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Revealing preferences for urban green spaces: a scale-sensitive hedonic pricing analysis for the city of Leipzig

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Abstract

The value of urban green spaces (UGS) is recognized as an important issue for real estate developers as much as for urban planners, since UGS influence housing prices and the attractiveness of locations and neighborhoods. Decisions related to UGS are made on different spatial scales (renting a home versus urban spatial planning), which have not yet been distinguished in hedonic studies. Therefore, the purpose of this paper is to investigate the scale dependency of UGS values based on revealed preferences. We propose to apply a stepwise scale-sensitive hedonic pricing analysis to residential rental units in Leipzig, Germany. First, we run the hedonic analysis on the city level. Second, we break up the data set and analyze revealed preferences on the district level. Third, we statistically model revealed preferences on the district level. The results demonstrate that revealed preferences differ for different spatial levels. UGS variables, which were not important at the city level, appear to influence prices once scaled down to the district level. Finally, revealed preferences on the district scale can be explained with socio-economic variables. We conclude, applying a scale-sensitive approach yields improved insights and is also promising for other complex systems.

I. Introduction

Several scholars have advocated for improving land-use decision making by considering ecosystem services (Bateman et al., 2013). Ecosystem services can be fundamental to finding sustainable solutions for many societal challenges and are also increasingly considered in urban planning (Gomez-Baggethun and Barton, 2013; Haase et al., 2014; Hubacek and Kronenberg, 2013). Urban green spaces (UGS) are of significant relevance for a population's well-being (Bai et al., 2013; Brander and Koetse, 2011) and the provision of urban ecosystem services, such as temperature regulation, noise reduction, air purification and recreation (Fuller and Gaston, 2009; Gomez-Baggethun and Barton, 2013). However, recognizing urban ecosystem services in planning and land management is challenged by the complexity of these systems - in particular, as being interwoven with societal institutions, such as the real estate market (Bartke and Schwarze, 2015; Hagedorn, 2008).

Several methods have been suggested to assess the importance that people attribute to certain ecosystem functions and derived services (Bateman et al., 2011; Häyhä and Franzese, 2014; Reid et al., 2005) and specifically related to the effects of environmental amenities in properties (Czembrowski and Kronenberg, 2016). The most commonly applied methods for the latter are hedonic pricing and contingent valuation (Brander and Koetse, 2011; Czembrowski and Kronenberg, 2016). Hedonic pricing analysis infers values from data on price differences that reflect behavioral changes in real (estate) markets. These are related to simultaneous decisions on components of the environment, which have no market on their own (Martín-López et al., 2011).

In general, the hedonic pricing approach is based on the principle that the price of a marketed good is influenced by specific implicit characteristics of that good and these characteristics can be disentangled and understood to either raise or lower the overall price of the good

(Rosen, 1974). To date, hedonic pricing analysis has been performed on the city level (Ahlfeldt and Maennig, 2011; Bolitzer and Netusil, 2000; Din et al., 2001; Donovan and Butry, 2011; Jim and Chen, 2006; Kong et al., 2007; Melichar and Kaprová, 2013; Tyrväinen, 1997), on the county level (Kovacs, 2012) or on the country level (Luttik, 2000). Yet, it is obvious there are characteristics that not only vary between cities, but also within any given city. For example, the meta-analysis by Brander and Koetse (2011) suggests that population density influences preferences for UGS. In fact, several hedonic pricing studies report spatial heterogeneity when comparing different spatial delineations. The core assumption underlying these studies has been the presence of submarkets based on, for example, elementary school zones, zip code zones or census tracts (Bourassa et al., 1999; Goodman and Thibodeau, 2003, 1998). Another line of reasoning is related to preferences, acknowledging that they are context-specific (Levine et al., 2015), heterogeneous (Boxall and Adamowicz, 2002) and likely not homogenously distributed within a city, for instance, due to segregation, which in turn also leads to spatial differences in preferences. Having this in mind, we contribute to the existing body of literature by investigating scale dependency of preferences regarding UGS on the district versus the city level.

Differentiating the districts in existing studies reflects differences in neighborhoods' quality and in housing characteristics as well as demand and preferences of the different households (Watkins, 2008). In our study, we go one step further and explore the possibility of statistically explaining the preferences revealed in a hedonic pricing analysis. Thus, we present here a stepwise analytical *scale-sensitive approach*. This study builds on a recent study of Liebelt et al. (unpublished), which analyzed the influence of UGS on prices of flats and houses in Leipzig, Germany, on the city scale. Here, we differentiate the analysis to city districts and explain district-level preferences with district characteristics. The following two hypotheses guide the analysis in this paper:

- H1: Scale dependency: revealed preferences regarding UGS are scale-dependent, that is, revealed preferences differ on the city and on the district level.
- H2: Explaining preferences: revealed preferences on the district scale can be explained with district characteristics, including socio-economic variables.

In the following, we introduce the scale-sensitive approach and its translation into methodology in more detail. Section II provides materials and methods. In Section III, we demonstrate the application of the proposed methodology for the case of Leipzig, Germany. Section IV relates the results from this application to the hypotheses and discusses the general concept. Section V concludes on the presented approach.

II. Material and methods

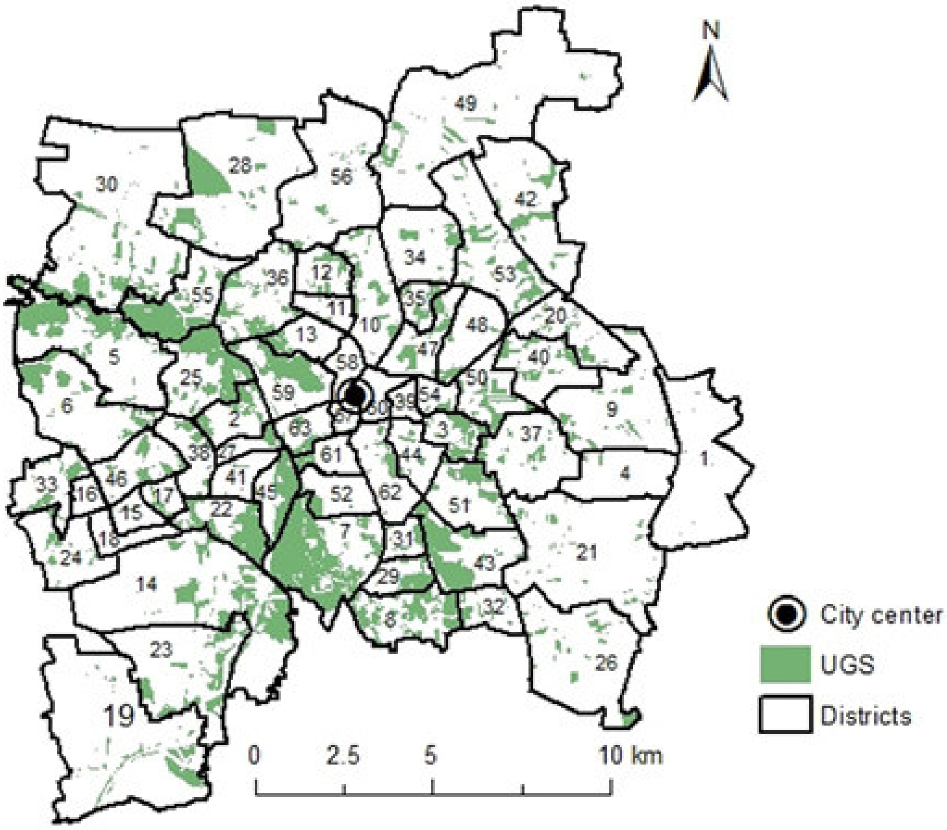
2.1. Case study

The study is conducted using data from the city of Leipzig, as it is one of the largest cities in Germany and encompasses a large amount of UGS within its administrative boundaries. Leipzig is quite comparable with several other central European cities, e.g. Brno, Genoa or Liverpool, which blossomed in times of Industrial Revolution, faced restructuring in the previous decades and now have a fair amount of UGS and diversified building stock (Bartke et al., 2016; Couch et al., 2012).

This city has approximately half a million inhabitants, average population density of 1,742 per sq. km for the years 2007–2013 (Amt für Statistik und Wahlen, 2014, 2012a, 2010, 2008a) and an area of 297.6 km². Leipzig is a monocentric city and has 63 districts (Figure 1, Appendix A).

Leipzig's UGS in total comprise approximately 4,900 ha, compared to 6,300 ha of residential area. In fact, large parks are located very close to the city center and even some forested areas are located within the city boundary, which makes UGS easily accessible for most citizens.

Figure 1: Urban green spaces and city districts of Leipzig



District names corresponding to the district numbers are given in Appendix A.

2.2. Data

The real estate data is about flats in Leipzig, which were available to rent during 2007–2013, in total 261,827 unique entries. The data were obtained from the German real estate web portal Immobilienscout24 and were carefully analyzed for inconsistencies, double entries and missing values. To avoid inconsistencies, cut-off criteria were applied to exclude unrealistic outliers. For example, the minimum size for all flats was set to 15 m^2 and the maximum to

300 m^2. As described in more detail in Liebelt et al., (unpublished), missing data were filled by logical recoding and imputation. Flats to rent are the most common form of living property in German cities and were thus the focus of the present study.

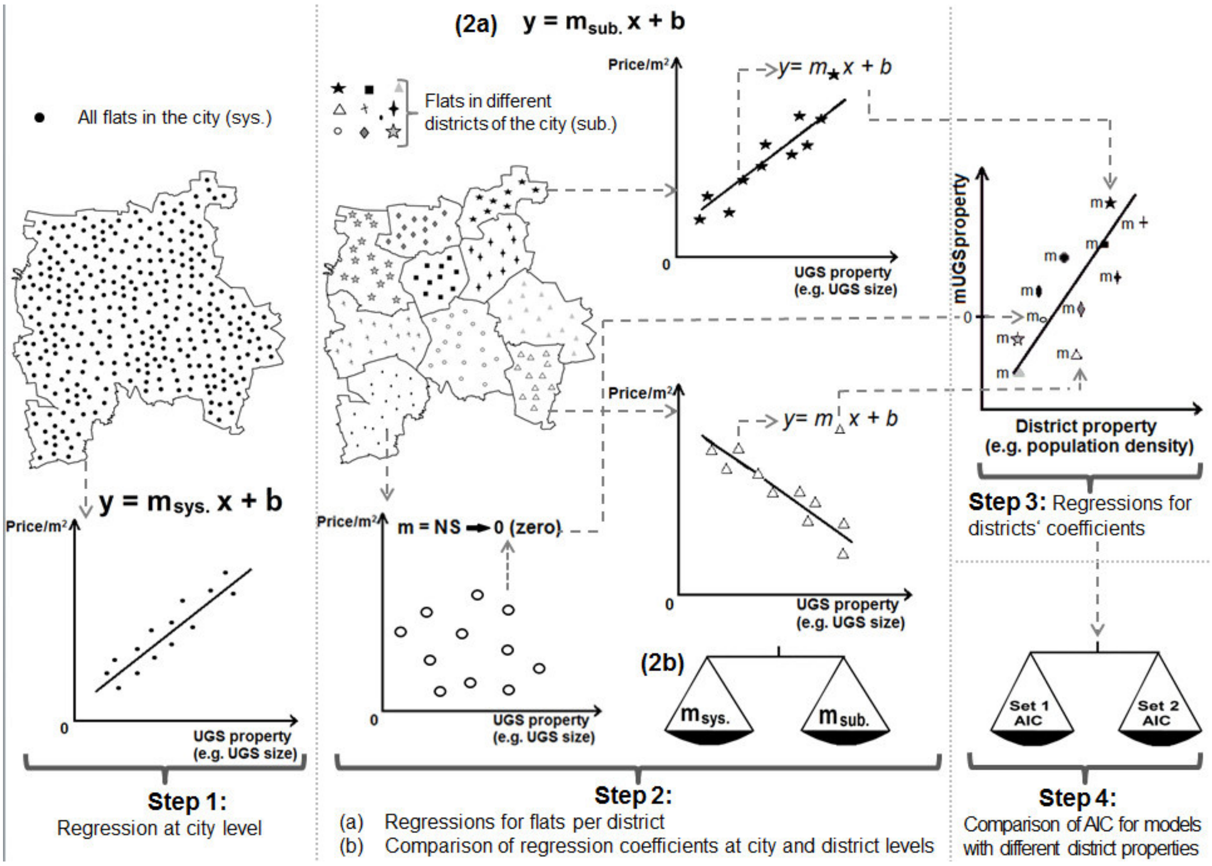
In addition, study variables include *UGS variables* as well as some *housing* and *spatial* variables (Table 1). Regarding the UGS variables, size, distance from flat to the next UGS and share of UGS in a 300 m buffer were included as they are most commonly used variables in hedonic pricing studies (Donovan and Butry, 2011; Kong et al., 2007; Kovacs, 2012; Tyrväinen, 1997). We also included the shape of the UGS as a variable (Liebelt et al., unpublished.). Prior to the UGS variables calculation, we combined land cover types of parks, forests, woods, cemeteries and allotments to represent UGS providing to some extent recreational services to local population.

Considering the size of the city and its characteristics as well as data availability, we decided to use districts to investigate spatial heterogeneity. The analysis at the district level covered 62 districts of Leipzig; we omitted one district, because the number of available cases was too small. Socio-economic variables that characterize the districts were obtained from statistical yearbooks (Amt für Statistik und Wahlen, 2014, 2012a, 2012b, 2011, 2010, 2009, 2008a, 2008b, 2007; Amt für Statistik und Wahlen Leipzig, 2014).

2.3. From city to district level: Foundations of a scale-sensitive approach

In order to investigate our hypotheses, we focus on conducting a detailed analysis of the revealed preferences. In order to do so, we have chosen a nested approach that links the city scale to the districts. The following four-step approach is illustrated in Figure 2 and builds on the classical linear regression approach in hedonic pricing (e.g.(Bolitzer and Netusil, 2000; Donovan and Butry, 2011; Hamilton, 2007; Jim and Chen, 2006; Kong et al., 2007; Luttik, 2000; Melichar and Kaprová, 2013; Rehdanz and Maddison, 2008; Tyrväinen, 1997). Details on each step of the methodology are given in Section 2.4.

Figure 2: Overview of the four-step regression analysis in the study



Notes: Set 1 AIC: results from a model with all independent variables; *Set 2 AIC:* results from a model that does not include socio-economic variables (Table 2).
AIC: Akaike's information criterion (Akaike, 1974).
"y"**:* price of housing unit (Euro/m²); ***"x"**:* UGS characteristics; ***"m": slope (outcome of the hedonic regression), represents the value on which ***"y"*** will increase/decrease by increase of 1 in the input variable (i.e.*" **x**");* ***b***: intercept value (represents the value of ***"y"*** when **"*x*"**=*0*); ***"NS"***: non-significant.

Step 1 is a linear regression model for the city level – as was done by Liebelt et al. (unpublished).

Step 2 is a linear regression model using the same data set, but at the district level. The dependent variables are again the prices for the flats (Euro per m²), but individual linear regressions are run for each district. The outcomes of the hedonic study at the district level (i.e. revealed preferences as given in the regression coefficients) are compared with those at the city level.

Step 3 is a series of linear regressions with the regression coefficients found in the district-level regressions (step 2) as dependent variables. These regression coefficients represent the revealed preferences, that is, the importance of UGS for the price of a flat in a specific district. By explaining these regression coefficients in another linear regression, we can shed light onto the determinants of the revealed preferences. We apply independent variables describing, first, district characteristics , including *UGS* and *flat characteristics,* which had the highest impact in step 1 (Figure 3) and are similar to those used in step 2, but re-calculated for every district). Second, we added *socio-economic variables* that were available for the districts (Table 2). To test H2, the linear regressions of step 3 make use of different sets of independent variables, namely one including socio-economic variables and one without them (Set 1 AIC and Set 2 AIC in Figure 2, respectively).

Step 4 is a comparison of the AIC values, which were calculated in step 3. This provides information on the value of socio-economic variables.

2.4. Methodology

2.4.1. Step 1: Hedonic pricing analysis at the city level

First, we analyzed residential property prices in Leipzig in relation to how these prices have been influenced by UGS of various shapes and sizes, as well as their distance from the respective housing units. The impact of UGS was assessed by applying a hedonic pricing analysis with multiple linear regressions. The parsimonious hedonic model was found by using AIC, Akaike’s information criterion (Akaike, 1974), which is based on the trade-off between the goodness of fit and number of parameters required by model parsimony. An automatized model simplification procedure assured that the final model consisted of a parsimonious set of variables.

The study variables included *price per m²* as well as three groups of independent variables, namely, *UGS variables* (Table 1), *housing variables* (e.g. size of the housing unit, presence of a garden, etc.), and *spatial variables* (e.g. distance to the city center, playgrounds, etc.). Table 1 indicates the main variables used in the hedonic study within step 1 (the complete list of variables with a detailed explanation is provided in Appendix B).

To ensure the comparability of the outcomes, regression results were standardized and variables having the biggest impact on the residential prices were indicated (Figure 3).

2.4.2. Step 2: Hedonic pricing analysis at the district level

At step 2, multiple linear regressions, with the same variables as in step 1 and again using AIC to reduce the number of variables in the final models, were run for every district in Leipzig. A notable exception is that considering the *housing* and *spatial variables,* only those which appeared to have the biggest impact on residential prices were included (cf. Section 2.4.1). Table 1 lists all the variables included in the hedonic pricing analysis at the district level (step 2).

2.4.3. Step 3: Explaining revealed preferences at the district level

Going to the district level raises the question of collinearity again within the respective regression models. To avoid collinearity, some of the variables representing district characteristics were excluded from the analysis. For instance, '*Population density per residential area*' was excluded in favor of '*Household size*' and '*Population density*'; etc.

The remaining variables representing district characteristics as well as the dependent variables for step 3 are given in Table 2.

To further analyze the results of the hedonic study performed at the district level, four regressions with additional district characteristics were run with different sets of variables (Tables 3 and 4).

Here, the marginal effects on price identified as regression coefficients calculated in step 2 (Appendix C) were included as dependent variables. Whenever an UGS characteristic was excluded due to the automatic variable reduction (i.e. the AIC result) in step 2, its value was set to “0” (zero) (Figure 2) and still was included as a dependent variable in step 3. This enabled us to differentiate these variables from missing data (Figure 4). Furthermore, a variable being not significant implies that it is not important for the price in this district, which we wanted to include as information for the final step of the analysis.

2.4.4. Step 4: Comparing the explanatory value of district characteristics

Step 4 serves as a test to discover whether the revealed preferences on the district level can be better explained with socio-economic district characteristics. In other words, here we compare the AIC results of regressions calculated in step 3 using different sets of variables with and without socio-economic variables (i.e. Set 1 and Set 2, Figure 2).

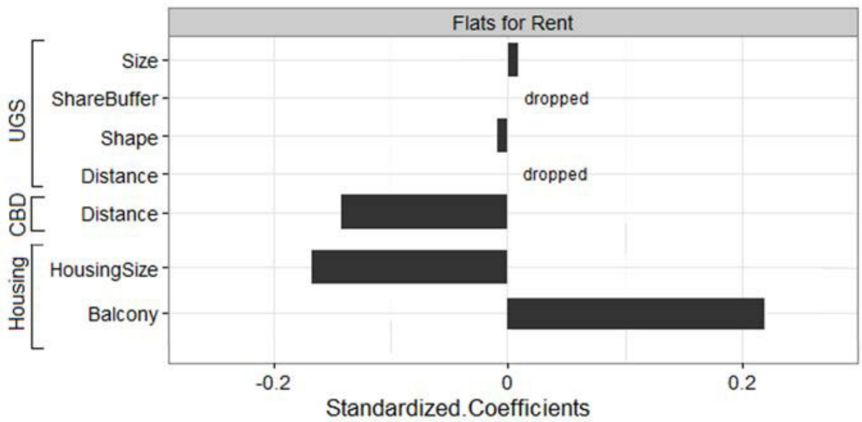
2.5. Statistical analysis

Although having in mind the advantages of the spatial hedonic modelling (e.g. Ahlfeldt & Maennig, 2011; Czembrowski & Kronenberg, 2016; Kovacs, 2012), we applied a classical linear approach (e.g. Bolitzer & Netusil, 2000; Donovan & Butry, 2011; Luttik, 2000) as we believe that due to its straightforward interpretation, multiple linear regression method fits us the best in order to illustrate, interpret and visualize the proposed scale-dependent approach. To avoid collinearity, variables were excluded if they exceeded a Pearson's correlation coefficient of 0.7 on a level of significance p > 0.95, following an established approach for analyzing data sets with large numbers of explanatory variables (Dormann et al., 2013). Handling of spatial variables as well as visualization of some results was conducted by applying ArcGIS v.10.1. Landscape metrics (for calculating *UGS shape*) were computed using FRAGSTATS v4 (McGarigal et al., 2012). All statistics were calculated using R v.3.1.2 software (R Core Team, 2014).

III. Results

3.1 Step 1: Hedonic pricing analysis at the city level

Figure 3: Standardized hedonic pricing results at the city level: UGS and the next three most important variables*

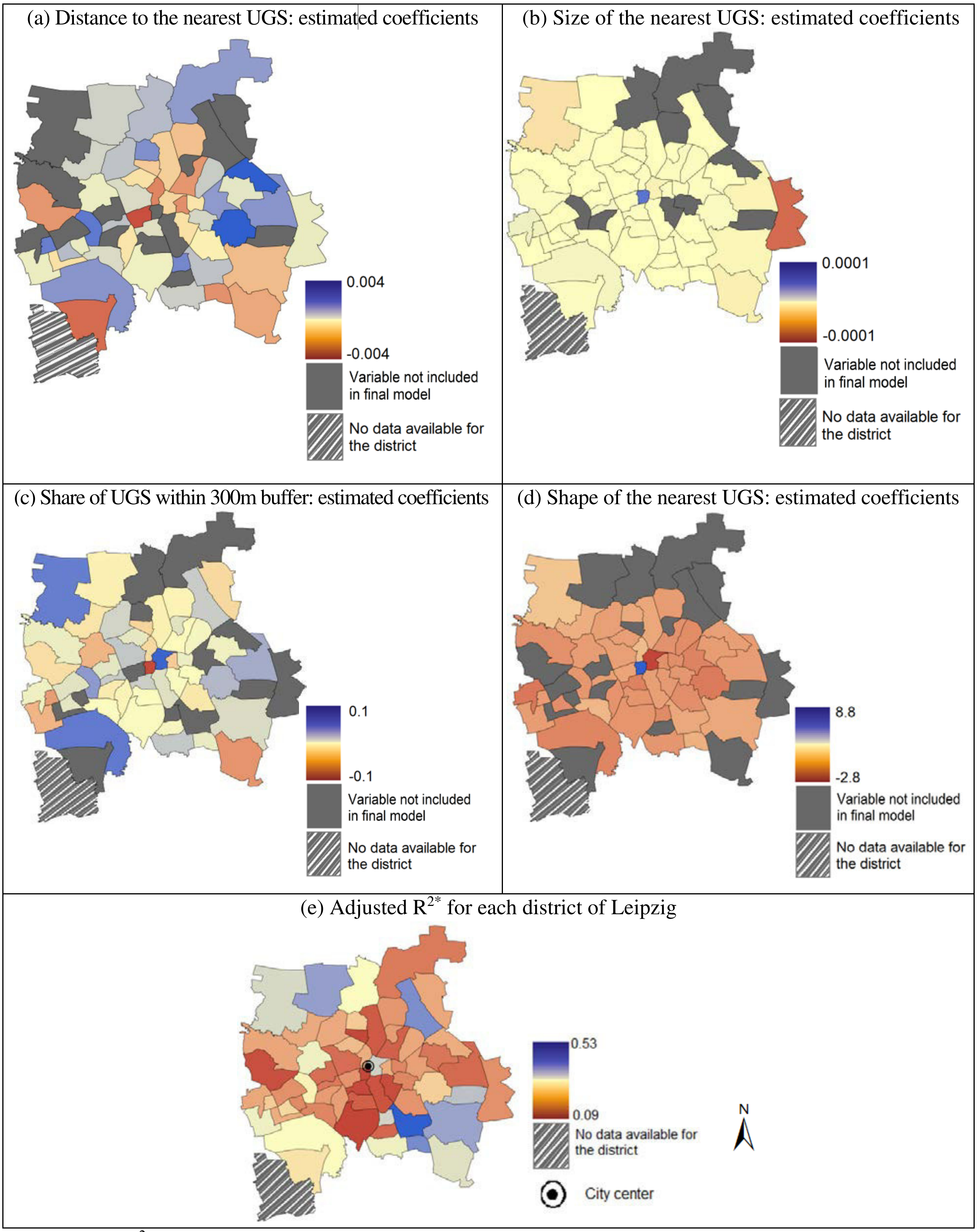


* Table 1 gives a detailed description of the variables.

The hedonic pricing analysis at the city level (step 1) demonstrates that, first of all, compared to other independent variables, UGS have a relatively low impact on the level of flat rents. Nonetheless, two significant impacts were identified. The rent increases with an increase of the *size of the nearest UGS*. This effect is more relevant for the flat prices than for the *distance to the nearest UGS* (which was dropped from the final model). Second, UGS that are more simply *shaped* are related to higher flat prices. More details, discussion, and interpretation of these results can be found in Liebelt et al. (unpublished).

3.2 Step 2: Hedonic pricing analysis at the district level

Figure 4: Hedonic pricing results per district (step 2): unstandardized regression estimates and adjusted R^{2*}



* Adjusted R^2 demonstrates the goodness of the model fit, adjusted for the number of explanatory variables relative to the number of data points; thus, including many explanatory variables into a model is punished.

Also in step 2, AIC was applied to find parsimonious models; thus, for some districts UGS variables were excluded. In contrast to the analysis at the city level, all UGS variables appear to be important at the district level, which varies by district (Figure 4, Appendix C). Also, the explained variance in flat prices varies from only 10% to almost 50%, indicating the varying importance of other determinants.

3.3 Step 3: Explaining revealed preferences at the district level

Table 3 summarizes the results of the regression analysis explaining the UGS preferences (i.e. coefficients from step 2) with the full set (Set 1 in Table 2) of district characteristics.

When explaining the revealed preferences for *UGS Size,* UGS characteristics at the district level have some influence, as well as flat characteristics and socio-economic variables. For example, *UGS Size coefficient* decreases when the degree of *importance* people associate with the *proximity to UGS* within the district increases. In other words, when people prefer having UGS close to their homes, the impact of *UGS size* on renting price loses its importance. An increase *of population density* by $1/km^2$ is associated with an increase of the impact of the *UGS size* on the housing price (i.e. *UGS Size coefficient*).

When it comes to revealed preferences for *UGS shape,* UGS characteristics at the district level do not have an influence, whereas flat characteristics and socio-economic variables do. For example, when stated *proximity to UGS* is less important for people, they prefer UGS with a more complicated shape (i.e. rather "wild" or natural-looking UGS like, for example, forests).

Regarding the revealed preferences for *distance to the next UGS,* all analyzed characteristics are important. Therefore, an increase in the *mean distance to UGS* within a district causes a decrease of the *UGS Distance coefficient.* In other words, if the mean distance to UGS per district is high, people want to live closer to UGS. Another example is when the *mean share of balconies* within districts increases, *UGS Distance coefficient* increases.

In case of the *UGS share within a 300 m* around the flat, only flat and socio-economic variables have an influence. For example, when the *city center distance coefficient* increases, the *UGS ShareBuffer coefficient* also increases or, in other words, people living further from the city center prefer having more UGS within their flat's 300 m buffer zone.

3.4 Step 4: Comparing the explanatory value of the district characteristics

Table 4 summarizes the linear regression to explain revealed preferences on the district level, yet skips the socio-economic variables (Set 2).

A comparison of the AIC values (Table 3 and Table 4) for the hedonic pricing results at the district level demonstrates that AIC for the regression with the socio-economic variables are smaller than the AICs without these variables. This leads us to the acceptance of the H2: "Revealed preferences regarding UGS can be explained by socio-economic variables". In cases where socio-economic variables were not considered, fewer variables entered the final model; however, in general, the value of remaining coefficients was similar in magnitude and signs.

IV. Discussion

4.1 Hypothesis 1: scale dependency of revealed preferences

The impact of UGS on rental flat prices at the city level is low compared to other independent variables (step 1). This can be caused by the structure of UGS and its easy accessibility by the citizens. *Distance to the next UGS* as well as the *share of UGS* in the surroundings had actually been dropped for the city-wide analysis probably due to spatial auto-correlation (see also section 4.4). Another explanation could be that the heterogeneity of findings for both variables at the district level leads to a non-significant effect on the city-scale as the effects are being averaged at that level. Interestingly, several districts show that an increasing *distance to UGS* has a positive impact on renting prices, which we will discuss further in section 4.2. The low importance of *share of UGS* contradicts findings of Kong et al.(2007), who found that an increase of UGS percentage lead to a rise of housing prices.

At the district level, the *size of the nearest UGS* has both a positive and negative influence on the renting prices (Figure 4): averaging those effects on the city-scale led to a relatively small positive value. For *shape* of the nearest UGS, a simpler shape is preferred for the majority of the districts (Appendix C), which is in line with the analysis result at the city level.

On the one hand, the results support *Hypothesis 1,* as it is clearly shown there are different outcomes of the hedonic pricing analysis at the city and district levels, as well as differences between the districts. On the other hand, however, for 18% to 29% of the districts, either the automatic variable reduction mechanism dropped the UGS characteristics or the UGS characteristics were close to zero (i.e. having no measurable influence on the price). Therefore, there is still some indication that the importance of UGS characteristics for flat prices is not overwhelmingly scale dependent; thus, still also underlining the outcomes of the analysis at the city level.

4.2 Hypothesis 2: explanatory value of district characteristics

The adjusted R^2 values for the linear regressions on the revealed preferences at the district level clearly show that they can be explained by district characteristics (step 3). AIC values indicate that the socio-economic district characteristics (such as stated *satisfaction with the condition of the UGS*) have an added value. *Hypothesis 2 is thus supported*. Some of the most interesting results are discussed in the following sub-sections.

UGS Size estimated coefficient

The UGS *Size coefficient* increases whenever the importance which people associate with *proximity to UGS* decreases. In other words, those people who appreciate UGS and, therefore, do not mind traveling to them, prefer bigger-sized UGS. We assume that, if people are already willing to travel in order to reach UGS, they would rather do it for a larger one, as larger parks offer a greater access to recreational opportunities for hiking and access to flora and fauna, whereas smaller UGS usually have playgrounds and fields (Larson and Perrings, 2013). Increasing *population density* is related to an increase of the *UGS Size coefficient*. This means that people pay higher prices for flats located next to small UGS in case of low population density and vice versa. Thus, low population density means less competition for a public good (i.e. small UGS). This corresponds to Brander and Koetse's (2011) meta-analysis, with a finding that there is a significant positive relationship between the population density and the value of UGS size.

UGS Shape estimated coefficient

Talking about the estimated coefficient of the *UGS Shape*, it appears that if people appreciate UGS and are ready to travel in order to reach UGS (i.e. decreasing importance of stated *proximity to UGS*), they would rather do that for UGS exhibiting a more complicated shape. Therefore, more natural landscapes are preferred when compared to those that are more artificially trans-bounded and obviously human-influenced (O'Neill et al., 1988; Tian et al., 2014). This could be related to Herzog et al. (2003) who argue that well-kept natural environments strongly increase restoration of concentration. Additionally, such factors as criminality might be related to UGS *shape*, as it is more complicated to monitor complex UGS especially on edges and borders (Liebelt et al., unpublished).

Distance to the next UGS estimated coefficient

As it was intuitively expected, in districts where the *mean distance to UGS* is high, people prefer to live closer to UGS. Additionally, regression results show that the higher the *share of balconies* per district, the higher the *UGS distance coefficient*, implying that, for high *shares of balconies*, people pay more for flats that are further away from an UGS. As the coefficient for distance to the next UGS can also be negative (i.e. people also pay more for being close to UGS in some districts), we assume that balconies can be perceived as a small and personal form of UGS and, thus, are able to substitute UGS. Averaging over this heterogeneity at the city scale (see already section 4.1) might also be a reason why distance to UGS was dropped in step 1. Additionally, other factors, which were not included in the model, might influence the outcomes. In contrast to Nilsson (2017) for whom the value of the green space proximity was related to the population density in the neighborhoods, population density did not enter the final model in our case.

Share of UGS in 300 m Buffer estimated coefficient

While analyzing the *share of UGS in 300 m buffer,* it appeared that if people are living *further* from the *city center*, they prefer having more UGS within the 300 m buffer. This might mean that people living in the city center are at least partly living there because they favor the benefits of short distances to city center amenities, such as the main station, but also shopping malls, cinemas, and others. Contrary to that, districts further from the city center are of interest for people with different preferences, including the higher prioritization of UGS.

These findings also have challenging implications for urban ecosystem services research, as they suggest that ecosystem services demand (preferences) and supply (UGS) are intertwined. A large supply of ecosystem services provided by public green spaces or private balconies seems to go along with lower preferences. This is on the one hand indicated by the decrease of price effects in green and low-density districts. On the other hand, the comparatively large share of UGS in Leipzig could be related to the rather low impact of UGS onto prices on the city level.

4.3 Reflection on the scale-sensitive approach

The proposed scale-sensitive approach revealed significant insights for UGS in Leipzig. Namely, we were able to check the explanatory power of district characteristics with respect to the revealed preferences, including also socio-economic variables., Admittedly, socio-economic characteristics were not included in the hedonic pricing analyses of steps 1 or 2a as it would have led to answering a different research question, for example, on the effect of population density onto prices and would investigate a *direct* effect on prices. However, our aim was to check whether socio-economic variables have an *indirect* effect by revealing if they are influencing preferences.

Additionally, in our case, the UGS characteristics that were not important at the city level were important at the district level.

Thus, we believe that our approach provides added value to the existing hedonic studies by providing a spatially explicit picture of preferences and explaining the regression coefficients by another regression analysis (i.e. step 3).

In general, our approach is based on the assumption that complex systems are composed of subsystems and that the results of the analysis will yield different outcomes when analyzing different levels of the system – overall providing a more colorful and adequate picture of reality. This suggests that the scale approach presented here could potentially also be used for other complex systems exhibiting spatial heterogeneity, as has already been done, for example, in environmental modeling (Veldkamp and Lambin, 2001) or for complex landscapes (Reynolds and Wu, 1999).

4.4 Limitations of the study

Our study faces a number of limitations, which offer a basis for further research. First, our study is limited by the unavailability of further socio-economic variables which might be valuable for the analysis, for example, *distance to work* or *quality of schools*. Also, a thorough sensitivity analysis would be helpful to estimate the effects of decisions taken at the operational level, such as a buffer size of 300 m.

Second, as the real estate dataset depends on user entries on the website, it does not have high reliability throughout. In fact, there were many missing values that required various statistical procedures to overcome the given obstacles (more details in section 2.2). There is no reason to think, however, that any systematic error prevailed.

Third, analyzing only flats available for rent does not give us a complete picture of the residential options in Leipzig, as there are other housing categories (i.e. flats and houses available for selling) present in the city. However, considering the characteristics of the German housing market with rather low occurrence of housing purchase in contrast to renting, we focused on flats for rent to explore the scale-sensitive approach.

Forth, when statistically implementing our scale-sensitive approach, we decided to use simple OLS regressions in order to illustrate it and interpret its result in a straightforward way. Implementing it with other statistical models, such as spatial error models (review in von Graevenitz and Panduro, 2015), would enable tests for spatial auto-correlation and thus a check for robustness of results. Also, instead of step-by-step regression, a likelihood ratio test (Baltagi et al., 2015) could be employed to check whether the individual models for the districts are nested within the city scale. Such future work could increase robustness of results and allow for a transfer into planning practice, which is an obvious strength of the proposed approach.

V. Conclusion

To conclude, in this paper we presented a stepwise approach that enabled us to analyze the impact of UGS, being an important source of the urban ecosystem services, on the housing market in a spatially explicit way as well as to explain the spatial heterogeneity revealed preferences regarding UGS. This type of information can be meaningful for urban planners, who need to consider the societal value of UGS at different scales when creating and demolishing UGS. Additionally, when deciding on future landscape design, it is worth analyzing the situation with respect to UGS at different scales (e.g. city versus district level). Finally, understanding the logic behind the preferences' heterogeneity can be helpful for real estate-businesses for matters of price-formation.

This study was guided by two hypotheses.

The *first hypothesis* aimed to investigate the scale dependency, stating that "revealed preferences regarding UGS are scale-dependent, i.e. revealed preferences differ on the city and on the district level". Outcomes of the analysis indeed demonstrated such differences. Thus, the *first hypothesis* was *accepted.*

The *second hypothesis* focused on the explanation of revealed preferences related to UGS, stating "revealed preferences on the district scale can be explained with district characteristics, including socio-economic variables". Based on the study results, the *second hypothesis* was also *accepted.*

Directions for future research include exploring several scales at once within the scale sensitive approach for instance, for larger parts of the city, electoral districts or zip codes, as done separately by Bourassa et al. (1999) and Goodman and Thibodeau (1998). This allows investigating the outcomes at varying degrees of detail. As an alternative, real-estate agents can be involved to discuss whether and which spatial entities other than districts would be more appropriate for investigation. Additionally, it might be interesting (also for matters of urban planning) to differentiate various types of UGS (e.g. parks, forests and cemeteries) when applying this approach. Finally, we encourage applying the stepwise approach to elucidate scale dependency of other complex systems of different backgrounds.

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Tables

Table 1: Variables used in the hedonic pricing analysis at the district level (step 1)

Name	Description
	I. Dependent Variables
RentingPrice	Renting price of flats per m^2 (in €).
	II. Independent Variables
	a. UGS Variables:
Shape	Measures the complexity of the UGS spatial form (nearest to the housing unit) by comparing it to a square as standard shape form. Shape is equal to 1 when the patch is maximally compact (i.e., it is a square) and increases without limit as patch shape becomes more irregular (McGarigal et al., 2012). The UGS shape equals patch perimeter (m) divided by the square root of patch area (m^2), adjusted by a constant for a square standard. Possible values: 1 to ∞ (units*).
Size	Size (m^2) of the nearest UGS to a flat.
ShareBuffer	Share (%) of UGS within the circle of a 300 m radius of a flat.
Distance	Distance (m) from a flat to the nearest UGS, calculated in ArcGIS from the housing unit to the boundary of the nearest UGS using Euclidean distances.
	b. Housing Variables:
FlatSize	Size (m^2) of the flat.
Balcony	Presence (1 if yes, 0 otherwise) of a balcony.
	c. Spatial Variables:
CBD	Distance (m) from the flat to the city's central business district (Central station).

* for simplicity we use "units" while discussing the UGS Shape, whereas following the calculation algorithm of McGarigal et al. (2012) it would be m/m^2.

Table 2: Variables used when explaining the revealed preferences at the district level (step 3)

Variable	Description
I. Dependent Variables	
UGS Size coefficient	Estimated regression coefficient for "Size of nearest UGS" calculated in step 1
UGS Shape coefficient	Estimated regression coefficient for "Shape of nearest UGS" calculated in step 1
UGS Distance coefficient	Estimated regression coefficient for "Distance to nearest UGS" calculated in step 1
ShareBuffer coefficient	Estimated regression coefficient for "Share of UGS in 300 m buffer" calculated in step 1
II. Independent Variables	
1. Variables used at the city level adjusted to the district analysis	
a. UGS characteristics	
UGS ShareBuffer district	Percentage of UGS per district
UGS Distance district	Mean Distance (m) to the next UGS per district
UGS Shape district	Mean shape of UGS per district
b. Flat characteristics	
Share balconies	Share of flats (%) which have balconies per district
Flat size mean	Mean size of the flat (m^2) per district
CBD coefficient	Estimated regression coefficient for distance to CBD calculated in step 1
2.- Variables added at the district level analysis	
c. Socio - economic variables	
UGS Condition satisfaction*	Level of inhabitants' satisfaction with the condition of the UGS per district for the year of 2013 (from citizens' survey); mean value, where: ***1*** – very unsatisfied, ***2*** – not satisfied, ***3*** – partially satisfied, ***4*** – satisfied, and ***5*** – very satisfied.
UGS Proximity importance*	The importance of the proximity to the UGS for inhabitants per district for the year 2013 (from citizens' survey); mean value, where: ***1*** – not important at all, ***2*** – rather not important, ***3*** – partially important, ***4*** – rather important, and ***5*** – very important.
District satisfaction*	Level of the inhabitants' satisfaction with the district for the year 2013 (from citizens' survey); mean value, where: ***1*** – very unsatisfied, ***2*** – not satisfied, ***3*** – partially satisfied, ***4*** – satisfied, and ***5*** – very satisfied.
Mean age*	Mean age of the residents per district, calculated as mean value for the years 2009, 2011, and 2013.
Crime*	Number of crime cases per 1,000 inhabitants per district. Mean value for years 2007, 2009, and 2013.
Population density*	Population density per km^2 per district. Mean value for years 2007, 2009, 2011, and 2013.
UGS per capita*	Mean area of UGS (m^2) per total population within the district. Population data calculated as an average value for years 2007, 2009, 2011, and 2013.
Household size*	Average number of people in household per district, mean value for the years 2009, 2011, and 2013.
Median Income*	Median income of the households per district for the year 2013.

* Variables included into Set 1 and excluded from Set 2 (Figure 1).

Table 3: Explanation of the revealed preferences per district (Set 1): regression estimates, adjusted R^2 and AIC values

Variables	**UGS Size coef.**		**UGS Shape coef.**		**UGS Distance coef.**		**ShareBuffer coef.**	
	Estimate	**Stand.**	**Estimate**	**Stand.**	**Estimate**	**Stand.**	**Estimate**	**Stand.**
(Intercept)	-8.2E-06	0	-0.24	0	0.01	0	0.08	0
a. UGS Characteristics								
UGS ShareBuffer district	2.5E-07	0.25	-	-	-	-	-	-
UGS Distance district	-	-	-	-	-1E-05	-0.42	-	-
UGS Shape district	-	-	-	-	-	-	-	-
b. Flat Characteristics								
Share balconies	-2.1E-07	-0.20	-1.5E-02	-0.18	2.8E-05	0.25	-	-
Flat size mean	4.8E-07	0.29	3.9E-02	0.29	-	-	0.001	0.22
CBD coefficient	-9.8E-03	-0.42	-1.3E+03	-0.67	-	-	22.82	0.50
c. Socio-Economic Variables								
UGS Condition satisfaction*	2.3E-05	0.34	-	-	-	-	-0.03	-0.24
UGS Proximity importance*	-2.3E-05	-0.26	-1.18	-0.16	-2.6E-03	-0.26	-	-
District satisfaction*	-1.7E-05	-0.32	-	-	-	-	-	-
Mean age	1.4E-06	0.46	7.4E-02	0.29	6.6E-05	0.20	-	-
Crime	-	-	1.3E-02	0.16	-	-	-	-
Median income	-	-	-	-	8.9E-07	0.19	-	-
Population density	1.6E-09	0.31	-	-	-	-	-2E-06	-0.21
UGS per capita	-	-	-	-	-	-	-	-
Household size	-	-	-	-	-	-	-	-
AIC	-1394.52		-12.15		-810.92		-456.13	
R^2 multiple	0.44		0.57		0.34		0.36	
adj R^2	0.35		0.52		0.28		0.31	

* Data from citizens' surveys (Amt für Statistik und Wahlen, 2012b, 2011, 2009, 2008b, 2007; Amt für Statistik und Wahlen Leipzig, 2014). When referring to results related to given variables we used the term "stated" to avoid confusion with "revealed preferences".

Table 4: Explanation of the revealed preferences per district without socio-economic variables (Set 2): regression estimates, adjusted R^2 and AIC values

Variables	**UGS Size coef.**		**UGS Shape coef.**		**UGS Distance coef.**		**ShareBuffer coef.**	
	Estimate	**Stand.**	**Estimate**	**Stand.**	**Estimate**	**Stand.**	**Estimate**	**Stand.**
(Intercept)	1E-05	0	-1.49	0	-4E-04	0	-0.03	0
a. UGS Characteristics								
UGS ShareBuffer district	-	-	-	-	-	-	-	-
UGS Distance district	-	-	-	-	-9E-06	-0.39	-	-
UGS Shape district	-	-	-	-	-	-	-	-
b. Flat Characteristics								
Share balconies	-2E-07	-0.18	-	-	4E-05	0.34	-	-
Flat size mean	-	-	2E-02	0.16	-	-	0.001	0.19
CBD coef.	-9E-03	-0.40	-1E+03	-0.66	-	-	21.63	0.47
AIC	**-1385.45**		**-8.17**		**-808.91**		**-455.41**	
R^2 multiple	**0.20**		**0.48**		**0.25**		**0.37**	
adj R^2	**0.17**		**0.46**		**0.23**		**0.32**	

Appendices

Appendix A: Districts of Leipzig

1. Althen-Kleinpoesna	33. Miltitz
2. Altlindenau	34. Mockau-Nord
3. Anger-Crottendorf	35 Mockau-Sued
4. Baalsdorf	36 Moeckern
5. Boehlitz-Ehrenberg	37 Moelkau
6. Burghausen	38 Neulindenau
7. Connewitz	39 Neustadt-Neuschoenefeld
8. Doelitz-Doesen	40 Paunsdorf
9. Engelsdorf	41 Plagwitz
10. Eutritzsch	42 Plaußig-Portitz
11. Gohlis-Mitte	43 Probstheida
12. Gohlis-Nord	44 Reudnitz-Thonberg
13. Gohlis-Sued	45 Schleußig
14. Großzschocher	46 Schoenau
15. Gruenau-Mitte	47 Schoenefeld- Abtnaundorf
16. Gruenau-Nord	48 Schoenefeld-Ost
17. Gruenau-Ost	49 Seehausen
18. Gruenau-Siedlung	50 Sellerhausen
19. Hartmannsdorf *	51 Stoetteritz
20. Heiterblick	52 Suedvorstadt
21. Holzhausen	53 Thekla
22. Kleinzschocher	54 Volkmarsdorf
23. Knautkleeberg	55 Wahren
24. Lausen-Gruenau	56 Wiederitzsch
25. Leutzsch	57 Zentrum
26. Liebertwolkwitz	58 Zentrum-Nord
27. Lindenau	59 Zentrum-NordWest
28. Lindenthal	60 Zentrum-Ost
29. Loeßnig	61 Zentrum-Sued
30. Luetzschena	62 Zentrum-SuedOst
31. Marienbrunn	63 Zentrum-West
32. Meusdorf	

* District Hartmannsdorf was excluded from the analysis, due to the small amount of available cases.

Appendix B: Variables used in hedonic analysis at the city level (Step 1)

Name	Description
I. Dependent Variables	
RentingPrice	Renting price per m^2 (in €)
II. Independent Variables	
a. UGS Variables:	
Shape	The shape of UGS equaling patch perimeter (m) divided by the square root of patch area (m^2), adjusted by a constant for a square standard. Possible values: 1 to ∞
Size	Size (m^2) of the nearest UGS to housing unit (units*).
ShareBuffer	Share (%) of UGS within the circle of a 300 m radius of each housing unit
Distance	Distance (m) from the housing unit to the nearest UGS, calculated in ArcGIS from the housing unit to the boundary of the nearest UGS using Euclidean distances.
b. Housing Variables:	
HousingSize	Size of the housing unit (m^2)
Garden	Presence of garden (1 if yes, 0 otherwise)
Year	Year when the housing unit was available for rent/sale, included as a categorical variable
Proxy coordinates	Dummy binary variable to check that approximation of addresses did not bias the results (1 for years 2007-2011, 0 otherwise)
GuestWC	Presence of a guest bathroom (1 if yes, 0 otherwise)
BathroomNr	Number of bathrooms (count.)
Elevator	Presence of an elevator (1 if yes, 0 otherwise)
Kitchen	Presence of a built-in kitchen (1 if yes, 0 otherwise)
Balcony	Presence of a balcony (1 if yes, 0 otherwise)
Floor	Floor of the building on which the housing unit is located (count.)
Condition	Housing condition (1-'Excellent state,' 2-'Good state,' 3-'Bad state')
HeatType	Type of heating: self-contained central heating ('Heat_Self-cont'), central heating ('Heat_Centr'), furnace heating ('Heat Furnace')
HeatCostsIncl	If heating costs are included in the rent (1 if yes, 0 otherwise)
Deposit	If rent deposit is required (1 if yes, 0 otherwise)
AddCosts	Additional costs (in €) rate for heating, warm water, waste disposal etc.
c. Spatial Variables:	
CBD	Distance (m) from the housing to the city business center (Central Station)
Playground	Distance (m) from the housing unit to the nearest playground
Agriculture	Distance (m) from the housing unit to the nearest agriculture site
Disamenities	Distance (m) from the housing unit to the nearest disamenity (e.g., disposal site, industrial area, etc.)
Sport	Distance (m) from the housing unit to the nearest sport place
Leisure	Distance (m) from the housing unit to the nearest place for leisure time
Districts	63 districts of Leipzig were included in hedonic analysis
AreaType	Type of the area in which the housing unit is located: residential area ('ResidArea') without any shops, mixed area ('MixArea'), other area type
Water	Distance (m) from the housing unit to the nearest water body (e.g, lake)
Waterway	Distance (m) from the housing unit to the nearest river, canal or stream.
TransportStop	Distance (m) from the housing unit to the nearest public transportation stop
LargeRoad	Distance (m) from the housing unit to the nearest large road
MunicipalRd	Distance (m) from the housing unit to the nearest municipal road
RailwayTrack	Distance (m) from the housing unit to the nearest rail or tram road

Appendix C: Hedonic pricing results per district: unstandardized regression estimates and adjusted R^2

Nr	Districts	UGS				Housing		Spatial	AdjR
		Shape	Size	Distance	ShareBuffer	FlatSize	Balcony	CBD	
1	Althen-Kleinp	-	-7.9E-05	0.0004	-	-0.0071	-	-	0.18
2	Altlindenau	-	1.7E-07	-	0.0136	-0.0069	0.3659	-0.0002	0.15
3	Anger-Crott	-0.0602	-	0.0009	0.0021	-0.0133	0.3326	0.0002	0.18
4	Baalsdorf	-	-	-	-	-0.0060	0.7148	-	0.38
5	Böhlitz-Ehren.	-0.2977	1.9E-07	-	0.0100	-0.0032	0.6710	-	0.21
6	Burghausen	-	1.2E-06	-0.0021	-0.0165	-	0.2796	-0.0002	0.10
7	Connewitz	-0.1501	2.3E-07	0.0003	0.0033	-0.0023	0.4716	-0.0004	0.09
8	Dölitz-Dösen	-0.0269	-1.2E-07	0.0011	0.0298	-0.0041	0.4982	-	0.33
9	Engelsdorf	0.1152	-4.9E-06	0.0025	0.0467	-0.0068	0.3681	-0.0001	0.14
10	Eutritzsch	0.4272	-4.6E-07	-0.0009	-0.0072	-0.0056	0.3909	-0.0004	0.12
11	Gohlis-M	-	1.4E-06	-0.0010	-0.0204	-0.0038	0.4710	0.0004	0.09
12	Gohlis-N	0.5435	-3.8E-06	0.0026	-	-0.0024	0.3344	-0.0006	0.25
13	Gohlis-S	0.1526	5.2E-07	-0.0006	0.0118	-0.0032	0.7339	-0.0009	0.24
14	Großzschocher	-0.3203	3.7E-07	0.0015	0.0135	-0.0061	0.6762	0.0003	0.27
15	Grünau-M	0.0617	6.8E-06	0.0031	-0.0502	-0.0131	0.1974	0.0007	0.26
16	Grünau-N	-	1.2E-06	0.0004	-	-0.0093	0.2166	-0.0005	0.18
17	Grünau-O	-	-5.5E-07	-0.0006	-	-0.0148	-	-0.0004	0.22
18	Grünau-Siedl	-0.6343	5.8E-06	0.0024	0.0796	-0.0077	-	0.0012	0.31
20	Heiterblick	0.1806	-	0.0041	-	-0.0094	0.2313	-	0.22
21	Holzhausen	0.4552	-4.3E-06	-0.0013	0.0192	-	0.6843	-0.0003	0.42
22	Kleinzschocher	0.8803	-8.7E-07	0.0008	0.0020	-0.0105	0.3613	-0.0006	0.17
23	Knautkleeberg	-	1.2E-06	-0.0031	-	0.0074	0.2025	-0.0004	0.28
24	Lausen-Grünau	0.0822	-7.7E-07	0.0004	-0.0373	-0.0122	0.2516	0.0013	0.33
25	Leutzsch	0.3826	-	0.0006	-0.0055	0.0021	0.4831	-	0.21
26	Liebertwolkwitz	-	-7.2E-06	-0.0018	-0.0553	-0.0144	0.6570	-0.0005	0.35
27	Lindenau	0.2505	3.9E-06	0.0013	0.0284	-0.0069	0.5831	0.0007	0.16
28	Lindenthal	-	-4.4E-07	0.0010	-0.0070	0.0011	-	-0.0005	0.43
29	Lößnig	-	-1.0E-07	-	0.0062	-0.0030	0.4431	0.0004	0.13
30	Lützschena	1.3440	-1.5E-05	-	0.0768	0.0033	0.4251	0.0003	0.36
31	Marienbrunn	-0.4484	7.1E-07	0.0028	-	-0.0145	0.6657	-0.0002	0.36
32	Meusdorf	0.7289	-7.7E-07	-0.0022	0.0115	-0.0205	0.1828	-0.0004	0.46
33	Miltitz	-1.1008	8.2E-06	-	0.0081	-0.0042	0.2752	0.0004	0.21
34	Mockau-N	0.1347	-	-0.0012	-0.0059	-0.0106	0.4992	-0.0003	0.19
35	Mockau-S	-	-1.2E-06	-	0.0156	-0.0248	0.3995	-0.0001	0.20
36	Möckern	0.1685	-1.1E-06	0.0013	0.0239	-0.0115	0.5258	0.0000	0.22
37	Mölkau	-0.9036	2.8E-06	0.0041	0.0393	-0.0055	0.4677	-	0.26
38	Neulindenau	-0.0554	-	0.0032	0.0582	-0.0130	0.7696	-0.0004	0.30
39	Neustadt-Neu	-0.2770	2.1E-06	-0.0023	-0.0257	-0.0122	0.5170	-	0.22
40	Paunsdorf	0.1010	-5.2E-07	0.0006	0.0088	-0.0051	0.3056	-0.0007	0.15
41	Plagwitz	-	-	-	-0.0102	-0.0036	0.7233	-0.0006	0.20
42	Plaußig-Portitz	-	-	-	-0.0180	-	0.2864	-0.0008	0.21
43	Probstheida	0.4339	-6.0E-07	0.0013	-	-0.0029	0.6268	0.0007	0.53
44	Reudnitz-Thon	0.0196	-	-0.0006	0.0024	-0.0074	0.4301	-0.0003	0.10
45	Schleußig	-0.2088	6.6E-07	-0.0005	-0.0060	-0.0035	0.6997	-	0.21
46	Schönau	-	-2.2E-06	-	0.0149	-0.0078	-	-0.0007	0.19
47	Schönefeld-A	-0.2360	1.5E-06	-0.0021	-0.0028	-0.0043	0.3558	0.0004	0.13
48	Schönefeld-O	-0.3819	1.7E-06	0.0011	0.0057	-0.0163	0.2675	-	0.21
49	Seehausen	-	-	0.0023	-	-0.0070	0.2526	-0.0002	0.16
50	Sellerhausen	-0.7184	2.1E-06	0.0023	-	-0.0095	0.3489	-	0.20
51	Stötteritz	-0.3488	5.8E-07	-0.0003	-0.0115	-0.0039	0.4228	0.0001	0.19
52	Südvorstadt	-0.1573	1.4E-06	-	0.0021	-0.0041	0.6068	-	0.12
53	Thekla	-	-1.7E-06	-	0.0286	-0.0133	0.6420	0.0014	0.46
54	Volkmarsdorf	-0.3174	8.9E-07	-0.0005	0.0099	-0.0127	0.1881	-0.0003	0.17
55	Wahren	0.6655	-2.4E-06	0.0010	-0.0126	-0.0052	0.5516	0.0001	0.22
56	Wiederitzsch	-	-	0.0015	-	-0.0092	0.5323	-0.0001	0.31
57	Zentrum	8.7784	8.3E-05	-	-0.0962	-	-0.2529	-0.0030	0.09
58	Zentrum-N	1.0628	-7.3E-07	-0.0025	-0.0182	-0.0033	0.6009	-0.0005	0.22
59	Zentrum-NW	0.2518	-2.9E-07	0.0008	0.0308	0.0029	0.5080	-0.0006	0.14
60	Zentrum-O	-2.8076	-6.9E-06	-0.0009	0.0960	-0.0130	0.6003	0.0014	0.37
61	Zentrum-S	-0.6915	2.0E-06	0.0007	0.0269	-0.0017	0.7166	0.0006	0.10
62	Zentrum-SO	0.1874	-4.1E-07	-	0.0156	-0.0150	0.4313	-0.0004	0.11
63	Zentrum-W	0.3574	-4.5E-07	-0.0037	-	-0.0037	0.8753	-0.0006	0.19

The '-' variable was not included in the final model due to AIC. 'NA' indicates the data was unavailable. As we used step AIC, the levels of significance were not indicated in the table; however, all values that are present are relevant to the study.

Figure 1 (a): Scatterplots for UGS Size coefficient

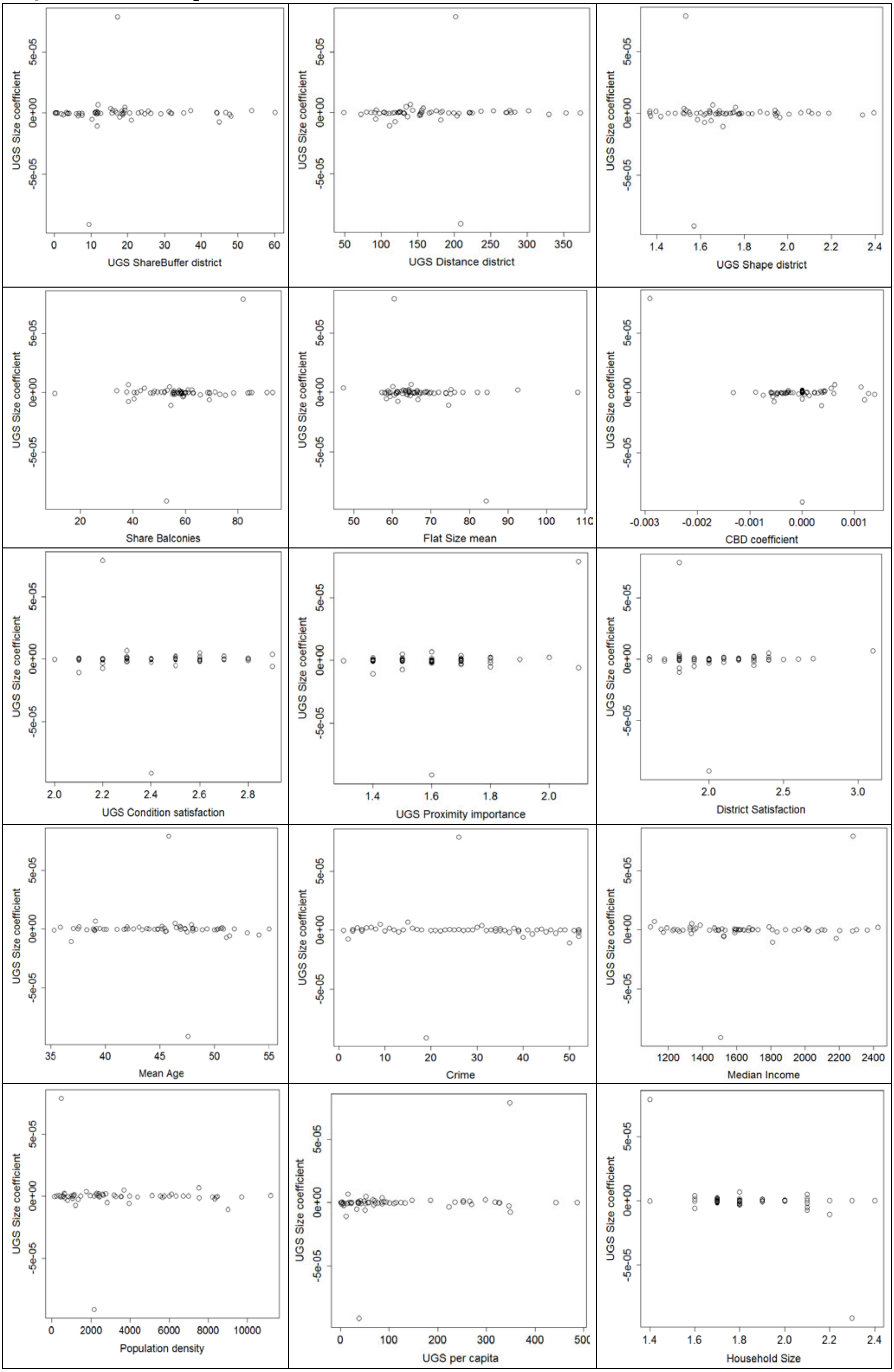

Figure 1 (b): Scatterplots for UGS Shape coefficient

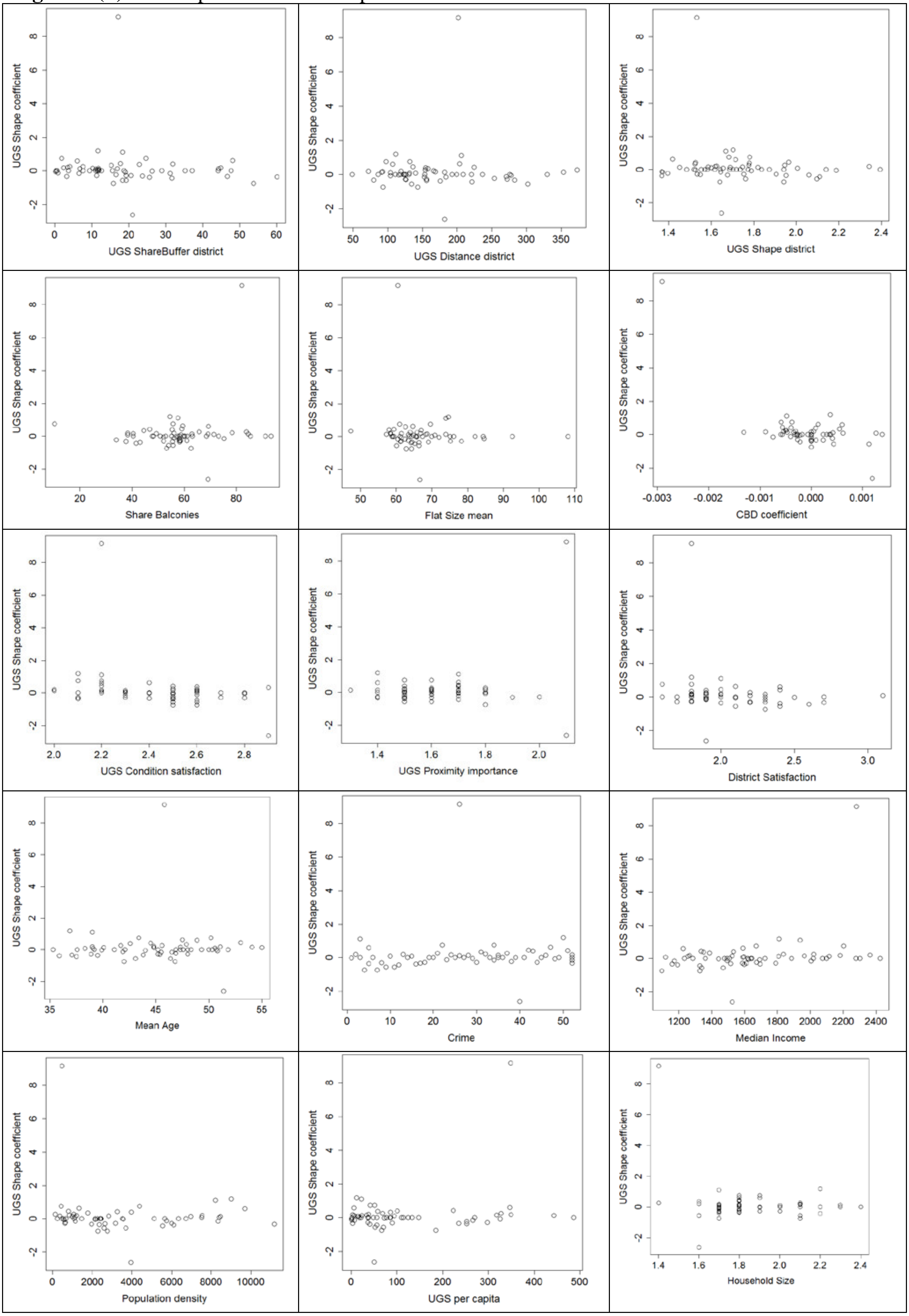

Figure 1 (c): Scatterplots for UGS Distance coefficient

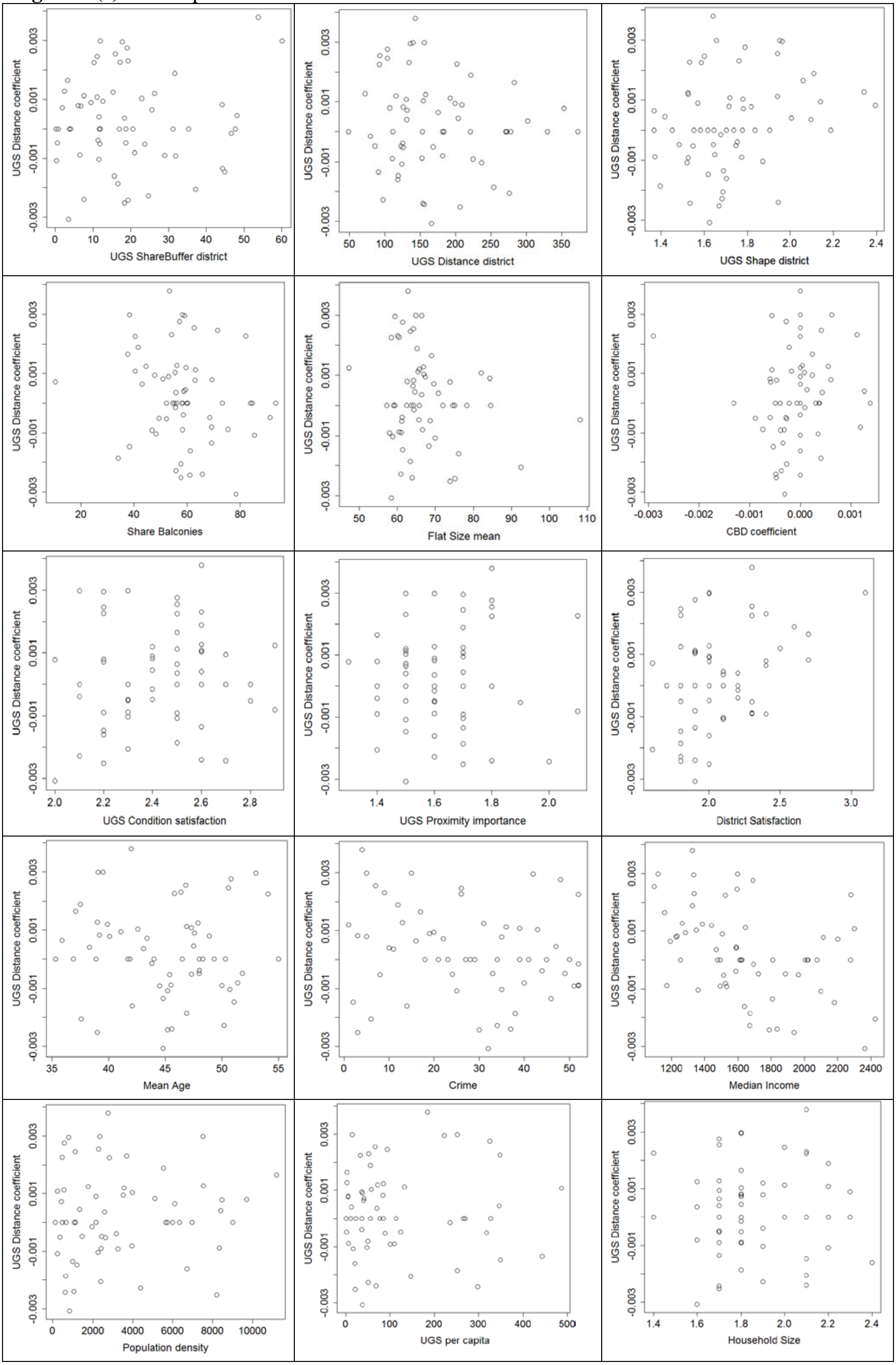

Figure 1 (d): Scatterplots for UGS Share in 300 m coefficient buffer zone