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Boosting the predictive accuracy of urban hedonic house price models through airborne laser scanning

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ABSTRACT

This paper introduces an integrative approach to hedonic house price modeling which utilizes high density 3D airborne laser scanning (ALS) data. In general, it is shown that extracting exploratory variables using 3D analysis – thus explicitly considering high-rise buildings, shadowing effects, etc. – is crucial in complex urban environments and is limited in well-established raster-based modeling. This is fundamental in large-scale urban analyses where essential determinants influencing real estate prices are constantly missing and are not accessible in official and mass appraiser databases. More specifically, the advantages of this methodology are demonstrated by means of a novel and economically important externality, namely incoming solar radiation, derived separately for each flat. Findings from an empirical case study in Vienna, Austria, applying a non-linear generalized additive hedonic model, suggest that solar radiation is significantly capitalized in flat prices. A model comparison clearly proves that the hedonic model accounting for ALS-based solar radiation performs significantly superior. Compared to a model without this externality, it increases the model's explanatory power by approximately 13% and additionally reduces the prediction error by around 15%. The results provide strong evidence that explanatory variables originating from ALS, explicitly regarding the immediate 3D surroundings, enhance traditional hedonic models in urban environments.

1. Introduction

Real estate markets are constantly in motion, thus leading to an increased risk awareness by investors, mortgage lenders, etc. Accordingly, the predictive accuracy of economic models has gained much attention and has stimulated research (e.g. Basu & Thibodeau, 1998; Bateman, Jones, Lovett, Lake, & Day, 2002; Bourassa, Cantoni, & Hoesli, 2010; Brunauer, Lang, Wechselberger, & Bienert, 2010; Case, Clapp, Dubin, & Rodriguez, 2004; Dubin, Pace, & Thibodeau, 1999; Goodman & Thibodeau, 2003; Helbich, Brunauer, Hagenauer, & Leitner, 2013; Pace, 1998; Páez, Fei, & Farber, 2008). Hedonic price modeling (Rosen, 1974) is an extensively applied framework for mass appraisal and price index construction. These models can be improved in two ways: (a) Through novel estimation techniques (e.g. Brunauer et al., 2010; Koschinsky, Lozano-Gracia, & Piras, 2011) and (b) by ancillary structural, locational, and neighborhood variables on the basis of Geographic Information System (GIS) algorithms (e.g. Hamilton & Morgan, 2010), which have the potential to mitigate violations of model assumptions and advance model reliability. However, recent studies are limited in that they use the raster and 2D vector data model when computing GIS-based variables (e.g. Bin, Crawford, Kruse, & Landry, 2008; Bourassa, Hoesli, & Sun, 2004; Hamilton & Morgan, 2010; Kong, Yin, & Nakagoshi, 2007; Lake, Lovett, Bateman, & Day, 2000; Orford, 2010; Paterson & Boyle, 2002).

Nowadays, ALS – also referred to as airborne LiDAR – data are increasingly available because of steadily declining costs, particularly in urban environments. Since the proliferation and substantial advances in ALS as state-of-the-art technology for 3D topographic data acquisition (Vosselman & Maas, 2010), it appears that GIS-models to derive explanatory variables based on the raster or 2D vector data model have serious weaknesses. Instead of utilizing the full richness and high resolution of ALS technology, the data are aggregated to representations using single valued (elevation) functions such as digital elevation models (DEMs) resulting in a loss of information (Vosselman & Maas, 2010). In general, raster-DEMs are further differentiated into digital terrain models (DTMs) of the bare Earth without objects (e.g. vegetation and buildings) and digital surface models (DSMs), which include objects above the ground (Höfle & Rutzinger, 2011). The consideration of the upper hull (topography) of the surface is particularly appropriate if the location of interest is located in highly complex urban environments, characterized by sudden variations in heights, shadowing effects, eaves, building shapes, etc. (Hachema, Athienitis, &

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Fazioc, 2012; Jochem, Höfle, & Rutzinger, 2011; Jochem, Höfle, Rutzinger, & Pfeifer, 2009; Lukac, Zlaus, Seme, Zalik, & Stumberger, 2012). The modeled determinants depend on the scale of aggregation and are merely a rough approximation of reality, potentially resulting in counterintuitive signs of the estimated regression parameters of the hedonic model and hence leading to erroneous conclusions (e.g. Lake et al., 2000).

Hedonic theory assumes that all essential characteristics are considered in the hedonic equation, which is seldom fulfilled due to limited data availability (Hulton, 2003; McMillen, 2010), thus resulting in model misspecification (Can, 1992). The lack of data is particularly crucial in large-scale analysis. Indeed, when it comes to this analysis, essential determinants influencing house prices are not available in traditional databases actuated by traditional federal statistical offices and rating agencies. It may also be the case that they cannot be modeled by traditional GIS algorithms (Orford, 2010). Thus, one is faced with the omitted variable bias, which states that relevant variables are missing in the model, although they influence the price significantly. Such misspecification results in, for example, ordinary least square (OLS) estimates being biased and inconsistent (see Wooldridge, 2008). A possible solution is a physical inspection of each flat[1] by an appraiser, which is only viable for a small number of objects and is strongly limited by temporal and monetary constraints. Regardless of these limitations, the subjectivity and fuzziness of such appraisals remain a problem and result in an insufficient data quality. Besides, these indices based on *in situ* data acquisition are mostly of a nominal or an ordinal nature.

Both weaknesses relate to a lack of theoretical and empirical work. Therefore, the overall objective of this research is to explore the potential of ALS for housing studies and to enhance the current methodology of hedonic house price models by utilizing ALS data in a reliable and integrative way. Moreover, this paper demonstrates, through the modeling incoming solar radiation, that 3D ALS data provide precise and objective numeric indices which can be computed in a consistent, standardized, and transferable manner, thus enhancing the predictive power of hedonic models and simultaneously mitigating model misspecifications. The case study addresses the housing market segment of owner-occupied flats in the third district of Vienna, Austria, and tests the effect of ALS-based solar radiation on flat prices in a non-linear hedonic pricing model. The main hypothesis is that accounting for the complexity of urban areas in terms of incoming solar radiation for individual flats, results in more accurate price predictions. In detail, the research at hand addresses the following main research questions:

- Is ALS capable of improving the predictive accuracy of large-scale hedonic price models?
- Does solar radiation have significant explanatory power, and does it account for a higher explained deviance, as well as for most of the reduction of the unexplained variance, respectively, in comparison to a model without this externality? If this is the case, is this covariate linearly or non-linearly related to the transaction prices of flats in Vienna?

The remainder of this paper is organized as follows: Section 2 gives an overview of hedonic modeling and the first attempts made to utilize ALS data. Following this, Section 3 introduces a 3D GIS algorithm to derive the incoming solar radiation of individual flats and a non-linear hedonic model. The potential of this method is explored by means of owner-occupied flats in Vienna (Section 4). Empirical results are discussed in Section 5, before Section 6 summarizes the implications and suggests future research avenues.

[1] A flat represents a residential apartment in a multi-level housing structure.

2. Related work

2.1. Hedonic pricing theory

Real estate is usually treated as a composite commodity traded in bundles, and valued for its utility-bearing characteristics (Rosen, 1974). Hence, households value the characteristics of a good rather than the good itself. Because property is fixed in space, a household implicitly chooses a bundle of different goods and services by selecting a specific object (Malpezzi, 2003; Sheppard, 1997). Methodologically, this is represented by the hedonic price function, which emerges from the competitive bidding of buyers (Bin, Poulter, Dumas, & Whitehead, 2011). The equilibrium between supply and demand persists when households maximize their utility, limited by their social and economic constraints (Quigley, 1985). Thus, the hedonic equation determines the functional relationship between the real estate price and its characteristics in a particular market, typically estimated by a regression equation (Sheppard, 1997). Such a model regresses the value of the property on non-traded structural and neighborhood characteristics. Assuming *ceteris paribus* conditions, the estimated coefficients mimic the implicit prices of certain characteristics and report how the price changes when one of these characteristics changes (Wooldridge, 2008).

Two challenges arise during the empirical application of hedonic regressions (McMillen, 2010): (1) The specification of the functional form, and (2) the modeling of spatial effects. Firstly, the valid model specification is not guided by economic theory, permitting either a linear or a non-linear relationship (Rosen, 1974). Pace (1998, p. 77) establishes that an incorrectly chosen functional form results in "disastrous consequences for traditional estimators" and may itself cause a spatially correlated error term (McMillen, 2010). To deal with emerging non-linearities, it is common in practice to use higher order polynomials and a log–log or semi-log model specification, further mitigating difficulties with heteroscedasticity and outliers (Malpezzi, 2003). Augmenting predictors with polynomials as parametric components, as suggested by Stevenson (2004), results in multicollinearity problems. In addition, it also distorts the fit through unevenly distributed data, and is only suitable to model the global nature of the data (Dubin, 1998; Pace, 1998). Despite the above mentioned constraints, these parametric approaches are frequently applied (e.g. Goodman & Thibodeau, 2003), although their estimation is tedious as they necessitate knowledge about the "true" functional form in advance (Brunauer et al., 2010). Pioneering attempts by Halvorsen and Pollakowski (1979) promote the more flexible Box–Cox transformation, while Cassel and Mendelsohn (1985) find contradictory evidence that this does not necessarily result in more accurate estimations. Thus, a less restrictive and more rational approach for overcoming functional specification problems is to apply non-parametric or semi-parametric models where non-linearities might be expected, as advocated by Anglin and Gençay (1996), Mason and Quigley (1996), Pace (1998), Thorsnes and McMillen (1998), and Brunauer et al. (2010). This is even more appropriate when the effect of a certain covariate is entirely unclear (e.g. solar radiation). Thorsnes and McMillen (1998) argue that fully non-parametric approaches result in imprecise estimates, and thus advise semi-parametric models which offer functional flexibility where needed, while imposing linear restrictions where appropriate. Concerning prediction capabilities, Anglin and Gençay (1996), as well as Pace (1998), achieve higher accuracies using semi-parametric models, compared to their parametric counterparts. In this context, generalized additive models (Wood, 2000, 2006) are growing in popularity. These comprise a flexible model family and result in valid and – compared to e.g. non-parametric neural networks (Do & Grudnitski, 1992) – highly interpretable models when economic processes are exceedingly complex, possibly non-linear, *a priori* largely unknown, and probably underlying spatial effects (Wood & Augustin, 2002).

Secondly, spatial effects, including spatial autocorrelation and spatial heterogeneity (Helbich, Leitner, & Kapusta, 2012), are deduced from the durability and spatial fixation of real estate (e.g. Basu & Thibodeau, 1998; Dubin, 1998). The former depicts the coincidence of locational and attribute similarity (Anselin & Bera, 1998), while the latter refers to the spatial variation in the hedonic function across space (Páez et al., 2008). The family of spatial autoregressive models (Anselin & Bera, 1998; LeSage & Pace, 2009), in combination with discrete spatial indicators representing submarkets (e.g. Helbich et al., 2013; Watkins, 2001), enables the integration of both spatial autocorrelation as well as heterogeneity in the pricing function. In fact, these spatial units do not necessarily coincide with "true" spatial economic processes. Thus, Fotheringham, Charlton, and Brunsdon (2002) propose geographically weighted regression in order to model non-stationarity adequately and independently of spatial indicators, resulting in spatially varying implicit prices (Páez et al., 2008), while still rigidly assuming linear relationships. Once again, generalized additive models provide a solution and can be extended to (a) explicitly model locational effects applying isotropic bivarite smoothing functions to the spatial coordinates (Wood & Augustin, 2002), and (b) explore non-stationarity using spatially varying coefficient models by additionally offering the flexibility of non-linear modeling (Wood, 2006).

2.2. Airborne laser scanning in real estate research

Rasterized DEMs have stimulated a variety of applications and their potential has recently been recognized in real estate research (e.g. Bin et al., 2008, 2011; Hamilton & Morgan, 2010; McKenzie & Levendis, 2010; Orford, 2010). Most of these empirical studies do not utilize the full capability of high-resolution laser scanning as a novel data source of 3D geoinformation. Object detection coupled with classification in urban environments (e.g. Höfle, Hollaus, & Hagenauer, 2012; Lukac et al., 2012) permits the generation of 3D digital city models (Haala & Kada, 2010). Based on these 3D data, precise and objective numeric indices (e.g. solar radiation) for hedonic price models can be computed.

Recent research (Bin et al., 2011; Hamilton & Morgan, 2010; McKenzie & Levendis, 2010; Orford, 2010) works solely in the DSM raster domain, which limits the analysis to the so-called 2.5D spatial domain, where the 3D analysis of objects at different heights (i.e. building levels) is not possible. It is expected that the results for flat characteristics derived using 3D algorithms, accounting for the vertical occurrence of phenomena, will differ from the derivation using raster-based modeling only. With this said however, Bishop (2003) has remarked that 2D or 2.5D GIS approaches are inadequate in situations containing vertically extended objects (i.e. in urban environments which consist of highly irregularly shaped silhouettes with a high variation in height), and that the potential of 3D analysis is currently unclear. For example, Hamilton and Morgan (2010) calculate DSM visibility indices for Pensacola Beach (FL), and provide evidence that determinants which are simply based on the DSM, result in a higher explanatory power compared to hedonic models which do not consider such covariates.

Beside viewsheds[2] (see Bourassa et al., 2004), numerous indices can be extracted from ALS data. A highly relevant index is incoming solar radiation (Jochem, Höfle, Rutzinger, et al., 2009; Jochem et al., 2011; Lukac et al., 2012; Popescu, Bienert, Schützenhofer, & Boazu, 2012). Solar radiation, and the associated energy efficiency of flats, is a central subject in real estate (Popescu et al., 2012). Besides cohuman benefits such as an enhancement of the quality of living, it is emphasized that larger amounts of solar radiation potentially reduce energy consumption, and operating costs. In the long term it has a positive monetary effect on households' budgets and, therefore, it is expected that households are willing to pay a premium for flats with an increased amount of incoming solar radiation. Furthermore, solar radiation differs greatly between individual flats and depends on other buildings, shadowing effects, roof overhangs, etc., thus making it an ideal candidate for this empirical investigation. With the exception of Löchl and Axhausen (2011) who analyze residential rents in Zurich, Switzerland, previous studies neglect solar radiation as a locational characteristic. Löchl and Axhausen's research operationalize solar exposure using a DTM with 25 m resolution and thus ignores buildings, vegetation, local shadowing effects, etc. This study demonstrates that solar radiation has a significantly positive effect on square meter rent prices, which are increased by more than one percent.

In summary, the literature review, on the one hand, clearly indicates that generalized additive models which do not predetermine any kind of relationship are needed in order to estimate emerging non-linearities in hedonic price functions, while possible spatial effects may also be presumed. On the other hand, it demonstrates the vast unexploited potential which remains when it comes to ALS-based pricing models.

3. Methodology

3.1. 3D point-based solar radiation modeling

In this paper, global solar radiation is defined as the sum of direct and diffuse solar radiation (see Šúri & Hofierka, 2004). In this respect, diffuse means that the radiation was already scattered or reflected before reaching the surface, whereas direct (beam) radiation reaches the surface of interest directly without being scattered by the atmosphere or reflected by any other objects (e.g. ground). The equations for solar potential computation are taken from Šúri and Hofierka (2004) whilst the position of the sun during the course of the year is determined using the freely available SOLPOS code (NREL, 2002). The position of the sun is necessary to derive the angle of incidence of the solar radiation at the surface of interest. Further, the solar radiation is modeled under clear-sky conditions only. In general, the clear-sky factor accounts for climate (e.g. cloud attenuation factor) and regional terrain conditions and reduces the clear-sky solar radiation to more realistic absolute values. The present study does not model overcast conditions, assuming relatively constant clear-sky factors across the area of interest. Furthermore, it is assumed that clear-sky global radiation values between flats are sufficient to gather the relative differences in insolation, which is mainly caused by local occlusion and shadowing effects, rather than regional climatic differences.

The assumed dominating effect of shadowing of nearby objects is considered in the radiation computation by modeling the horizon of any given 3D location (XYZ) of interest (Fig. 1). Around this location, a fixed search radius is determined, in which all nearby occluding objects are assumed to cast a shadow. For the shadow casting objects, the cell center points of the DSM with 1 m resolution within the search distance are selected as 3D points. In a recent work (Jochem, Höfle, Hollaus, & Rutzinger, 2009), this procedure is performed using the original 3D laser point cloud directly, in order to account for the effects of non-transparent objects (e.g. trees) and overhangs of building roofs, etc. However, in this study a similar approach is applied and buildings are modeled as

[2] Note that solar radiation is not a variant of the viewshed analysis. Both indices are based on distinct concepts and algorithms. Thus, due to the position of the sun, it is conceivable that a flat has an increased insolation, even though the view is restricted by adjacent buildings. It is possible that a flat has an extensive view but is oriented towards North and thus receives less incoming solar radiation.

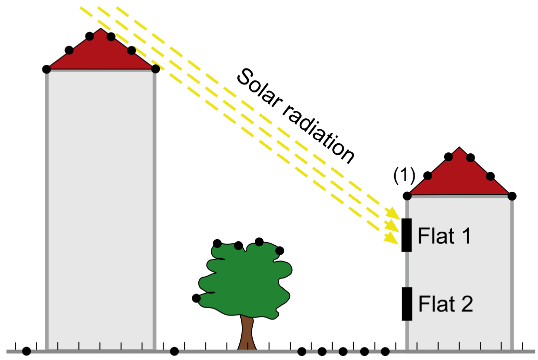

Fig. 1. Difference between the 3D point-based and the pure 2.5D raster approach in shadow calculation (horizontal tick marks denote raster cells and black points their corresponding cell value). Compared to raster-based modeling, this procedure allows the calculation of solar radiation for any given location in 3D space (XYZ), such as windows in different heights. This situation shows that Flat 1 (defined by XYZ) receives direct radiation, whereas Flat 2 merely receives diffuse radiation due to the shadow of the neighboring building. In the raster data model both flats are within the same cell and thus would receive equal incoming solar radiation (see marked cell (1) in Fig. 1), while using the 3D point-based approach individual floors (i.e. elevation) and the respective shadowing effects of surrounding buildings, etc. are considered.

solid objects without gaps through which the sun can shine. This assumption for the occluding objects corresponds to the DSM representation.[3] In dense urban areas, the chosen search radius for shadow modeling can be small (e.g. 10–20 m) because most of the objects, such as neighboring buildings, are generally close (e.g. across the street) occluding all other (even higher) buildings at a greater distance. To calculate the horizon for each location of interest, the distance and difference in height to each 3D point found in the defined neighborhood distance is derived. Following this, the maximum angle between the horizontal plane and all points per defined azimuth interval (0.3° class size) is stored. As a result of the 3D shadow mask calculation, a minimum solar elevation angle is assigned to each azimuth direction class, meaning that the sun altitude has to span a higher angle than the maximum angle in the shadow mask with regard to the azimuth direction.

The incoming global solar radiation is modeled for each day of the year from sunrise to sunset at 1 h intervals. The shadow mask takes effect if the current solar altitude angle is less than the previously determined minimum solar altitude angle with respect to azimuth direction. If at the current modeling timestamp the location is occluded by a nearby object, the direct radiation part is set to zero. The result is the sum of the annual global radiation in kW h per m^2 per year for the defined location of interest. Further details on the 3D point-based solar radiation modeling algorithm are provided in Jochem, Höfle, Hollaus, et al. (2009) and Jochem, Höfle, Rutzinger, et al. (2009) respectively, and are implemented in the OPALS (IPF, 2012) framework.

The location (XYZ) of interest for each flat is cross-checked and adapted manually as the generally available polygon layers of buildings and parcels (e.g. digital cadastral map) are not suitable for detailed 3D analysis e.g. by taking the centroid of the building footprint (see Bin et al., 2011; McKenzie & Levendis, 2010) which may lie on the roof facet point in a different direction than the flat's major orientation. Furthermore, it can be the case that the centroid defined as the center of gravity can lie outside the building polygon (e.g. in case of L-shaped footprints). The elevation of each flat is derived from *in situ* height above ground measurements using a hand-held laser range finder. For larger sample sizes, this value could be estimated from the flat's story and the average building level height. The defined flat location (XYZ), the manually estimated major orientation (i.e. aspect) of the flat and a defined slope of 90° for the vertical building facade, as well as the windows of the flat are used as the input data for the 3D solar radiation calculation. The derived annual sum is then assigned as an additional attribute to each flat, serving as an explanatory variable in the subsequent hedonic analysis.

3.2. Hedonic pricing model

Generalized additive models, introduced by Wood (2000, 2006), are a semi-parametric modeling approach, which utilize penalized regression splines to model non-linear relationships between variables in a regularized statistical framework (Brunauer, Feilmayr, & Wagner, 2012). This approach permits automatic smoothing parameter selection, which is integrated in the model calibration. Based on the discussion in Section 2.1, the hedonic price function in the case study is modeled by means of generalized additive models with a Gaussian link function (thereafter, it is it is referred to as additive model; AM). According to Wood (2006), the model is defined as:

$$y_i = \boldsymbol{X}_i^* \boldsymbol{\theta} + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + \varepsilon_i \quad (1)$$

where y_i denotes the (logged) transaction prices, $\boldsymbol{X}_i^*$ is a vector of parametric covariates, $\boldsymbol{\theta}$ the corresponding parameter vector, and f_j are penalized smooth functions of a covariate x_k. The error term ε_i is assumed to be independent identically distributed. The smoothers are represented as a linear combination of given basis functions. Due to technical advantages (e.g. no knot placement) discussed in Wood (2006), a set of thin plate regression splines are highly appealing as base functions to represent smoothing terms. The choice of the smoothing parameter is critical, because it controls a trade-off between smoothness and data fidelity. This trade-off is determined through generalized cross-validation (GCV) within the model fitting process. An optimal smoothing parameter minimizes the GCV score. The degree of smoothing is measured by the effective degrees of freedoms (EDF), where an EDF around 1 represents a linear relationship while larger EDF values correspond to more non-linear functions (Wood, 2006).

Housing data are likely to be characterized by spatial autocorrelation (e.g. Dubin, 1998), although independence is a crucial model prerequisite. According to Wood (2003, 2006), spatially explicit models can be fitted by multidimensional basis functions ($f_3(x_{3i}, x_{4i})$). Particularly, compared to tensor products for bivariate smoothing of quantities measured on different units (i.e. spatio-temporal effects), isotropic thin-plate splines are recommended to smooth interactions of quantities on the same units (i.e. the spatial coordinates), which hamper a violation of model assumptions. The necessity of such an extension can be evaluated with an autocorrelation analysis of the residuals (i.e. by estimating a semivariogram). In addition, model comparisons can also be made through an information criterion, including the Akaike information criterion (AIC), which describes a trade-off between the goodness of model fit and its complexity, penalizing overly complex models (Burnham & Anderson, 2002). Functions to estimate AMs are available in the R software environment (R Development Core Team, 2012).

4. Study area and data

4.1. Study area

The study area is situated in the city of Vienna (Austria), and comprises parts of the third district (Fig. 2). The choice of this study

[3] Only the shadow casting objects (i.e. buildings) are represented in 2.5D. The shadow calculation algorithm and the solar radiation calculation for different building levels is fully computed in 3D.

area is primarily driven by housing data availability. Furthermore, Vienna's housing market is fairly stable and despite the financial crises, investors have confidence in the market. However, for this analysis the assumption of a market equilibrium is plausible, with Wieser (2006) arguing that submarkets are of minor importance in Vienna. Brunauer et al. (2010) confirm heterogeneity between districts but have not found evidence of submarkets within districts. Finally, with the exception of Fischer and Aufhauser (1988), Wieser (2006), and Brunauer et al. (2010) who analyze different housing segments, the Viennese housing market has received little attention. However, note that the elaborated methods are not at all limited to this area and can principally be transferred to other urban environments.

4.2. Data and pre-processing

4.2.1. Housing data

The housing data are provided by the UniCredit Bank Austria AG, and are extracted from an automated real estate valuation system. The data comprises 48 geocoded owner-occupied flats (Fig. 2) for the time period spanning from 1999 to 2011. The main reason for this reduced sample is not due to availability of ALS data, but rather it is grounded in the restricted presence of the exact orientation of flats. Where entering the flat is permitted, *in situ* measurements of the orientation are conducted to increase the sample size. Although the sample size is limited, it is not unusually small (e.g. Brennan, Cannaday, & Coldwell, 1984; Dodgson & Topham, 1990; Hoesli, Thion, & Watkins, 1997). For instance, Hoesli et al. (1997) use 160 observations, while considering twice the number of predictors. Only 29 observations are used in Brennan et al. (1984) and 42 observations are investigated in Büchel and Hoesli (1995) for the subsidized housing sector in Geneva, Switzerland.

For each of the flats, individual transaction prices have been collected and are screened to ensure that they occur at arms-length transactions (e.g. symbolic transactions of 1 Euro are excluded). This research distinguishes between structural, temporal, and locational characteristics. Up to date socioeconomic and demographic conditions (e.g. diversity of ethnicities) are doubtlessly a major neighborhood discriminating factor (Can, 1998; Giffinger, 1998). Due to the small sized study area, neighborhood data on an extremely detailed resolution are required, which cannot yet be fulfilled by the official Austrian census. Table 1 introduces the variables considered in this empirical investigation.

4.2.1.1. Structural covariates. Floor area is the central property characteristic and thus the prime price differencing factor. A pronounced positive effect on the purchase price is expected. Malpezzi (2003) advises a logarithmic transformation considering multiplicative structures. Recently, Brunauer et al. (2010) has determined a highly non-linear floor area effect. Due to numerous advantages associated with flats on higher floors (e.g. higher solar radiation, a brighter and friendlier living space), the covariate "floor" should affect buyers' decisions positively. As in Morancho (2003), and because of the small sample size, the variable "floor" is modeled numerically, saving degrees of freedom. The existence of an elevator refers to the quality of the building and should have a positive coefficient sign (Büchel & Hoesli, 1995). Closely related to the floor, is the dummy variable "attic". Despite possible structural limitations like sloping roofs, high solar radiation during summer months, etc. attic flats should impact positively on the price. Finally, the flat's orientation is not directly considered in the model, and essentially reflects the main geographic cardinal direction of the flat, serving as an input from which to derive the incoming solar radiation.

4.2.1.2. Temporal covariate. Because the dataset covers an 11 year period, temporal dynamics through e.g. market trends, inflation, building obsolescence, etc. must be controlled in two ways: The

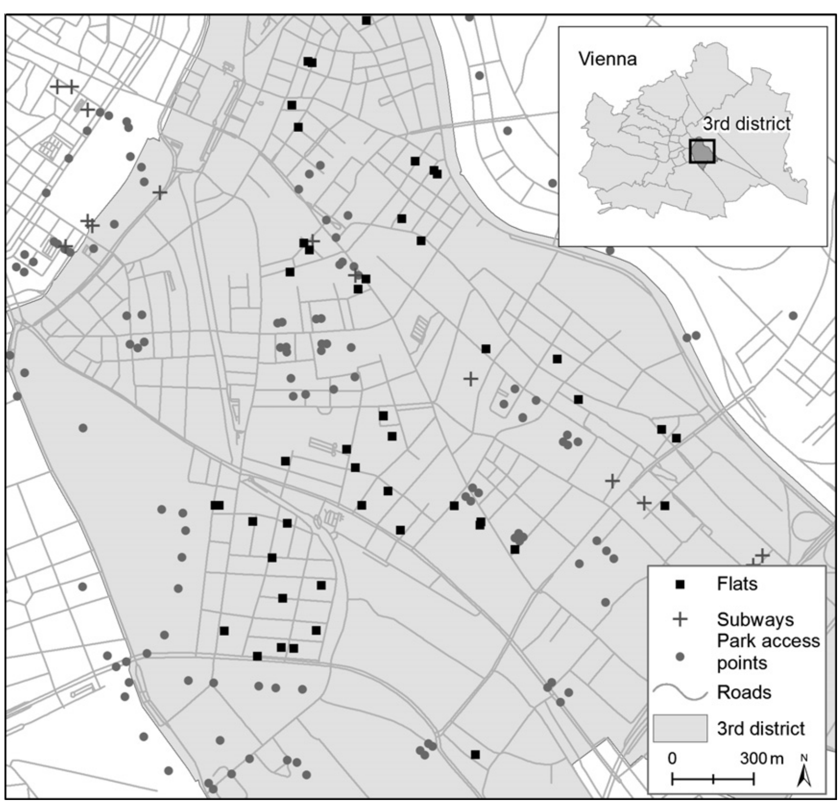

Fig. 2. Flats located in the third district of Vienna.

Table 1
Description and descriptive statistics of the variables.

Variable	Description	Source	1. QT	Mean	3. QT	St. dev.
Price	Transaction prices (in 1000 €)	Bank Austria AG	135.0	197.5	238.0	90.8
Structural covariates						
Area	Floor area of the flat (in m^2)	Bank Austria AG	71.6	89.1	100.3	30.4
Floor	Number of floor the flat is located in	Own survey	2.8	4.0	5.0	1.8
Elev	Existence of an elevator (0 = no, 1 = yes)	Bank Austria AG				
Attic	Attic flat (0 = no, 1 = yes)	Bank Austria AG				
Noise	Nuisance caused by noise (0 = low, 1 = moderate, 2 = high)	Bank Austria AG				
Orient	Main orientation of the flat	Bank Austria AG				
Temporal covariates						
Time	Time of sale (1999–2011)	Bank Austria AG	2008	2009	2010	1.0
Age	Age of the flat at the time of sale (in years)	Bank Austria AG	18.0	56.3	108.0	44.3
Locational covariates						
Park	Road network distance to the nearest park access (in meters)	Own calculation	207.2	299.8	408.2	143.9
Subw	Road network distance to the nearest subway station access (in meters)	Own calculation	469.0	724.0	874.0	351.3

flat's age at the time of sale, which is calculated as the difference between the year of sale and year of construction, reflects property depreciation over time and should therefore have a decreasing effect on flat prices. Nevertheless a vintage effect, which has the opposite consequences, is possible (Can, 1998). Goodman and Thibodeau (1995) and Brunauer et al. (2010) report non-linear age effects. The largest depreciation might occur for young flats, while positive effects are imaginable for renovated well-equipped flats constructed during the *Gründerzeit*. The year of the time of sale can be regarded as the remaining unexplained temporal heterogeneity. It is a measure for the quality adjusted development of prices over time and is modeled as a numeric covariate.

4.2.1.3. Locational covariates. Noise caused by traffic and non-residential land use is a negative externality reducing the quality of living, welfare, and thus property values (Duarte & Tamez, 2009; Lake et al., 2000). This ordinal covariate serves as a proxy for neighborhood disamenities and a negative sign should be associated with it. As Sander, Ghosh, van Riper, and Manson (2010) demonstrate, accessibility to facilities is not accurately represented by the Euclidian metric commonly used (e.g. Lake et al., 2000), which can, in the worst case, result in incorrect signs. A more valid distance approximation from each flat to the nearest park and subway station, are road-network-based distances (Sander et al., 2010). Additionally, instead of simply using the centroid of facilities, Hamilton and Morgan (2010) recommend using the nearest access points, instead of assuming ubiquitous access. This is particularly useful for Vienna's parks and subway stations, often having a limited number of entrances (e.g. Botanischer Garten). Due to their preserved nature and partly aesthetic merits, parks serve as prime recreation nuclei for residents in urban landscapes (Costanza et al., 1997). Intuitionally, a positive effect can be expected, although at a certain proximity parks emit negative externalities such as an increased noise level (e.g. through playgrounds), which may counter this effect (Chen & Jim, 2010). Urban economic theory states that shorter commuting distances to centers of economic activity, workplaces, amenities, etc. should raise property prices. Thus, access to the subway network serves as an important pricing factor (Can, 1998; Wieser, 2006). Beside access benefits, Bowes and Ihlanfeldt (2001) find that close proximity to subway stations can also have a negative impact on property values, especially when noise and pollution is emitted and/or the subway station attracts crime (Helbich & Kampitsch, 2010). Thus, it is somewhat unclear whether on average the effect is positive or negative. For both covariates, either linear or non-linear effects seem plausible.

4.2.2. Airborne laser scanning data

The 3D laser point cloud is acquired during a city-wide ALS campaign and is provided by the city administration of Vienna. The data are collected in December 2006 and in January 2007 under leaf-off conditions. The employed scanning system is a RIEGL LMS-Q560 airborne laser scanner (Riegl, 2012) with full-waveform capability. To obtain the single echoes from the recorded full-waveforms, a Gaussian decomposition (Wagner, Ullrich, Ducic, Melzer, & Studnicka, 2006) and transformation to Cartesian coordinates are applied. The laser pulse repetition rate is set to 200 kHz at a flying speed of 80 knots and a 500 m altitude above ground level. A scan angle of 60° and a minimum overlap of the neighboring strips of 45% results in the high average point density of around 30 echoes/m^2 in the overlapping areas, with approximately 11 cm horizontal and 1 cm vertical accuracy (Eberhöfer & Otter, 2007). The dataset is provided as ASCII point cloud files (XYZ, echo width, amplitude, etc.) in the Austrian Grid reference system (MGI Datum Austria) with the height reference system of Vienna (Wiener Null). Further processing of the highly dense ALS point cloud as well as solar radiation modeling are performed using the OPALS software (IPF, 2012).

5. Results

The research design is summarized in Fig. 3. It consists of two main steps: Firstly, the amount of incoming solar radiation for each flat is calculated directly in the 3D urban environment. Secondly, the marginal effect of this covariate is tested within the hedonic model. Furthermore, a model comparison statistically compares the predictive accuracy of an AM with and without the previously derived covariate solar radiation.

5.1. 3D modeling of solar radiation

3D solar radiation modeling delivers global and direct radiation values in kW h per m^2 per year for each location of interest defined by the XYZ position, constant orientation, and vertical slope of 90°. For example, the modeled global solar radiation for 15 m search radius exhibits a mean value of 914 kW h/m^2/year with a minimum value of 123, a maximum value of 1732, and a standard deviation of 551 kW h/m^2/year. These numbers indicate the large range and high variation of solar radiation between single flats. The effect of changing the local neighborhood parameter (i.e. search radius) for shadow mask calculation is shown in Table 2.

It can be observed that the distribution of global radiation values is more sensitive in the short ranges (5–30 m) and starts level-

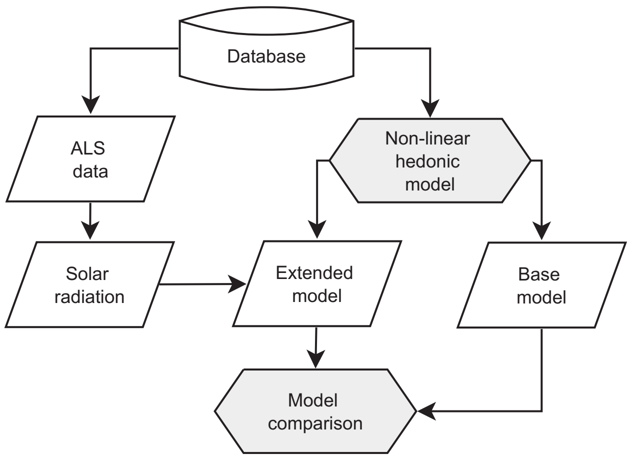

Fig. 3. Workflow for the solar radiation calculation and its application in the hedonic model framework.

ing off from 40 m to 500 m with high correlation coefficients. This points out the need for high density and highly accurate 3D data since most effects of occlusion and shadowing of flats are caused by nearby objects. The shadowing effect of buildings farther away is reduced due to the general decrease of shadow casts with distance for a given height and further by the fact that close buildings already occlude large parts of the horizon so that even large buildings further away cannot be "seen" from the flat and thus do not cast a shadow. Henceforth, these indices are integrated with hedonic models.

5.2. Hedonic models for flats in Vienna

Initially, Spearman correlation coefficients are computed between the predictors. The results in Table 3 indicate only low correlations between the covariates, confirming the necessary assumption of independence.

Subsequently, exploratory spatial data analysis (Fischer & Wang, 2011) is conducted to investigate possible spatial effects in the transaction prices. The Moran scatterplot (Anselin, 1996) depicts the type and strength of spatial autocorrelation by analyzing the relationship between location value and its neighbors, in this case the three nearest neighbors with inverse distance decay weighting. Fig. 4 indicates a slightly positive but non-significant autocorrelation (Moran's $I = 0.042$, $p = 0.304$). Thus, it is concluded that autocorrelation may not contradict the AM assumptions, but needs additional residual analysis.

The remaining section reports the estimation results of the additive hedonic models. For ease of interpretation and stabilization of the variance, purchase price and floor area are logarithmically transformed in both models. The base model consists of relevant covariates significantly explaining flat prices, and is restricted to a traditional set of covariates. This represents the benchmark model and serves for statistical evaluation purposes of the second hedonic model, called extended model, which additionally includes the ALS-based covariate solar radiation.

To realize a more parsimonious model, variable selection is carried out. A stepwise procedure iteratively includes a covariate when the model's AIC is reduced. As soon as the AIC score shows no further decrease between the iterations, the procedure is stopped. Additionally, the covariate must be at least significant at the 0.05 level. Overall, all variable combinations are tested. Whether a numeric variable enters the model in a linear or non-linear manner, the decision strategy discussed in Wood and Augustin (2002) is obeyed. During the determination of an optimal

Table 3
Spearman correlations of predictors (upper diagonal shows the coefficients and the p-values are given in the lower diagonal).

	log(area)	Floor	Age	Time	log(park)	log(subw)	SolRad (15 m)
log(area)		0.33	−0.15	−0.06	−0.08	0.06	0.19
Floor	0.02		−0.08	0.00	0.08	0.11	0.22
Age	0.32	0.60		0.05	−0.13	−0.15	−0.30
Time	0.68	0.98	0.72		0.49	−0.14	0.09
log(park)	0.57	0.61	0.39	0.00		−0.22	0.21
log(subw)	0.67	0.45	0.30	0.35	0.13		0.07
SolRad (15 m)	0.19	0.13	0.04	0.56	0.16	0.64	

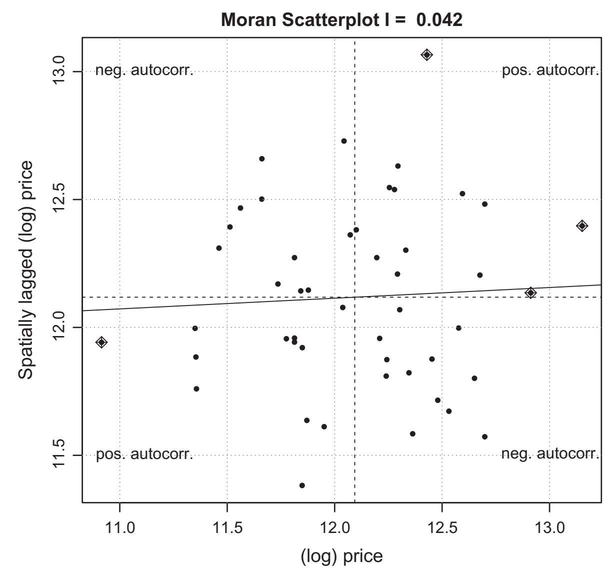

Fig. 4. Moran plot of flat prices (dashed lines represent mean values).

Table 2
Spearman's correlation coefficients ($p < 0.001$) of solar radiation using different search radii (5–500 m) for local shadow mask calculation (global radiation is shown in the upper diagonal and direct radiation in the lower diagonal).

	5 m	10 m	15 m	20 m	30 m	40 m	50 m	100 m	200 m	500 m
5 m		0.886	0.788	0.768	0.769	0.770	0.772	0.772	0.772	0.772
10 m	0.899		0.958	0.920	0.898	0.896	0.898	0.898	0.898	0.898
15 m	0.814	0.966		0.972	0.940	0.938	0.938	0.938	0.938	0.938
20 m	0.802	0.937	0.982		0.983	0.979	0.978	0.978	0.978	0.978
30 m	0.788	0.910	0.953	0.985		0.998	0.996	0.996	0.996	0.995
40 m	0.791	0.913	0.954	0.984	0.998		0.999	0.999	0.999	0.999
50 m	0.791	0.912	0.953	0.983	0.997	0.999		1.000	1.000	1.000
100 m	0.789	0.910	0.952	0.982	0.996	0.999	1.000		1.000	1.000
200 m	0.789	0.910	0.952	0.982	0.996	0.999	1.000	1.000		1.000
500 m	0.793	0.910	0.952	0.981	0.996	0.999	1.000	1.000	1.000	

degree of smoothing using GCV, the correction factor preventing overfitting is also considered (Wood, 2006). Thin plate regression splines are used as base functions. Another variable selection independent of the base model is conducted for the extended model. Within the extended model solar radiation is tested with different local search radii for shadow mask determination, ranging from 5 m to 500 m. Table 4 reports the regression results for the global and direct solar radiation with different parameterizations. It is shown that the effect of solar radiation only changes marginally. All alternatives show expected signs although not all of them show significance.

Furthermore, only the model with the lowest AIC is discussed (global radiation with 15 m search radius). Overall, both the base and the extended model have high explanatory power expressed by the percentage of explained deviation and the adjusted R^2. Both measures obviously prefer the extended model with an explained deviance of 77% and an adjusted R^2 of 0.690. These model fits are in accordance with Hamilton and Morgan (2010), Bourassa et al. (2010), and Helbich et al. (2013). In addition, the AIC is considerably reduced from nearly 27 to 18. This improved model fit from 0.610 to 0.690 through ALS-based variables agrees with Hamilton and Morgan (2010) who report an improved adjusted R^2 of 10% (63% vs. 73%). This provides evidence that the ALS-based variable has a substantial impact on model performance. The competing models are statistically compared using an F-test, indicating that the extended model is significantly better ($p = 0.015$). Fig. 5 plots the predicted prices against the observed prices. The extended model (right panel) scatters more closely around the 1:1 line. This is also confirmed by a lower in-sample root mean square prediction error (RMSE) which is noticeably reduced from 0.254 to 0.216.

Model diagnostics confirm that all assumptions are fulfilled: Measures of concurvity, the non-linear equivalent to co-linearity in linear models, indicate no problem. Following Wood (2006), semivariograms are used to explore remaining residual autocorrelation. Because the empirical semivariogram function is between the 999-times bootstrapped confidence envelopes (Diggle & Ribeiro, 2007), it is concluded that the model handles spatial autocorrelation well. This makes a bivariate smooth term of coordinates to explicitly model spatial effects unnecessary and increases the AIC score. Lastly, the Shapiro–Wilk test confirms normally distributed errors ($p > 0.05$) whilst a visual inspection confirms homoskedastic residuals, thus justifying the initial logarithmic transformations. Table 5 and Fig. 6 show detailed results of the final base model and extended model.

However, in the base model, as well as the extended one, neither the existence of an attic (positive effect), nor nuisances caused by noise (negative effect) serve as significant predictors. Most likely, the sample shows little variation serving as a discriminating factor. This is not consistent with results reported in Iten and Maibach (1992) who find a significant negative impact for Zurich (Switzerland) while, in turn, Büchel and Hoesli (1995) state a non-significant impact on flat rents in Geneva (Switzerland). Both studies measure noise in decibels not on an ordinal scale. In contrast with this are results compiled by Wieser (2006) although they are consistent with Chen and Jim (2010). Indeed, the latter study finds that park access within 500 m between the two logged acces-

Table 4
Estimated coefficients for solar radiation (divided by 1000) using different search radii for local shadow mask determination and model characteristics.

	Search radii for local shadow mask calculation									
	5 m	10 m	15 m	20 m	30 m	40 m	50 m	100 m	200 m	500 m
Global rad.										
Estim.	0.060	0.181	0.217	0.208	0.181	0.167	0.162	0.162	0.164	0.165
p-val.	0.523	0.039	0.020	0.029	0.070	0.101	0.113	0.113	0.113	0.112
AIC	28.752	19.007	18.294	19.937	25.131	25.426	25.501	25.527	25.819	25.740
RMSE	0.254	0.217	0.216	0.221	0.243	0.244	0.244	0.244	0.245	0.245
Direct rad.										
Estim.	0.062	0.208	0.246	0.240	0.202	0.189	0.184	0.185	0.186	0.184
p-val.	0.590	0.054	0.032	0.041	0.096	0.125	0.136	0.137	0.136	0.141
AIC	28.900	19.756	19.172	20.400	25.502	25.762	25.821	25.841	26.077	25.902
RMSE	0.255	0.219	0.218	0.222	0.244	0.245	0.245	0.245	0.246	0.245

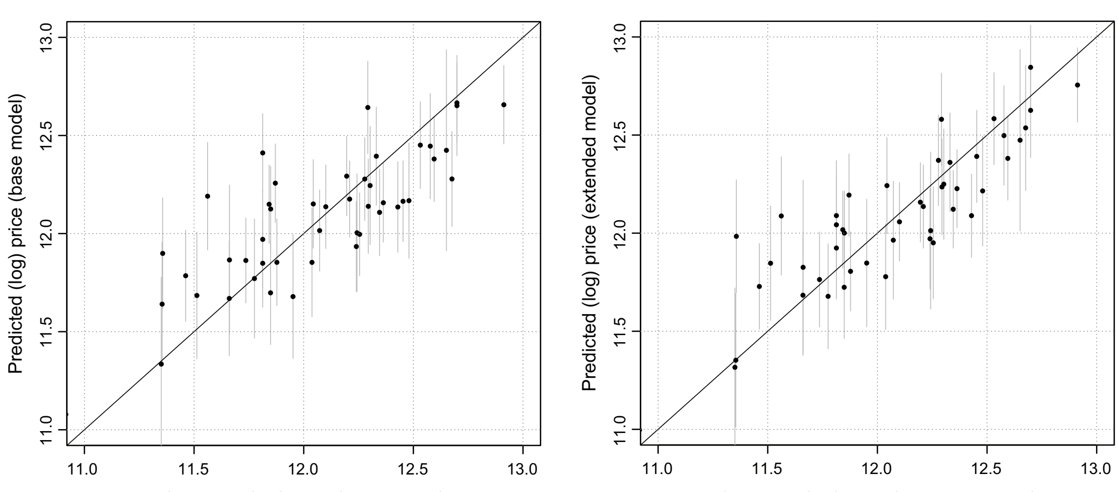

Fig. 5. Model predictions plus/minus two standard errors (bars) of the base model (left panel) and the extended model (right panel).

Table 5
Parameter estimates of the additive models.

	Base model			Extended model		
	Coeff.	Std. err.	*t*-val.	Coeff.	Std. err.	*t*-val.
Intercept	11.446	0.147	78.031***	11.347	0.140	80.980***
Floor	0.079	0.026	3.017**	0.072	0.025	2.852**
Elevator	0.397	0.138	2.882**	0.338	0.132	2.561*
SolRad/1000				0.217	0.089	2.438*
	EDF	Ref. df.	*F*-val.	EDF	Ref. df.	*F*-val.
s(log(area))	3.823	4.792	3.052*	3.375	4.210	3.123*
s(age)	3.356	4.105	8.651***	6.195	7.222	8.234***
Dev. expl. (%)	68.700			77.300		
Adj. R^2	0.611			0.690		
AIC	26.933			18.294		
RMSE	0.254			0.216		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05.

sibility measures "distance to the nearest park" (negative effect) and "subway access points" (negative effect) are not statistically relevant to explain flat prices and are possibly a result of equally access across space. Likewise, "time of sale" is positively related to flat prices but shows no significance, suggesting that temporal price effects are modeled by the "age" term.

Comparing the base and the extended model, the parametric control variables show only slight changes in their estimates. The parameters are similar in signs and magnitude, and are statistically significant at least at $p < 0.05$. Therefore, the following brief discussion is restricted to the extended model. The covariate "floor" is, as expected, significantly positively related to price at the 0.01 level. On average, each story further increases the price by approximately 7.5%. This is in line with a study by Chen and Jim (2010), which reports that households pay a premium for higher floors due to the improved view, brighter living space, less noise disturbance, etc. In addition, the existence of an elevator results in an increased purchase price. This seems rational because the dummy variable "elevator" acts as a proxy for the functional utility and facilities of a building. An elevator adds approximately 40% to the value of a flat compared to a building without one. This corresponds to previous findings of Morancho (2003) who also reports a positive effect. In order to test for possible interaction effects between the floor and elevator, the model is re-estimated considering an interaction term, resulting in non-significance and a considerable AIC increase. Solar radiation is linearly related to price,

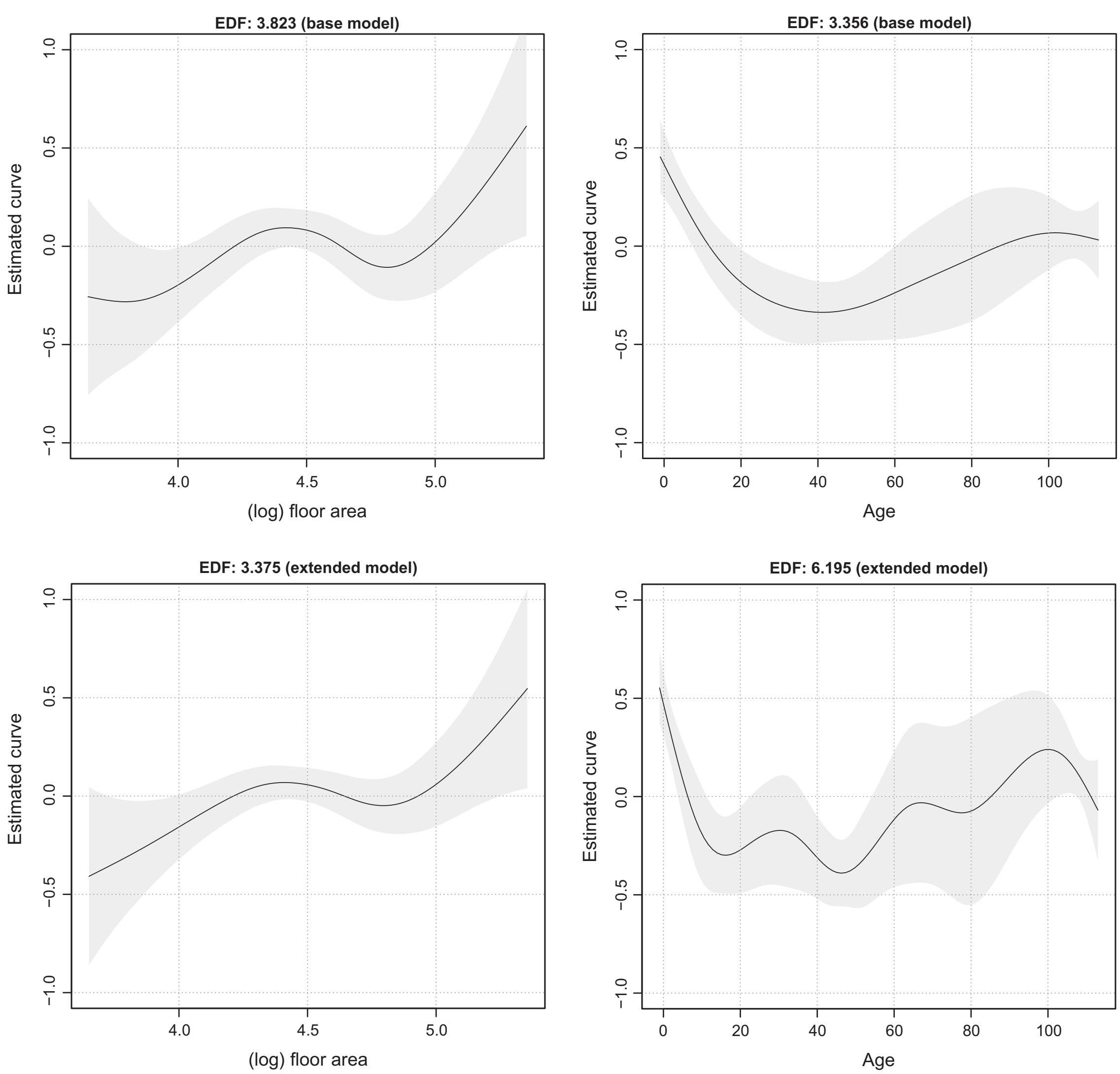

Fig. 6. Top panels display the non-parametric functions for the base model and the lower panels depict the functions for the extended model. Shown are the estimated price functions and the 95% confidence intervals (shaded regions).

confirmed by an EDF of nearly 1. The coefficient for solar radiation is positive and statistically significant at the 5% level. On the one hand, the pronounced effect of the estimated coefficient of 0.217 may refer to the division by 1000 of the initial index to avoid small coefficient values. On the other hand, flats with high solar radiation possibly belong to a higher overall quality real estate segment and thus this variable absorbs unobserved effects (see Bourassa et al., 2010). One unit increase of solar radiation in kW h/m^2/year divided by 1000 results in an average price premium of nearly 24%. Thus, incoming solar radiation is significantly capitalized in households buying decisions and reflects positively associated characteristics, such as reduced operation costs, a higher quality of living, and a comfortable feeling (e.g. Popescu et al., 2012). Löchl and Axhausen (2011), the only comparative study considering solar radiation on a DEM-basis, also reports a significant positive impact. An interaction with the covariate "floor" is insignificant.

Fig. 6 depicts the non-linear effects of logged floor area and age. Clearly, such relationships could not be modeled appropriately using linear model specifications and would result in false conclusions (i.e. age effect does not appear as significant). In general, a greater floor area (m^2) increases flat prices. This marginal effect is more pronounced in the first and third-third, while in the mid-third it is nearly constant, being in accordance with Brunauer et al. (2010). The highest price depreciation is in the first 18 years and has a strong negative marginal effect. Beyond this, the smoothing function is fairly uneven in the extended model. It is assumed that this is a statistical artifact due to a limited number of observations within this interval and provokes wide confidence intervals. Such a non-linear diminishing age effect is rational and additionally confirms earlier studies (e.g. Brunauer et al., 2010; Do & Grudnitski, 1992). Conventionally, a constant decline in value can be expected while the noticeable positive effect apparently occurs in older flats located in houses built during the *Gründerzeit*. These houses constitute appreciations i.e. through major repairs, replacements, modernizations, and reflect the new taste and lifestyle of property owners resulting in increasing values.

6. Conclusions

Real estate research demands indices describing flat specific characteristics in complex urban environments. With the exception of structural housing characteristics, analysis within large-scale urban fabric are foremost limited due to: (a) the lack of data availability, (b) temporal and monetary constraints of individual physical object inspections, and (c) these object-site inspections are affected by the appraiser's perception. To mitigate an emerging omitted variable bias, and to increase both explanatory power and the prediction accuracy of hedonic models, GIS-based algorithms (e.g. Kong et al., 2007) are increasingly used in combination with ALS data to derive alternative determinants possibly affecting house prices (e.g. Bin et al., 2011; Orford, 2010).

The study presents a methodology using the emerging laser scanning technology to extract exploratory variables necessary for hedonic price modeling directly from 3D data analysis. Objective and standardized quantitative measures depending on the flat-specific location, including its cardinal direction, as well as floor heights and the adjacent vicinity (e.g. shadowing effects) are the results. As a theoretically and economically important but still unexploited externality for flat prices, the incoming solar radiation is selected and tested within non-linear hedonic models for the third district of Vienna, Austria.

While the results do not confirm Paterson and Boyle (2002), that omitting solar radiation may lead to wrong conclusions regarding signs of other parameters, this study finds a high correspondence between the estimated parameters between both the base model and the extended one. However, significant differences are achieved in the goodness of fits. The reported additive models confirm that the model extended by solar radiation performs significantly better when compared to the base model not considering this index: (a) the adjusted R^2 as well as the percentage of explained deviance is considerably increased by approximately 13% through the ALS-based explanatory variable while (b) the prediction error is reduced by approximately 15% in comparison to the base model. Evaluation of different parameter settings of the solar radiation algorithm in the hedonic model consistently results in the correct coefficient signs, although (unrealistic) extreme settings of the search radii for determining local shadow effects show no significance at the 0.05 level.

Accounting for structural, temporal, and locational effects, solar radiation is linearly related to price and has a positive marginal effect, denoting that households are willing to pay a premium for flats with high incoming solar radiation. Rational reasons are reduced operation costs and a higher quality of living. Interaction effects between incoming solar radiation and floor could not be statistically verified. In addition, the model confirms non-linearities in the logged floor area and the age effect, which could not be modeled correctly using basic linear model specifications. Notwithstanding the relatively small sample size, it is recommended to take solar radiation in econometric housing analysis into account whenever possible, but to do so with care, only when the results are robust in accordance to the parameter sign.

Nevertheless, some limitations to this research can be identified. While the notion of deriving attributes on the basis of 3D laser data sounds particularly appealing for real estate studies, the practitioner's methodological toolbox still lacks off-the-shelf algorithms. The OPALS software framework (IPF, 2012) designed for large volumes of laser point clouds may provide a solution to this limitation. Since economic markets are diverse and the sample size of the case study is limited, it is also unclear whether other urban housing markets (e.g. Munich) act similarly. Although it is not comparable, it remains unclear whether the proposed approach performs better than pure raster-based radiation modeling, not making distinction between individual flats (e.g. orientation, floor). This demands comparative studies. Thus, the full potential of this 3D geoinformation with respect to the value for urban hedonic modeling is far from being exhausted and will continue to be a rich research area.

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