent variable as well as number of rooms and floor area are expressed in logarithms in order to account for possible nonlinearities and simplify the interpretation of results. The explanatory power of the model is large, with the adjusted R^2 mostly exceeding 70%. The number of districts is relatively large and the variables capturing the type of building are very heterogeneous. Therefore, the corresponding coefficients are not reported to save space but are available on request.

Area. A larger floor area should increase the housing price. Accordingly, area has a positive and highly significant influence on the price in all cities. The estimates range from 0.4 (Prague) to 1.58 (Riga). Most of the estimates imply an elasticity of 1, that is, a 1% larger apartment has a 1% higher price. Overall, this is in line with the literature (e.g., Goodman and Thibodeau, 1995 or Anselin and Lozano-Gracia, 2008).

Number of rooms. The effect of number of rooms on the dwelling price is far from being homogeneous. On the one hand, more rooms can decrease the price as decreasing size of rooms restricts their usage: In the extreme case, they can only be used as storerooms. On the other hand, if many inhabitants live in one apartment, more rooms, even smaller ones, allow for more privacy. Here, none of these effects is dominant, the sign of the number of rooms on the price varying across cities. For 7 cities the coefficient is not significant at the 5% level. For 14 cities it is significantly positive, mostly having a value of 0.1. For example, adding one room to a reference three-room apartment (the median of all cities) will imply an increase of number of rooms of about 33% and will lead to a $33 \times 0.1 = 3.3\%$ higher price. For 27 cities, the coefficient is significantly negative, mostly having a value of -0.1. This implies a 3.3% lower price if there is an additional room for a three-room apartment. Thus, once area is accounted for, the additional explanatory power of the number of rooms is limited. This is in line with Nicodemo and Raya (2012) who use a similar setup including both area and rooms to analyze the hedonic housing price in Spanish cities. They find the number of rooms to have a very moderate and insignificant impact on price.

Other structural characteristics. The dummy variables indicating if the respective apartment has a balcony or a garden are, except for St. Petersburg, only available for German cities. Garden is statistically significant at the 1% level and positive for Hamburg, Cologne, Berlin, Düsseldorf, Frankfurt, and St. Petersburg. Here, if a garden is available the apartment is mostly about 0.1 percentage points more expansive. The variable Balcony is only significant for Stuttgart and Berlin implying a price increase of 0.1% when a balcony is available in the dwelling.

The quality-adjusted asking price for dwellings in city j, $\tilde{P}_j$, is obtained using the estimated coefficients and plugging the average values of characteristics:

$$\log(\tilde{P}_j) = \bar{S}_j{}'\hat{\beta}_j + \bar{L}_j{}'\hat{\gamma}_j \tag{2}$$

Based on the total quality-adjusted price from equation (2) a square meter price is computed: $\tilde{p}_j = \frac{\tilde{P}_j}{A_j}$, where A_j is the average dwelling size in square meters in city j.

4.2 Fundamental price

The fundamental price is estimated using the city-level data. The dependent variable in the second step is the hedonic city-specific price estimated in the first step, $\tilde{p}_j$. The relationship between the quality adjusted prices and their potential determinants can be described as:

$$\log(\tilde{p}_j) = X_j'\delta + v_j \tag{3}$$

where $\tilde{p}_j$ is the hedonic (quality-adjusted) asking square meter price of housing in city j; X_j is the vector of city-specific house price determinants; and v_j is the disturbance term.

The fitted values of this regression can be treated as fundamental prices:

$$\log(\hat{p}_j) = X_j'\hat{\delta} \tag{4}$$

Thus, the corresponding residuals can be regarded as deviations from fundamental price:

$$\hat{v}_j = \tilde{p}_j - \hat{p}_j \tag{5}$$

Positive (negative) deviations imply overvalued (undervalued) dwellings in a given city.

The equation (3) is estimated using a simple **ordinary least squares** (OLS) regression. In addition, it is estimated using a semi-parametric **quantile regression**

(QR) method.[5] Under this technique, the quantiles of the conditional distribution of the dependent variable are expressed as functions of explanatory variables. Thus, the quantile regression allows estimating the effect of explanatory variables for the whole distribution, that is, at each quantile of dependent variable, p_j. Two additional advantages of the quantile regression are that it is robust to the outliers and it imposes no assumptions on the exact distribution form of the error term.

A list of potential explanatory variables is quite large, especially given a relatively small sample size. The simultaneous use of all these variables in a regression model is not feasible partly due to insufficient degrees of freedom and partly due to possible multicollinearity. Therefore, we decided to select an optimal model in an objective way using Bayesian Model Averaging (BMA, see Raftery et al. 1997). The results of the two best models according to the posterior probability are presented in Table 19. The selected model has a posterior probability of 0.935. It explains large part of the variation having an R^2 of 0.628. The second best model only obtains a posterior probability of 0.065.

The estimation results of the model selected based on the data of all 48 cities are reported in columns 1 and 2, and, as a robustness check, based on the 25 Euro area cities in columns 3 and 4 in Table 20. They contain the coefficient estimates, standard errors, and p-values of two models, respectively: OLS and quantile regression estimated for median quantile, $\tau = 0.5$. For OLS, the heteroskedasticity and autocorrelation consistent standard errors were computed using the Newey-West robust covariance matrix. For quantile regression, the standard errors are obtained using bootstrap.

For the whole set of cities, four variables have been selected: Population density, mortgage per capita, Gini index, and unemployment rate. The dependent variable as well as population density and mortgage per capita are expressed in logarithms.

Population density. When the population density is high, the land endowment is very limited and, thus, the possibilities to increase the supply of housing are restrained. This should lead to higher dwelling prices. In accordance with the expectations and the literature (see, for example, Borowiecki 2009), population

[5] See Koenker and Bassett (1978) and Koenker (2005) for a formal exposition of the quantile regression and Koenker (2012) for its **R** implementation in form of a package quantreg.

has a positive effect on price. As the dependent and the independent variable are specified in logs, an increase of population per square kilometer by 1% leads to an increase of a square-meter price by about a quarter a percentage point. Thus, for the minimum, mean, and maximum (1.32, 4.55, and 20.62 thousand inhabitants per square kilometer), an increase in density by 1,000 inhabitants leads to a price increase of 19.47, 5.63, and 1.24 percentage points, respectively.

Mortgage. High mortgage per capita means that more money has been raised and is, thus, raising demand. The elasticity of mortgage per capita is 0.145. An increase of the mortgage per capita by 1,000 euros at the minimum, mean, and maximum (0.19, 10.20, and 45.16 thousand euros per capita) increase the price by 76.32, 1.42, and 0.32 percentage points. This is in accordance with Hua and Craig (2011) and Égert and Mihaljek (2007), who find a positive effect of housing credit.

Income inequality. On the one hand, more income inequality means that a few very rich search for investment opportunities sending up prices. On the other hand, more equality implies that more people are able to buy houses. This leads to increasing demand and may induce higher prices (Shiller, 2007). In large cities that (due to their liquidity) attract more investments than small towns, the former effect seems to dominate with inequality having a positive effect. Still, the effect is comparatively small. The elasticity of the Gini coefficient is 0.039. For the minimum, mean, and maximum (23.60, 33.11, and 52.10%) a one percentage point increase of the Gini coefficient implies a 0.17, 0.12, and 0.07% price increase, respectively.

Unemployment. Higher unemployment excludes part of the population from investing in housing and is an indicator for labor market insecurity, which is detrimental to housing demand. The elasticity of the unemployment rate is –0.046. A one percentage point lower unemployment rate for the minimum, mean, and maximum (1.70, 9.55, and 23.12%) leads to a price decrease of 2.71, 0.48, and 0.20%. This corresponds to the results found in the literature, for example, Égert and Mihaljek (2007) or Iacoviello (2002).

The quantile regression (column 2), in which the standard errors and *p*-values are bootstrapped, largely confirms the OLS results. All coefficients remain significant and nearly unchanged.

The results obtained for the Euro area subsample (columns 3 and 4) are slightly different. In the OLS regression, mortgage per capita becomes insignificant. The coefficients differ very little when compared to the full sample results. While the coefficient estimates of the quantile regression have the same sign and are all comparatively lower in absolute value when compared to the other results, none of the coefficients is significant.

Figure 3 displays parameter estimates for the sequence of quantile regressions of the complete sample of 48 cities with $\tau = 0.1, 0.2, \ldots, 0.9$. The bold blue line shows the point parameter estimates, while the cyan area represents the corresponding confidence intervals. The red solid and dashed lines depict the coefficient estimate and the confidence bands of the OLS regression. The parameter estimates are significant for all variables, that is, the confidence bands of the quantile regression do not cross the zero line.

The estimates are relatively stable, never markedly crossing the 95% confidence bands of the OLS parameter estimates.

Income inequality. Gini index has more or less the same coefficients for all quantiles, which are very close to the OLS coefficient estimate. However, the quantile estimates for other variables reveal some trends.

Mortgage. For the mortgage per capita elasticity increases from about 0.10 for the second quartile to about 0.18 for the last quantile. This means that dwelling prices in cities with more expensive housing react more sensitively to the mortgage level. One possible explanation is that the inhabitants of cities with expensive real estate have to rely more upon borrowed capital to purchase dwellings. Thus, their demand for housing stronger depends upon the availability of mortgage loans.

Unemployment. The elasticity of unemployment rate decreases in absolute terms from –0.06 to about –0.04 from $\tau = 0.3$ to $\tau = 0.9$, respectively. This means that in the cities with more expensive housing, the prices are less subject to the fluctuations of the unemployment. Such cities are more affluent and have enough rich households to support high prices. In addition, they might be less plagued by the unemployment.

Population density. Furthermore, for the lowest quantile the elasticity of population density is 50% higher than the OLS estimate.

Figures 4 and 5 compare the actual quality-adjusted prices to the fitted prices obtained in the above regressions. The latter approximate the fundamental prices that one would expect, given the values of the price determinants. The cities, where the offer prices are overvalued—the actual price is higher than the fitted one—are denoted by blue color. The cities with undervalued flats are denoted by red color. When an observation is lying on the dashed 45^0-degree line, the fitted price is exactly equal to the actual price. In addition, the numeric values of the fitted prices as well as absolute and percentage deviations of the actual values from fitted (fundamental) prices for both estimation techniques are reported in Table 21. The relative percentage deviations are defined as:

$$d_j = 100 \times \frac{p_j - \hat{p}_j}{\hat{p}_j} \tag{6}$$

where j is the city index.

The results of the OLS and quantile regressions produce in all cases a qualitatively similar picture. Only in the case of Istanbul there is a notable difference. While the OLS regression indicates an undervaluation of –23.8%, the quantile regression indicates that the fundamental and the actual price are identical. More attention should be probably paid to the sign of the relative difference between actual and fitted price. Moreover, small deviations between the actual and fitted price can be purely random. Thus, the fact that a relative difference between these prices is very small may mean that the actual and fitted price are, in fact, identical.

In eleven cities, the actual prices are more than 20% lower than the fundamental prices: Barcelona, Brussels, Bucharest, Budapest, Copenhagen, Dusseldorf, Istanbul, Samara, Sofia, Stuttgart, and Turin. By contrast, in Dnepropetrovsk, Lisbon, Munich, Rome, Stockholm, Vienna, and Vilnius the actual prices are more than 20% over the fitted prices. The most overvalued is Vilnius, where the actual average price for flats per m^2 by 37.7% exceeds the fitted one. The most undervalued city in relative terms is Brussels where the actual prices are 81.1% lower than the expected ones. The dwellings in Athens, Berlin, Madrid, Oslo, Seville, and Tallinn appear to be correctly priced, given the fundamental factors. The relative deviations between the actual and the fitted prices in both OLS and quantile regressions are close to zero.

5 Conclusion

In this paper, we construct a data set of Internet offer prices for flats in 48 large European cities from 24 countries. For this purpose the prices as well as several most important characteristics of the dwellings, which are contained in the Internet ads, were downloaded from 33 websites in January to May 2012. The dwelling-specific data were cleaned of outliers and qualitatively adjusted using hedonic regressions to obtain the city-specific prices.

Using the Internet data, we investigate the determinants of the city-specific prices for flats. We select the relevant explanatory variables in an objective way using Bayesian Model Averaging. In the Euro area, square meter prices are significantly higher. As expected, higher population density, higher mortgage per capita, and higher income inequality are associated with higher flats' prices. Higher unemployment leads to the lower prices for flats. However, the impact of income inequality is rather moderate.

The results were checked for robustness using quantile regression and by analyzing a Euro area subsample. The estimation results are quite similar for the quantile regression, while there are some differences in the results when only a Euro area subsample is considered. In particular, mortgage per capita becomes insignificant.

The comparison of the actual prices to the fitted ones, which were obtained from the OLS and quantile regressions, allows examining the question, where the flats are overvalued and where they are undervalued. In our data, 11 cities have a square meter price that is 20% lower and 7 cities that have 20% higher square meter price than the fundamental price. Notably, Paris, London, and Moscow are overvalued but rather moderately by 15.3%, 8.5%, and 6.3%, respectively.

Like in five other cities, Berlin's housing seems to be correctly valued in 2012. Therefore, the recent property price increases in German capital—observed, for instance, in Kholodilin et al. (2014)—can be considered as an emerging overvaluation. Thus, rephrasing the famous slogan of Berlin's former mayor Wowereit, Berlin is poor but sexy enough to support higher property prices.

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Appendix

Table 1: Sources of flats' price data

City original language	City English	City short	Country	Website	Number of ads	Price, euros per m^2 median	Price, euros per m^2 average	Total area, m^2 median	Total area, m^2 average	Number of rooms median	Number of rooms average
Amsterdam	Amsterdam	AMS	Netherlands	funda.nl	7308	3395.3	3405.1	72.0	75.9	3.0	2.8
Athina	Athens	ATH	Greece	spiti24.gr	9865	2075.3	2106.1	76.0	77.1	3.0	2.9
Barcelona	Barcelona	BCN	Spain	pisos.com	4448	3231.5	3356.6	77.0	80.8	3.0	2.8
Berlin	Berlin	BER	Germany	immobilienscout24.de	11202	2142.2	2295.9	75.0	82.5	2.5	2.6
Bruxelles	Brussels	BRU	Belgium	immoweb.be	4505	2343.8	2413.8	88.0	90.9	3.0	2.7
Bucuresti	Bucharest	BUH	Romania	imopedia.ro	11272	1019.2	1049.8	60.0	61.8	2.0	2.4
Budapest	Budapest	BUD	Hungary	maganingatlan.hu	1236	896.7	936.9	54.0	56.3	2.0	2.2
Dnepropetrovsk	Dnepropetrovsk	DNK	Ukraine	est.ua/dp	2113	725.3	784.9	56.0	58.2	2.0	2.3
Dublin	Dublin	DUB	Ireland	myhome.ie	499	3026.7	3134.3	65.0	64.3	3.0	2.7
Düsseldorf	Dusseldorf	DUS	Germany	immobilienscout24.de	1337	1956.8	2168.6	74.0	79.4	3.0	2.6
Ekaterinburg	Yekaterinburg	EKA	Russia	upn.ru	7473	1611.5	1629.5	49.0	53.8	2.0	2.2
Frankfurt am Main	Frankfurt	FRF	Germany	immobilienscout24.de	1652	2910.9	2953.3	84.0	91.0	3.0	3.0
Hamburg	Hamburg	HAM	Germany	immobilienscout24.de	1876	3072.6	3199.5	84.4	89.4	3.0	3.0
Istanbul	Istanbul	IST	Turkey	emlak.net	37866	486.6	517.2	100.0	110.0	3.0	3.4
Kazan	Kazan	KZN	Russia	kazan.mlsn.ru	5194	1268.1	1276.9	53.4	57.4	2.0	1.9
Kharkov	Kharkov	HRK	Ukraine	gorod.kharkov.com	6071	641.0	646.8	52.0	55.0	2.0	2.1
Kiev	Kiev	KIV	Ukraine	address.ua	53136	1331.7	1453.3	61.0	65.9	2.0	2.2
København	Copenhagen	CPH	Denmark	dba.dk	3541	2874.0	3039.0	74.0	78.0	3.0	2.6
Köln	Cologne	CGN	Germany	immobilienscout24.de	2130	1905.3	2081.8	75.0	75.6	3.0	2.7
Lisboa	Lisbon	LIS	Portugal	casa.trovit.pt	11261	2292.7	2392.3	100.0	109.6	3.0	3.4
London	London	LDN	UK	foxtons.co.uk	3944	6677.6	7362.7	63.0	64.8	3.0	2.8
Lyon	Lyon	LYN	France	seloger.fr	4267	3106.3	3185.2	74.0	77.2	2.0	2.2
Madrid	Madrid	MAD	Spain	pisos.com	13363	2787.5	2987.4	75.0	82.6	3.0	2.5
Marseille	Marseille	MRS	France	seloger.fr	8244	2507.4	2575.4	65.0	66.6	2.0	2.1
Milano	Milan	MLN	Italy	casa.it	17043	3518.5	3829.4	80.0	83.8	2.0	2.5
Moskva	Moscow	MSK	Russia	egsnk.ru	16161	3966.8	4145.1	55.0	60.4	2.0	2.1
München	Munich	MUC	Germany	immobilienscout24.de	3497	4067.5	4213.9	80.0	82.3	3.0	2.7
Napoli	Naples	NAP	Italy	casa.it	3117	3550.0	3721.2	90.0	90.7	3.0	3.2
Nij. Novgorod	Nizhniy Novgorod	NNG	Russia	gipernn.ru	5871	1262.8	1283.6	48.0	51.5	2.0	2.1
Odessa	Odessa	ODS	Ukraine	alians.com.ua	6761	922.7	972.6	64.0	68.1	2.0	2.2
Oslo	Oslo	OSL	Norway	finn.no/eiendom	805	5187.6	5186.8	64.0	64.0	3.0	2.7
Paris	Paris	PAR	France	seloger.fr	16989	8586.8	8864.1	55.0	61.6	2.0	1.9
Praha	Prague	PRG	Czech Republic	bytyvpraze.cz	7763	1953.4	2026.3	66.0	67.3	2.0	2.4
Riga	Riga	RIG	Latvia	ss.lv	11871	700.0	839.8	56.0	59.6	2.0	2.3
Roma	Rome	ROM	Italy	casa.it	20593	4375.0	4556.9	90.0	91.7	3.0	3.2
Rostov/Don	Rostov-on-Don	RND	Russia	rostov.life-realty.ru	67835	1312.0	1325.2	50.0	52.0	2.0	1.9
S.-Peterburg	St. Petersburg	SPB	Russia	restate.ru	12336	2165.0	2170.1	50.0	57.3	2.0	2.0
Samara	Samara	SAM	Russia	dom63.ru	9690	1233.8	1245.1	50.0	52.6	2.0	2.0
Sevilla	Seville	SEV	Spain	pisos.com	1383	1942.9	2123.8	85.0	87.9	3.0	2.7
Sofia	Sofia	SOF	Bulgaria	imoti.net	8822	750.0	773.0	80.0	83.9	2.0	2.4
Stockholm	Stockholm	STO	Sweden	bovision.se	4305	5245.9	5122.4	63.0	64.9	2.0	2.5
Stuttgart	Stuttgart	STU	Germany	immobilienscout24.de	1655	2187.5	2333.2	74.0	80.0	3.0	3.0
Tallinn	Tallinn	TAL	Estonia	ekspresskinnisvara.ee	5649	1065.2	1067.7	54.0	54.9	2.0	2.3
Torino	Turin	TUR	Italy	casa.it	6075	2225.0	2318.0	75.0	81.3	3.0	3.1
Valencia	Valencia	VAL	Spain	pisos.com	12127	1773.3	1883.1	93.0	96.5	3.0	2.8
Vilnius	Vilnius	VIL	Lithuania	reals.lt	2597	1262.0	1311.6	59.0	59.7	2.0	2.3
Warszawa	Warsaw	WAW	Poland	oferty.net	114189	1938.8	1982.7	54.0	56.7	2.0	2.4
Wien	Vienna	VIE	Austria	immobilien.net	7871	3636.4	3715.5	90.0	95.6	3.0	3.0

Table 2: Definitions of flat in different countries and websites

Country	Site	Type	Currency
Austria	immobilien.net	Eigentumswohnung	euro
Belgium	immoweb.be	appartement, duplex, flat/studio, loft/entrepôt, penthouse, rez-de-chaussée, triplex	euro
Bulgaria	imoti.net	апартамент/apartament	euro (> 99% of ads), lev, and US dollar
Czech Republic	bytyvpraze.cz	byt	Czech crown
Denmark	dba.dk	ejerbolig	Danish crown
Estonia	ekspresskinnisvara.ee	korter	euro
France	seloger.fr	appartement, duplex, loft, studette, studio, triplex	euro
Germany	immobilienscout24.de	Dachgeschoss, Loft, Maisonette, Penthouse, Terrassenwohnung, Souterrain, Erdgeschoß, Etagenwohnung, Hochparterre, Sonstige	euro
Greece	spiti24.gr	$\delta\iota\alpha\mu\varepsilon\rho\iota\sigma\mu\alpha$/diamerisma	euro
Hungary	maganingatlan.hu	lakás	forint
Ireland	myhome.ie	apartment, dormer, duplex, penthouse, studio	euro
Italy	casa.it	appartamento, attico, loft, mansarda, monolocale	euro
Latvia	ss.lv	квартира/kvartira or dzivoklis	euro (> 52% of ads) and lat
Lithuania	reals.lt	butas	Lithuanian litas
Netherlands	funda.nl	appartement	euro
Norway	finn.no/eiendom	bolig	Norwegian crown
Poland	oferty.net	mieszkanie	zloty
Romania	imopedia.ro	apartament, garsoniera	euro
Russia	upn.ru	квартира/kvartira	Russian ruble
Russia	kazan.mlsn.ru	квартира/kvartira	Russian ruble
Russia	egsnk.ru	квартира/kvartira	Russian ruble
Russia	gipernn.ru	квартира/kvartira	Russian ruble
Russia	rostov.life-realty.ru	гостинка/gostinka, квартира/kvartira	Russian ruble
Russia	restate.ru	квартира/kvartira	Russian ruble
Russia	dom63.ru	квартира/kvartira	Russian ruble
Spain	pisos.com	ático, apartamento, dúplex, estudio, loft, piso	euro
Sweden	bovision.se	bostadsraetter	Swedish crown
UK	foxtons.co.uk	apartment, flat, maisonette	British pound
Ukraine	est.ua/dp	квартира/kvartira	US dollar
Ukraine	gorod.kharkov.com	квартира/kvartira	US dollar (denoted as conditional units)
Ukraine	address.ua	квартира/kvartira	US dollar
Ukraine	alians.com.ua	квартира/kvartira	US dollar
Turkey	emlak.net	daire	Turkish lira (> 99% of ads), US dollar, and euro

Table 3: Home price determinants in the literature

Determinants	Number of uses of determinant			Share of uses of determinant, %		
	total	sign +	sign –	total	sign +	sign –
			Income			
GDP per capita	2	2	0	2.2	2.2	0.0
income	3	2	1	3.3	2.2	1.1
income per capita	2	2	0	2.2	2.2	0.0
real GDP	4	3	1	4.4	3.3	1.1
GNP growth	0	1	0	0.0	1.1	0.0
economic activity	1	0	1	1.1	0.0	1.1
real wage	1	1	0	1.1	1.1	0.0
average monthly wage	1	1	0	1.1	1.1	0.0
Total Income	14	12	3	15.4	13.2	3.3
			Interest rate			
real interest rate	7	0	7	7.7	0.0	7.7
mortgage rate	3	1	2	3.3	1.1	2.2
real mortgage rate	1	0	1	1.1	0.0	1.1
discount rate	1	0	1	1.1	0.0	1.1
Total Interest rate	12	1	11	13.2	1.1	12.1
			Demography			
population	4	3	1	4.4	3.3	1.1
proportion of the population ≤ 15	1	1	0	1.1	1.1	0.0
net migration	1	1	0	1.1	1.1	0.0
marriage rate	1	1	0	1.1	1.1	0.0
divorces	1	1	0	1.1	1.1	0.0
number of households	1	0	1	1.1	0.0	1.1
proportion of non-elderly singles	1	1	0	1.1	1.1	0.0
number of black or hispanic	1	1	0	1.1	1.1	0.0
demographic demand	1	1	0	1.1	1.1	0.0
Total Demography	12	10	2	13.2	11.0	2.2
			Credit			
domestic credit	2	2	0	2.2	2.2	0.0
housing credit	1	1	0	1.1	1.1	0.0
trend of mortgage/GDP ratio	1	0	1	1.1	0.0	1.1
loans	1	0	1	1.1	0.0	1.1
real non-food credit	1	0	1	1.1	0.0	1.1
Total Credit	6	3	3	6.6	3.3	3.3
			Labor market			
unemployment	4	0	4	4.4	0.0	4.4
employment	1	1	0	1.1	1.1	0.0
vacancies/labour force	1	1	0	1.1	1.1	0.0
Total Labor market	6	2	4	6.6	2.2	4.4
			Land supply			
land supply index	1	1	0	1.1	1.1	0.0
land supply	1	0	1	1.1	0.0	1.1
land prices	1	1	0	1.1	1.1	0.0
agricultural land prices	3	3	0	3.3	3.3	0.0
Total Land supply	6	5	1	6.6	5.5	1.1
			Housing supply			
completed apartments	1	1	0	1.1	1.1	0.0
number of apartments per 1000 inhabitants	1	1	0	1.1	1.1	0.0
supply of dwellings	1	0	1	1.1	0.0	1.1
log of the number of dwellings per person	1	1	0	1.1	1.1	0.0
improvements in quality of new constructed or modified dwellings	1	1	0	1.1	1.1	0.0
number of home sales	1	0	1	1.1	0.0	1.1
Total Housing supply	6	4	2	6.6	4.4	2.2
			Overall prices			
inflation	1	1	0	1.1	1.1	0.0
expected inflation	1	0	1	1.1	0.0	1.1
unexpected inflation	1	1	0	1.1	1.1	0.0
non-housing price	1	0	1	1.1	0.0	1.1

Table 3: Home price determinants in the literature (continued)

Determinants	Number of uses of determinant			Share of uses of determinant, %		
	total	sign +	sign –	total	sign +	sign –
Total Overall prices	4	2	2	4.4	2.2	2.2
	Institutions					
development of housing markets and housing financial institutions	1	1	0	1.1	1.1	0.0
institutional factor	1	1	0	1.1	1.1	0.0
municipalities / 100,000 households	2	0	2	2.2	0.0	2.2
Total Institutions	4	2	2	4.4	2.2	2.2
	Miscellanea					
construction cost	6	6	0	6.6	6.6	0.0
real construction cost	2	2	0	2.2	2.2	0.0
real effective exchange rate	1	1	0	1.1	1.1	0.0
equity price	5	3	2	5.5	3.3	2.2
rent per month	1	1	0	1.1	1.1	0.0
composite index of taxes, wages, and utilities	1	1	0	1.1	1.1	0.0
turnover rate	1	0	1	1.1	0.0	1.1
risk premium	1	1	0	1.1	1.1	0.0
remittances	1	1	0	1.1	1.1	0.0
foreign inflows	1	1	0	1.1	1.1	0.0
FDI-to-GDP ratio	1	1	0	1.1	1.1	0.0
GRAND TOTAL	91	59	33	100.0	64.8	36.3

Table 4: Data: definitions, transformations, and sources

Code	Description	level	Source
Price	hedonic price per square meter at purchasing power parity	city-specific	own calculations based on microdata downloaded from Internet ad portals
Gini	Gini index, %	city-specific	Eurostat, national and regional statistical offices, own calculations
HOR	homeownership rate	city-specific	Eurostat, national and regional statistical offices, own calculations
Inflation	inflation rate	national	Eurostat, national statistical offices
URate	unemployment rate	city-specific	Eurostat, national and regional statistical offices
Capital	capital city dummy	city-specific	own calculations
Euro_area	Euro area dummy	national	own calculations
EU	European Union dummy	national	own calculations
Population	population, thousand persons	city-specific	Eurostat, national and regional statistical offices, own calculations
Density	population density, thousand persons per square km	city-specific	Eurostat, national and regional statistical offices, own calculations
Housing_stock	housing stock, thousand dwellings	city-specific	Eurostat, national and regional statistical offices, own calculations
Pop2HS	population per dwelling, persons	city-specific	Eurostat, national and regional statistical offices, own calculations
GDP_PC_PPP	per-capita GDP at purchasing power parity, 1000 international dollars	city-specific	Eurostat, national and regional statistical offices, own calculations
GBL_10y	government bond 10 year lending rates, %	national	World Bank
MIR	mortgage interest rates	national	Hypostat
DMIR	year-on-year change rate of mortgage interest rates	national	Hypostat, own calculations
Mortgage_PC	residential debt per capita (over 18 year old), 1000 euros	national	Hypostat

Table 5: Estimation results of hedonic regressions

	Dependent variable:		
	LValue		
	Amsterdam	Brussels	Vienna
	(1)	(2)	(3)
Constant	9.0*** (0.03)	8.0*** (0.04)	7.5*** (0.1)
LRoom	−0.04*** (0.01)	0.05*** (0.01)	−0.02 (0.01)
LArea	0.9*** (0.01)	0.9*** (0.01)	1.2*** (0.01)
Type	No	Yes	Yes
District	Yes	Yes	Yes
Observations	9,479	7,332	10,307
R^2	0.8	0.8	0.8
Adjusted R^2	0.8	0.8	0.8
Residual Std. Error	0.2 (df = 9397)	0.2 (df = 7301)	0.3 (df = 10272)
F Statistic	570.1*** (df = 81; 9397)	878.3*** (df = 30; 7301)	1,141.2*** (df = 34; 10272)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6: Estimation results of hedonic regressions (continued)

	Dependent variable:		
	LValue		
	Lyon	Marseille	Paris
	(1)	(2)	(3)
Constant	8.2*** (0.04)	7.9*** (0.04)	8.9*** (0.01)
LRoom	−0.1*** (0.01)	−0.2*** (0.01)	0.004 (0.01)
LArea	1.0*** (0.01)	1.0*** (0.01)	1.0*** (0.004)
Type	Yes	Yes	Yes
District	Yes	Yes	Yes
Observations	7,215	12,455	28,861
R^2	0.8	0.7	0.9
Adjusted R^2	0.8	0.7	0.9
Residual Std. Error	0.2 (df = 7199)	0.2 (df = 12432)	0.2 (df = 28833)
F Statistic	1,851.7*** (df = 15; 7199)	1,689.4*** (df = 22; 12432)	15,979.0*** (df = 27; 28833)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 7: Estimation results of hedonic regressions (continued)

	Dependent variable: LValue		
	Berlin	Dusseldorf	Frankfurt/Main
	(1)	(2)	(3)
Constant	5.6*** (0.1)	6.2*** (0.1)	6.7*** (0.2)
LRoom	−0.1*** (0.01)	−0.2*** (0.03)	−0.2*** (0.03)
LArea	1.4*** (0.01)	1.4*** (0.03)	1.3*** (0.03)
Balcony	0.1*** (0.01)	0.02 (0.01)	0.02 (0.01)
Garden	0.1*** (0.01)	0.1*** (0.02)	0.05*** (0.01)
Type	No	No	No
District	Yes	Yes	Yes
Observations	16,976	1,926	2,323
R^2	0.8	0.8	0.8
Adjusted R^2	0.8	0.8	0.8
Residual Std. Error	0.3 (df = 16893)	0.2 (df = 1875)	0.3 (df = 2273)
F Statistic	779.0*** (df = 82; 16893)	203.9*** (df = 50; 1875)	256.9*** (df = 49; 2273)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 8: Estimation results of hedonic regressions (continued)

	Dependent variable: LValue			
	Hamburg	Cologne	Munich	Stuttgart
	(1)	(2)	(3)	(4)
Constant	7.8*** (0.1)	6.8*** (0.2)	7.3*** (0.1)	6.4*** (0.3)
LRoom	0.1*** (0.03)	−0.1** (0.05)	−0.03 (0.03)	−0.01 (0.1)
LArea	1.0*** (0.03)	1.3*** (0.1)	1.2*** (0.03)	1.2*** (0.1)
Balcony	0.01 (0.02)	−0.01 (0.02)	−0.01 (0.02)	0.1*** (0.03)
Garden	0.1*** (0.02)	0.1*** (0.03)	0.02 (0.02)	0.05 (0.04)
Type	No	No	No	No
District	Yes	Yes	Yes	Yes
Observations	2,623	3,041	4,944	2,226
R^2	0.8	0.5	0.5	0.4
Adjusted R^2	0.7	0.5	0.5	0.4
Residual Std. Error	0.4 (df = 2538)	0.5 (df = 2954)	0.5 (df = 4898)	0.6 (df = 2169)
F Statistic	91.2*** (df = 84; 2538)	32.9*** (df = 86; 2954)	132.2*** (df = 45; 4898)	29.5*** (df = 56; 2169)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 9: Estimation results of hedonic regressions (continued)

	Dependent variable:			
	LValue			
	Milan	Naples	Rome	Turin
	(1)	(2)	(3)	(4)
Constant	8.5*** (0.03)	7.8*** (0.1)	9.1*** (0.03)	6.8*** (0.1)
LRoom	0.1*** (0.01)	0.1*** (0.03)	0.05*** (0.01)	−0.1*** (0.02)
LArea	0.8*** (0.01)	1.0*** (0.03)	0.8*** (0.01)	1.2*** (0.02)
Type	Yes	Yes	Yes	Yes
District	Yes	Yes	Yes	Yes
Observations	24,934	4,385	29,121	8,215
R^2	0.7	0.7	0.7	0.7
Adjusted R^2	0.7	0.7	0.7	0.7
Residual Std. Error	0.3 (df = 24908)	0.4 (df = 4347)	0.3 (df = 29077)	0.3 (df = 8180)
F Statistic	1,984.6*** (df = 25; 24908)	256.6*** (df = 37; 4347)	1,591.9*** (df = 43; 29077)	614.8*** (df = 34; 8180)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 10: Estimation results of hedonic regressions (continued)

	Dependent variable:			
	LValue			
	Barcelona	Madrid	Seville	Valencia
	(1)	(2)	(3)	(4)
Constant	8.1*** (0.1)	7.3*** (0.04)	6.2*** (0.2)	6.2*** (0.1)
LRoom	−0.1*** (0.01)	−0.2*** (0.01)	−0.3*** (0.03)	−0.3*** (0.01)
LArea	1.1*** (0.02)	1.1*** (0.01)	1.4*** (0.04)	1.4*** (0.01)
Type	Yes	Yes	Yes	Yes
District	Yes	Yes	Yes	Yes
Observations	5,391	15,940	1,747	14,368
R^2	0.7	0.8	0.7	0.6
Adjusted R^2	0.7	0.8	0.7	0.6
Residual Std. Error	0.3 (df = 5311)	0.3 (df = 15802)	0.3 (df = 1671)	0.3 (df = 14275)
F Statistic	140.6*** (df = 79; 5311)	437.8*** (df = 137; 15802)	63.9*** (df = 75; 1671)	226.9*** (df = 92; 14275)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 11: Estimation results of hedonic regressions (continued)

	Dependent variable:		
	LValue		
	Kazan	Moscow	Nizhniy Novgorod
	(1)	(2)	(3)
Constant	11.5*** (0.03)	12.0*** (0.02)	11.6*** (0.03)
LRoom	−0.1*** (0.01)	−0.1*** (0.004)	−0.03*** (0.005)
LArea	0.8*** (0.01)	1.1*** (0.01)	0.8*** (0.01)
Floor	No	No	Yes
Type	Yes	Yes	Yes
District	Yes	Yes	Yes
Observations	16,696	36,348	16,692
R^2	0.7	0.8	0.8
Adjusted R^2	0.7	0.8	0.8
Residual Std. Error	0.2 (df = 16683)	0.2 (df = 36332)	0.1 (df = 16668)
F Statistic	3,067.4*** (df = 12; 16683)	8,504.2*** (df = 15; 36332)	3,907.6*** (df = 23; 16668)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 12: Estimation results of hedonic regressions (continued)

	Dependent variable:			
	LValue			
	Rostov/Don	St. Petersburg	Samara	Yekaterinburg
	(1)	(2)	(3)	(4)
Constant	10.9*** (0.01)	11.1*** (0.05)	10.7*** (0.02)	11.4*** (0.02)
LRoom	−0.1*** (0.001)	−0.1*** (0.004)	−0.1*** (0.003)	−0.2*** (0.003)
LArea	0.9*** (0.002)	0.9*** (0.005)	0.9*** (0.004)	0.9*** (0.004)
Balcony none		0.04*** (0.004)		
Floor	Yes	Yes	No	No
Type	No	Yes	Yes	No
District	Yes	Yes	Yes	Yes
Observations	199,486	30,028	28,670	20,101
R^2	0.8	0.8	0.8	0.9
Adjusted R^2	0.8	0.8	0.8	0.9
Residual Std. Error	0.2 (df = 199446)	0.2 (df = 29974)	0.2 (df = 28652)	0.1 (df = 20052)
F Statistic	19,019.0*** (df = 39; 199446)	2,982.2*** (df = 53; 29974)	8,349.1*** (df = 17; 28652)	2,409.2*** (df = 48; 20052)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 13: Estimation results of hedonic regressions (continued)

	Dependent variable:			
	LValue			
	Dnepropetrovsk	Kharkov	Kiev	Odessa
	(1)	(2)	(3)	(4)
Constant	5.5*** (0.2)	7.7*** (0.1)	7.1*** (0.01)	7.2*** (0.04)
LRoom	−0.1** (0.1)	0.1*** (0.01)	−0.1*** (0.002)	−0.001 (0.01)
LArea	1.4*** (0.1)	0.7*** (0.01)	1.1*** (0.002)	1.0*** (0.01)
Type	No	No	No	Yes
District	No	Yes	Yes	Yes
Observations	6,583	29,777	161,524	12,138
R^2	0.1	0.8	0.8	0.8
Adjusted R^2	0.1	0.8	0.8	0.8
Residual Std. Error	1.0 (df = 6580)	0.3 (df = 29295)	0.2 (df = 161512)	0.2 (df = 12104)
F Statistic	568.4*** (df = 2; 6580)	238.5*** (df = 481; 29295)	44,460.5*** (df = 11; 161512)	1,394.6*** (df = 33; 12104)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 14: Estimation results of hedonic regressions (continued)

	Dependent variable:		
	LValue		
	Copenhagen	Oslo	Stockholm
	(1)	(2)	(3)
Constant	9.3*** (0.2)	11.1*** (0.1)	11.6*** (0.1)
LRoom	0.1*** (0.01)	0.1*** (0.04)	0.03* (0.02)
LArea	1.2*** (0.02)	0.8*** (0.04)	0.8*** (0.02)
Sellerprivat	0.003 (0.03)		
Property	No	Yes	No
Type	Yes	No	No
District	Yes	Yes	Yes
Observations	4,838	1,742	7,295
R^2	0.9	0.7	0.7
Adjusted R^2	0.9	0.7	0.6
Residual Std. Error	0.2 (df = 4619)	0.2 (df = 1712)	0.3 (df = 7212)
F Statistic	137.5*** (df = 218; 4619)	116.3*** (df = 29; 1712)	164.5*** (df = 82; 7212)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 15: Estimation results of hedonic regressions (continued)

	Dependent variable:		
	LValue		
	Dublin	London	Lisbon
	(1)	(2)	(3)
Constant	9.3*** (0.1)	10.2*** (0.1)	7.9*** (0.3)
LRoom	0.3*** (0.04)	−0.1*** (0.02)	−0.1*** (0.01)
LArea	0.6*** (0.03)	0.8*** (0.01)	1.0*** (0.01)
Type	Yes	Yes	No
District	Yes	Yes	Yes
Observations	2,486	6,387	14,621
R^2	0.7	0.7	0.6
Adjusted R^2	0.7	0.7	0.6
Residual Std. Error	0.3 (df = 2449)	0.2 (df = 6222)	0.3 (df = 14387)
F Statistic	132.3*** (df = 36; 2449)	102.1*** (df = 164; 6222)	110.5*** (df = 233; 14387)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 16: Estimation results of hedonic regressions (continued)

	Dependent variable:			
	LValue			
	Budapest	Bucharest	Prague	Warsaw
	(1)	(2)	(3)	(4)
Constant	13.1*** (0.2)	7.7*** (0.03)	12.7*** (1.4)	8.8*** (0.01)
LRoom	0.05* (0.03)	0.1*** (0.01)	0.2*** (0.05)	−0.1*** (0.002)
LArea	0.9*** (0.03)	0.8*** (0.01)	0.4*** (0.05)	1.1*** (0.003)
Building	Yes	No	No	No
Floor	Yes	No	No	No
Type	Yes	No	Yes	No
District	Yes	Yes	Yes	Yes
Observations	1,412	14,877	13,295	187,995
R^2	0.8	0.8	0.1	0.7
Adjusted R^2	0.8	0.8	0.1	0.7
Residual Std. Error	0.3 (df = 1250)	0.1 (df = 14757)	1.4 (df = 12837)	0.2 (df = 187975)
F Statistic	28.2*** (df = 161; 1250)	487.9*** (df = 119; 14757)	3.6*** (df = 457; 12837)	25,355.5*** (df = 19; 187975)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 17: Estimation results of hedonic regressions (continued)

	Dependent variable:		
	LValue		
	Athens	Istanbul	Sofia
	(1)	(2)	(3)
Constant	7.1*** (0.1)	7.5*** (0.2)	6.9*** (0.04)
LRoom	0.1*** (0.02)	0.05*** (0.01)	0.1*** (0.01)
LArea	1.1*** (0.02)	0.9*** (0.01)	0.9*** (0.01)
Type	No	No	No
District	Yes	Yes	Yes
Observations	10,547	53,944	12,397
R^2	0.5	0.7	0.8
Adjusted R^2	0.5	0.7	0.8
Residual Std. Error	0.4 (df = 10538)	0.2 (df = 53380)	0.2 (df = 12177)
F Statistic	1,147.2*** (df = 8; 10538)	185.7*** (df = 563; 53380)	203.9*** (df = 219; 12177)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 18: Estimation results of hedonic regressions (continued)

	Dependent variable:		
	LValue		
	Riga	Tallin	Vilnius
	(1)	(2)	(3)
Constant	4.39*** (0.05)	6.48*** (0.05)	6.77*** (0.09)
LRoom	−0.22*** (0.01)	−0.15*** (0.01)	−0.28*** (0.02)
LArea	1.58*** (0.02)	1.14*** (0.01)	1.44*** (0.03)
Type	No	No	No
District	Yes	Yes	Yes
Observations	13,635	7,151	2,734
R^2	0.72	0.78	0.81
Adjusted R^2	0.72	0.78	0.80
Residual Std. Error	0.40 (df = 13584)	0.26 (df = 7136)	0.26 (df = 2685)
F Statistic	714.90*** (df = 50; 13584)	1,781.79*** (df = 14; 7136)	235.00*** (df = 48; 2685)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 19: Results of Bayesian Model Averaging

	p!=0	EV	SD	model 1	model 2
Intercept	100.0	6.663	0.3134	6.702	6.088
Capital	0.0	0.000	0.0000	.	.
Euro_area	0.0	0.000	0.0000	.	.
EU	0.0	0.000	0.0000	.	.
LPopulation	0.0	0.000	0.0000	.	.
LGDP_PC_PPP	6.5	0.020	0.0791	.	0.314
LDensity	100.0	0.257	0.0738	0.256	0.275
LGBL_10y	0.0	0.000	0.0000	.	.
LMortgage_PC	93.5	0.135	0.0440	0.145	.
LHousing_stock	0.0	0.000	0.0000	.	.
Gini	100.0	0.038	0.0081	0.039	0.026
MIR	0.0	0.000	0.0000	.	.
DMIR	0.0	0.000	0.0000	.	.
HOR	0.0	0.000	0.0000	.	.
Inflation	0.0	0.000	0.0000	.	.
URate	100.0	-0.045	0.0093	-0.046	-0.029
DPop	0.0	0.000	0.0000	.	.
LPopulation_EU	0.0	0.000	0.0000	.	.
LGDP_PC_PPP_EU	0.0	0.000	0.0000	.	.
LDensity_EU	0.0	0.000	0.0000	.	.
LPop2HS_EU	0.0	0.000	0.0000	.	.
LGBL_10y_EU	0.0	0.000	0.0000	.	.
LMortgage_PC_EU	0.0	0.000	0.0000	.	.
LHousing_stock_EU	0.0	0.000	0.0000	.	.
Gini_EU	0.0	0.000	0.0000	.	.
MIR_EU	0.0	0.000	0.0000	.	.
DMIR_EU	0.0	0.000	0.0000	.	.
HOR_EU	0.0	0.000	0.0000	.	.
Inflation_EU	0.0	0.000	0.0000	.	.
URate_EU	0.0	0.000	0.0000	.	.
DPop_EU	0.0	0.000	0.0000	.	.
nVar				4	4
r2				0.628	0.584
BIC				-31.983	-26.641
post prob				0.935	0.065

Table 20: Estimation results of OLS and quantile regressions

	Dependent variable: LPrice			
	OLS	*quantile regression*	*OLS*	*quantile regression*
	whole sample		Euro area	
	(1)	(2)	(3)	(4)
Constant	6.702*** (0.206)	7.073*** (0.445)	7.023*** (0.363)	7.654*** (0.934)
LDensity	0.256*** (0.068)	0.211** (0.092)	0.251*** (0.042)	0.183 (0.165)
LMortgage_PC	0.145*** (0.023)	0.114*** (0.035)		
Gini	0.039*** (0.005)	0.035*** (0.010)	0.035*** (0.013)	0.015 (0.028)
URate	−0.046*** (0.008)	−0.064*** (0.015)	−0.034*** (0.008)	−0.025 (0.021)
Observations		48		25
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 21: Actual vs. fitted prices

City	Actual price	OLS regression			Quantile regression, $\tau = 0.5$		
		Fitted	Absolute difference	Relative difference, %	Fitted	Absolute difference	Relative difference, %
	P	$\widehat{P}_{OLS}$	$P-\widehat{P}_{OLS}$	$100\frac{P-\widehat{P}_{OLS}}{\widehat{P}_{OLS}}$	$\widehat{P}_{QR}$	$P-\widehat{P}_{QR}$	$100\frac{P-\widehat{P}_{QR}}{\widehat{P}_{QR}}$
Amsterdam	4,294.2	3,466.2	827.9	19.3	3,133.5	1,160.7	27.0
Athens	3,030.4	2,951.8	78.6	2.6	3,030.4	-0	-0
Barcelona	4,305.0	5,697.5	-1,392.5	-32.3	5,102.1	-797.2	-18.5
Berlin	2,621.3	2,685.3	-64.0	-2.4	2,621.3	0	0
Brussels	2,539.2	4,598.5	-2,059.2	-81.1	4,542.2	-2,002.9	-78.9
Bucharest	2,821.4	4,002.7	-1,181.3	-41.9	3,661.4	-840.0	-29.8
Budapest	2,209.4	2,879.0	-669.6	-30.3	2,687.0	-477.7	-21.6
Cologne	2,575.7	3,045.9	-470.2	-18.3	2,921.8	-346.1	-13.4
Copenhagen	3,077.6	4,359.4	-1,281.8	-41.7	4,003.3	-925.7	-30.1
Dnepropetrovsk	2,551.1	1,775.4	775.7	30.4	2,134.9	416.2	16.3
Dublin	3,454.2	2,968.0	486.1	14.1	2,765.2	689.0	19.9
Dusseldorf	2,603.0	4,026.8	-1,423.8	-54.7	3,768.7	-1,165.7	-44.8
Frankfurt	3,685.5	4,374.4	-689.0	-18.7	4,117.8	-432.3	-11.7
Hamburg	4,102.5	3,699.6	402.9	9.8	3,636.9	465.6	11.4
Istanbul	1,149.9	1,423.6	-273.6	-23.8	1,149.9	0	0
Kazan	2,697.3	3,178.2	-480.9	-17.8	3,494.8	-797.5	-29.6
Kharkov	1,699.2	1,995.0	-295.9	-17.4	2,246.7	-547.5	-32.2
Kiev	4,063.3	4,797.7	-734.4	-18.1	5,631.1	-1,567.8	-38.6
Lisbon	3,918.5	3,107.6	810.9	20.7	3,077.3	841.2	21.5
London	8,723.4	7,981.1	742.3	8.5	8,048.4	675.0	7.7
Lyon	4,090.1	3,733.4	356.7	8.7	3,924.4	165.7	4.1
Madrid	4,395.1	4,330.7	64.4	1.5	4,395.1	-0	-0
Marseille	3,362.5	3,331.4	31.1	0.9	3,692.4	-329.9	-9.8
Milan	3,755.5	4,227.6	-472.1	-12.6	3,889.3	-133.8	-3.6
Moscow	8,936.7	8,372.9	563.7	6.3	8,838.4	98.3	1.1
Munich	5,349.7	3,942.7	1,406.9	26.3	3,673.2	1,676.4	31.3
Naples	3,905.6	4,176.1	-270.5	-6.9	3,955.7	-50.0	-1.3
Nizhniy Novgorod	2,822.9	2,576.5	246.4	8.7	2,784.6	38.4	1.4
Odessa	2,768.0	2,345.8	422.2	15.3	2,520.1	247.9	9.0
Oslo	4,339.3	4,569.9	-230.6	-5.3	4,339.3	-0	-0
Paris	10,901.7	9,237.5	1,664.2	15.3	8,601.5	2,300.2	21.1
Prague	3,978.0	3,241.9	736.1	18.5	2,886.9	1,091.1	27.4
Riga	1,629.8	1,715.2	-85.4	-5.2	1,680.1	-50.3	-3.1
Rome	4,448.5	2,987.9	1,460.6	32.8	2,948.1	1,500.5	33.7
Rostov-on-Don	2,933.4	2,396.2	537.2	18.3	2,614.6	318.9	10.9
Samara	2,709.7	3,380.6	-670.9	-24.8	3,810.6	-1,100.9	-40.6
Seville	2,292.7	2,322.7	-30.0	-1.3	2,292.7	0	0
Sofia	2,213.3	3,233.5	-1,020.2	-46.1	3,178.0	-964.7	-43.6
St. Petersburg	4,814.5	4,283.8	530.6	11.0	4,672.6	141.9	2.9
Stockholm	5,008.3	3,233.2	1,775.1	35.4	2,738.9	2,269.4	45.3
Stuttgart	2,651.9	3,590.9	-939.0	-35.4	3,346.2	-694.3	-26.2
Tallinn	2,341.2	2,305.2	36.0	1.5	2,341.2	0	0
Turin	2,525.7	3,513.4	-987.7	-39.1	3,259.1	-733.4	-29.0
Valencia	2,638.5	2,767.8	-129.3	-4.9	2,568.0	70.6	2.7
Vienna	4,281.4	2,980.7	1,300.7	30.4	2,653.5	1,627.9	38.0
Vilnius	2,914.9	1,816.3	1,098.7	37.7	1,756.7	1,158.2	39.7
Warsaw	4,622.3	5,501.9	-879.6	-19.0	5,558.3	-936.1	-20.3
Yekaterinburg	3,536.6	3,160.7	375.9	10.6	3,536.6	-0	-0

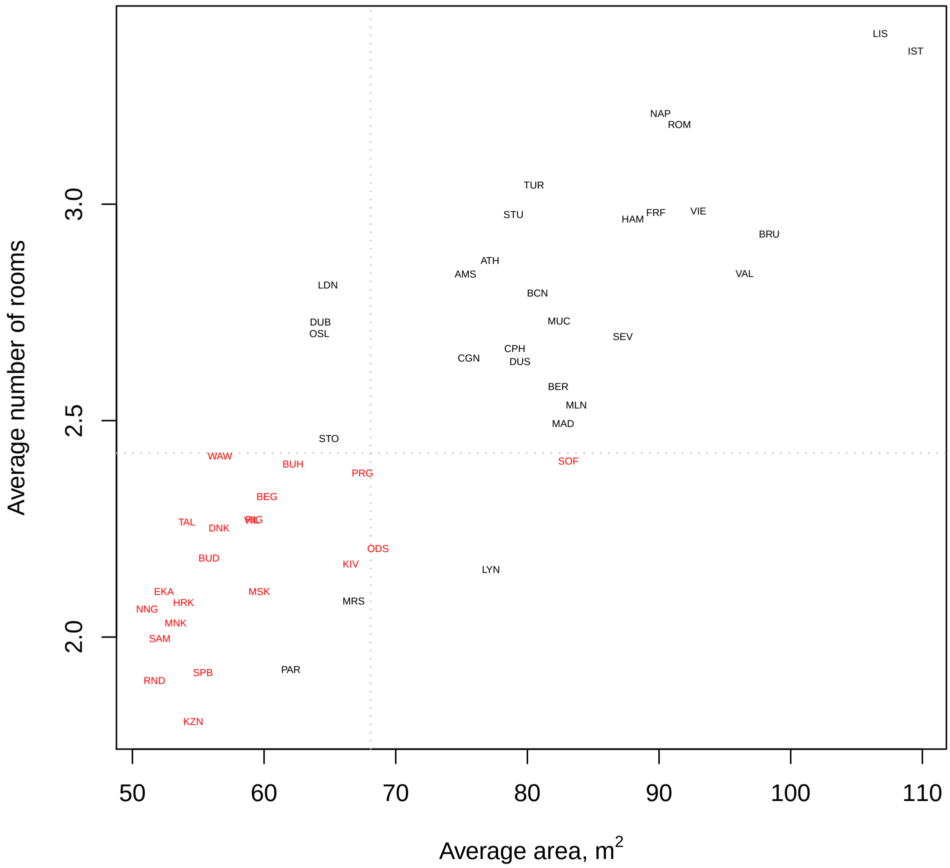

Figure 1: Size of flats in large European cities, January – May 2012

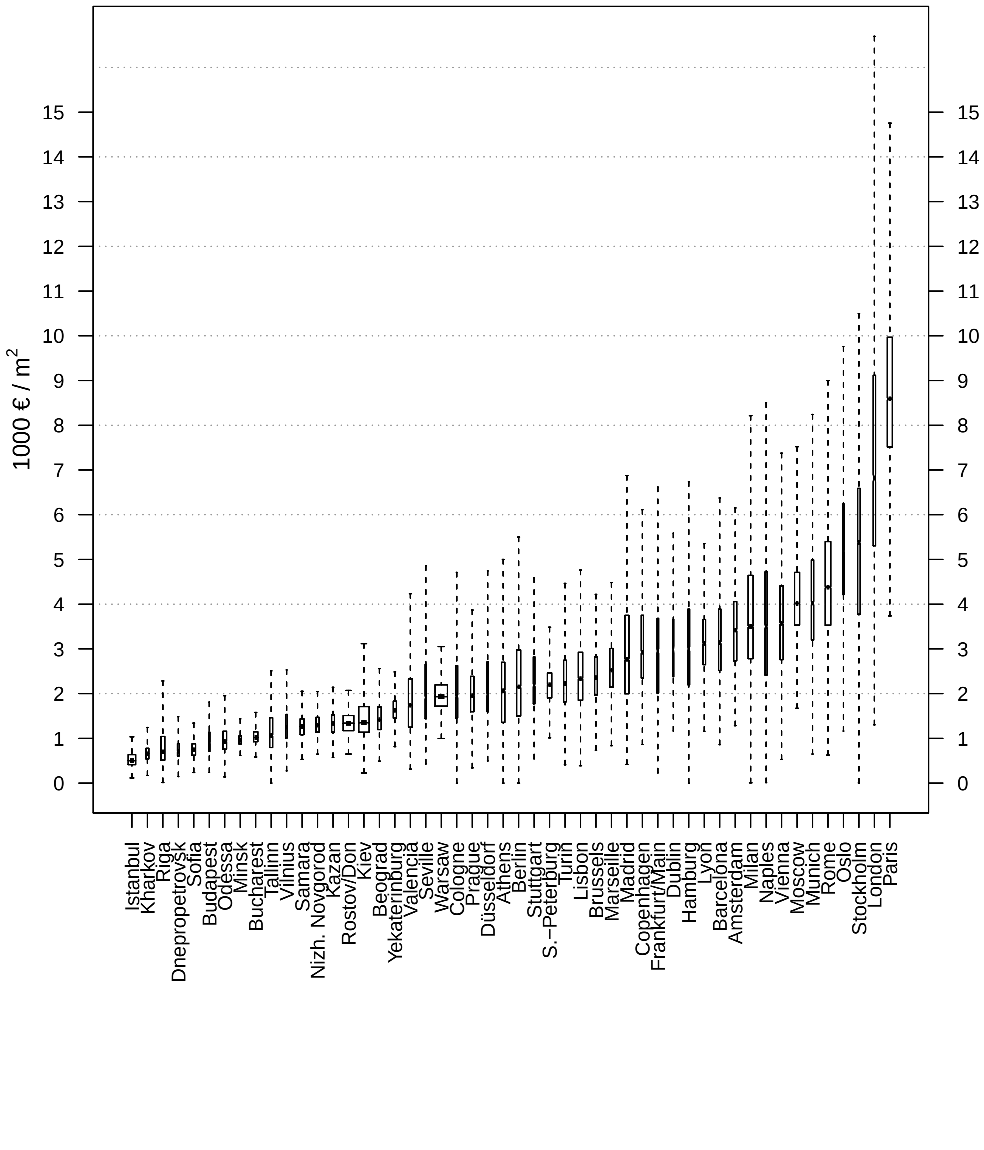

Figure 2: Internet offer prices for flats in large European cities, January – May 2012

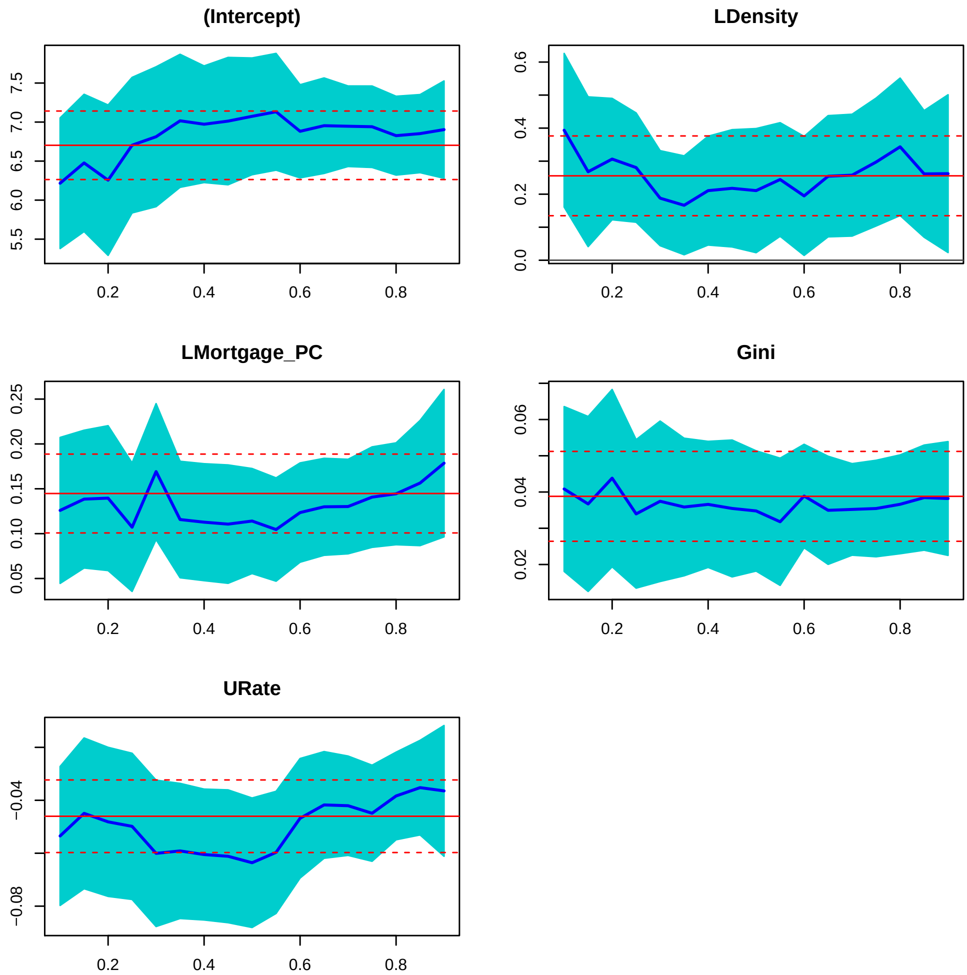

Figure 3: Quantile regression's coefficient estimates at different quantiles

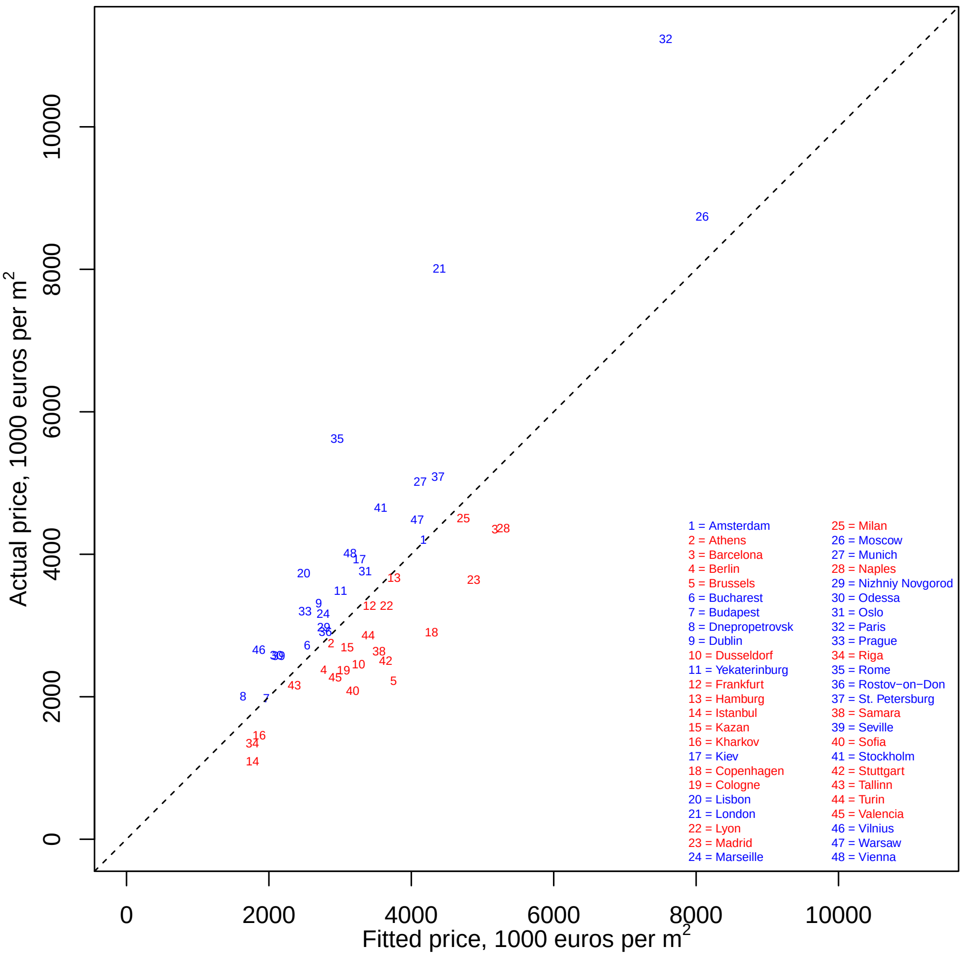

Figure 4: Actual vs. fitted prices (OLS regression)

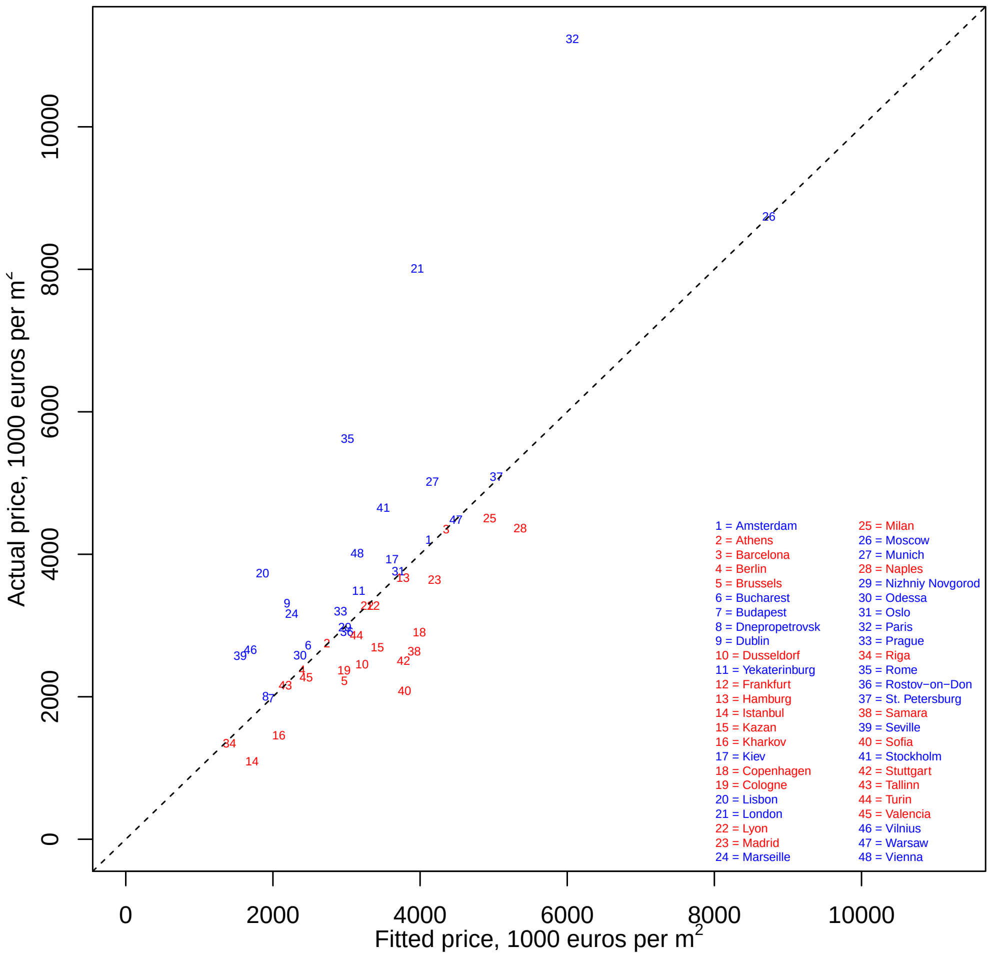

Figure 5: Actual vs. fitted prices (quantile regression, $\tau = 0.5$)

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