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Valuing water resources in Switzerland using a hedonic price model

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Key Points:
- Most variation in house prices is explained by structural house characteristics
- Significant effects are found for water abundance and the distance to large rivers
- The distance to the nearest bathing site has the largest marginal contribution

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Abstract In this paper, linear and spatial hedonic price models are applied to the housing market in Switzerland, covering all 26 cantons in the country over the period 2005–2010. Besides structural house, neighborhood and socioeconomic characteristics, we include a wide variety of new environmental characteristics related to water to examine their role in explaining variation in sales prices. These include water abundance, different types of water bodies, the recreational function of water, and water disamenity. Significant spatial autocorrelation is found in the estimated models, as well as nonlinear effects for distances to the nearest lake and large river. Significant effects are furthermore found for water abundance and the distance to large rivers, but not to small rivers. Although in both linear and spatial models water related variables explain less than 1% of the price variation, the distance to the nearest bathing site has a larger marginal contribution than many neighborhood-related distance variables. The housing market shows to differentiate between different water related resources in terms of relative contribution to house prices, which could help the housing development industry make more geographically targeted planning activities.

1. Introduction

There is a growing concern in Switzerland and elsewhere about the increase in urbanization as there is a great appreciation for green space and water amenities. The spatial planning and location of housing is thereby of great value and plays an important role in the price setting [*Löchl and Axhausen*, 2010]. In addition, with rising household income, the demand for environmental quality and the natural environment increases as well [*Salvi*, 2007]. Often, however, there is no economic value assigned to these environmental amenities, such that they are ignored in urban planning [*Sander and Polasky*, 2009; *Sander and Haight*, 2012].

A way to value these environmental amenities is through the housing market, given that the price or rent of a house reflects the value of structural house, neighborhood, and environmental characteristics. Hedonic price models estimate the house price or rent as a function of these characteristics. The method hence enables estimation of the marginal contribution of each attribute to the house price and as such finds its theoretical basis in consumer theory [*Lancaster*, 1966]. Literature on hedonic price modeling can be traced back to the work of *Rosen* [1974]. Since then, numerous studies have applied hedonic pricing as a way to derive the implicit price of environmental amenities. Some of the valued environmental amenities in the literature include air quality [*Won Kim et al.*, 2003; *Salvi*, 2007; *Yusuf and Resosudarmo*, 2009], noise [*Nelson*, 2004; *Baranzini and Ramirez*, 2005; *Day et al.*, 2007; *Baranzini et al.*, 2010; *Crespo and Grêt-Regamey*, 2013], open green space [*Tyrväinen*, 1997; *Tyrväinen and Miettinen*, 2000; *Morancho*, 2003; *Cho et al.*, 2006; *Kong et al.*, 2007; *Mayor et al.*, 2009; *Sander and Polasky*, 2009; *Sander et al.*, 2010; *Brander and Koetse*, 2011], beach and coral reef quality [*Hamilton*, 2007; *Brouwer et al.*, 2011; *Gopalakrishnan et al.*, 2011; *Landry and Hindsley*, 2011], water quantity and quality [*Loomis and Feldman*, 2003; *Löchl*, 2007; *Schaerer et al.*, 2007; *Muller*, 2009; *Baranzini et al.*, 2010; *Netusil et al.*, 2014]. The traditional linear modeling approach of *Rosen* [1974] was later extended by *Anselin* [1988a] into a spatial autoregressive model in order to be able to account for spatial dependency of house price observations. Although both approaches are found in the literature, the spatial approach is preferred as it reduces problems of biased coefficient estimates and heteroskedasticity that occur if spatial effects are ignored. Spatial econometric models in general, and of the kind discussed in this paper more specifically, have been criticized in the literature for lacking empirical validity and for depending on assumed known functional forms [*McMillen*, 2010; *Gibbons and Overman*, 2012]. This problem of identification is caused by the common practice of choosing a model based on comparison techniques. Nevertheless, spatial autoregressive models have their origins in actual behavior of economic agents, that is, they make decisions based on the behavior of other neighboring agents. This causes a pattern of spatial dependency, hence the development of spatial autoregressive models. Contrary to models that do not control for spatially explicit information, these models furthermore provide a range of regression structures that enable controlling for spatial lags in the dependent and independent variables, and account for unobserved heterogeneity in the stochastic part of the estimated function [*LeSage and Pace*, 2009].

Several hedonic price models have been applied to the Swiss housing market, also incorporating environmental variables [*Banfi et al.*, 2007; *Löchl*, 2007; *Salvi*, 2007; *Schaerer et al.*, 2007; *Salvi*, 2008; *Baranzini et al.*, 2010; *Löchl and Axhausen*, 2010; *Crespo and Grêt-Regamey*, 2013]. Typical for these Swiss studies is that those that consider water as an environmental element, only a single variable for the distance to water in general is used rather than making a distinction between different types of water bodies. In Switzerland, there are many types of water bodies and they may have different recreational values and hence different impacts on house prices. Swiss studies furthermore mostly focus either on selected cantons or a smaller area within a canton. Although this gives a good idea of how certain amenities are valued in a specific region, it does not reveal anything about the national level to which current housing policies apply such as low tax rates and a lenient planning system. Finally, studies carried out in Switzerland have mainly looked at the rental market, because it is larger than the house sales market. However, renting behavior may differ from purchase behavior and hence limit the contribution to the policy discussion regarding the geographic location of a substantial share of private housing development.

The objective of this study therefore is to analyze the Swiss house sales market at the national level, while controlling for regional differences in order to get a better understanding of the economic values that home buyers place on the presence of water-related amenities provided by different types of water bodies. We address this by deriving the economic values of these environmental characteristics, as well as those of structural house, neighborhood, and socioeconomic characteristics, with a hedonic price model. We first analyze a nation-wide spatial hedonic price model that includes structural house, neighborhood, and socioeconomic characteristics, as well as control for regional differences by incorporating all cantons and the distance to the nearest park for which hedonic price models were originally developed in the environmental economics literature. The latter variable enables us to study the impact of green space on house prices. Then, water abundance in the neighborhood is included to assess the overall contribution of water to house prices compared to green space. This is followed by the incorporation of distances to different types of water bodies, such as the nearest lake, large and small rivers. Finally, we study the recreational value of water and the impact of water disamenity through the inclusion of distances to the nearest bathing site and wastewater treatment plant, respectively. In order to analyze the impact of spatial effects in the explanatory power of the model, all models are estimated in their linear and spatial forms.

The contribution of this study to the existing literature is threefold. First, this is a first attempt to analyze the Swiss house market at the national level, while in addition controlling for regional differences. Second, we incorporate a wide variety of water-related variables, which enable us to assess the economic value of each of these (dis)amenities and how much people are willing to pay more (or less) for a house located closer to these different water-related (dis)amenities. More specifically, it allows us to test to what extent the presence of water plays a more or less important role in the price of a house compared with green space. Finally, by presenting the model in its linear and spatial forms, we are able to test also the impact of incorporating unobserved spatial effects in the model.

Results show that most variation in house prices is explained by structural house characteristics, but that there are significant effects for green and water related amenities. Although it is conform the expectation that proximity to parks and water abundance improve the explanatory power of the model by a small percentage, water abundance has a much larger relative contribution than green space. When we extend the model with several other distance variables to different types of water bodies, the explanatory power is again little improved. Here, however, it shows that out of all water related characteristics, the distance to the nearest lake has the largest relative contribution. By further extending the model with the recreational value of water and the disamenity value represented by WWTPs, we show that it is the recreational value that plays a more important role. Out of all environmental characteristics, it is this recreational value that has the largest contribution and even exceeds the contribution of other amenities such as distances to nearest schools and shopping centers.

The remainder of the paper is organized as follows. Section 2 presents the hedonic price model. This is followed by a description of the available data in section 3 and presentation of the results in Section 4. The paper finishes in section 5 with a discussion and conclusions.

2. Hedonic Price Model

The traditional hedonic price model is a linear model that estimates house prices based on a set of structural house, neighborhood, and environmental characteristics [*Rosen*, 1974]. Such a linear model may be expressed as:

$$\ln P_i = \beta_0 + \beta_1 H_i + \beta_2 N_i + \beta_3 E_i + \varepsilon_i, \quad (1)$$

where for each house i, $\ln P_i$ is the natural logarithm of the sale price, H_i is a vector of structural house characteristics, N_i is a vector of neighborhood characteristics, and E_i is a vector of environmental characteristics. The error term is denoted as ε_i and is assumed to be normally and independently distributed.

Because of the incorporation of geographical information with respect to each house i, two problems may arise when using the linear model, namely heteroskedasticity and spatial autocorrelation. Significant heteroskedasticity indicates that the model is misspecified, which may be due to the ignored presence of spatial heterogeneity. A Breusch-Pagan test is typically used to examine whether the linear model is misspecified or not. Spatial autocorrelation means that a house price observation is spatially dependent on another house price observation. Spatial dependence may be explained by the fact that houses in the same neighborhood share similar characteristics, such as proximity to public transportation, shops, and business districts [*Goetzmann and Spiegel*, 1997; *Goodman and Thibodeau*, 2003]. Spatial autocorrelation can be tested with Moran's I test. The outcome of the test statistic ranges between -1 (perfect dispersion) and 1 (perfect correlation), with 0 indicating that the data are not systematically correlated.

To incorporate spatial autocorrelation in the linear hedonic price model, *Anselin* [1988a] proposed a spatial autoregressive model, where the spatial effect is incorporated either in the deterministic part of the model (spatial lag model) or in the error term (spatial error model). The spatial lag model is specified as follows:

$$\ln P_i = \beta_0 + \beta_1 H_i + \beta_2 N_i + \beta_3 E_i + \varepsilon_i + \rho W \ln P_j \quad (2)$$

while the spatial error model has the following structure:

$$\ln P_i = \beta_0 + \beta_1 H_i + \beta_2 N_i + \beta_3 E_i + \varepsilon_i \quad (3a)$$

$$\varepsilon_i = \lambda W \varepsilon_i + \mu_i \quad (3b)$$

The error component in the spatial lag model has the same statistical properties as in the linear model. In the spatial error model, the error term is extended to also include spatial heteroskedasticity. In both equations, W is an $n \times n$ spatial weight matrix, which indicates to which extent the price of each house i is explained by the price of neighboring houses j. That is, house i's price is partly explained by the price of all other houses in the data, where some houses affect the price more than others. In some cases, houses are too far away to affect the price at all. The corresponding spatial autocorrelation coefficients are ρ in the spatial lag model and λ in the spatial error model. Based on the spatial weight matrix, a Lagrange Multiplier test can be used to determine which spatial autoregressive model is more appropriate [*Anselin*, 1988b].

In this study, in the first model in we estimate a linear hedonic price model to relate house prices to structural house, neighborhood, and socioeconomic characteristics, as well as canton dummies, year dummies, and the distance to the nearest park. We investigate the explanatory power of the variables and discuss the role of green space. For the purpose of showing reasonably sized coefficients, the dependent and explanatory variables have been divided by 1000. The second model nests the first model and adds the variable water abundance. The focus is thereby on the contribution of water abundance and to what extent this contribution is larger or smaller than the distance to the nearest park. In the third model, we zoom in on the contribution of different types of water bodies to house prices. This model therefore nests model two and adds the distances to the nearest lake, large river, and small river. Finally, model four focusses on the

Table 1. Overview of Hedonic Price Models in This Study

	Model 1: Green Space	Model 2: Water Abundance	Model 3: Water Bodies	Model 4: Recreational Amenity And Disamenity
Structural house characteristics	X	X	X	X
Neighborhood characteristics	X	X	X	X
Socioeconomic characteristics	X	X	X	X
Canton dummies	X	X	X	X
Year dummies	X	X	X	X
Distance to nearest park	X	X	X	X
Water abundance		X	X	X
Distance to nearest lake			X	X
Distance to nearest large river			X	X
Distance to nearest small river			X	X
Distance to nearest bathing site				X
Distance to nearest WWTP				X

recreational value of water and the disamenity value. For that, we nest model three and include the distances to the nearest bathing site and WWTP, respectively. All models are presented in their linear and spatial functional forms. Table 1 gives an overview of the different models in this study.

3. Data

Data on house sale prices are expressed in Swiss francs (CHF) and are obtained from *Comparis* [2005/10], a price comparison website in Switzerland. The data set includes 85,684 house price observations across the 26 cantons in Switzerland, covering the time period 2005–2010. Due to privacy laws, house transaction prices are not publicly available. Therefore, ask prices of houses are used as a proxy for actual sales or transaction prices. *Georgiadis* [2015] tests the equality of Swiss transaction prices and ask prices over a 10 year time period (2005–2015) and shows that the two time series are “co-integrated,” implying that the use of ask prices is an accurate measure of actual transaction prices. The descriptive statistics and data sources for each variable are presented in Table 2. They show that there is a high variation in house prices, ranging from a minimum of CHF 20,000 to a maximum of CHF 17,000,000. Three outliers (below CHF 20,000 and above 17,000,000) are excluded from the analysis. Average house prices also differ significantly between cantons. Compared to the other cantons, the canton of Geneva has the highest average house price of CHF 1,487,500. The canton of Wallis has the lowest prices with an average of CHF 475,000. Figure 1 shows a map of Switzerland with the average and rounded house prices per canton.

In the hedonic price model in this study, the dependent variable is converted into the natural logarithm of the house price. Data for house, neighborhood, socioeconomic, and environmental characteristics are obtained from multiple sources, including *Comparis* [2005/10] and the Swiss Federal Offices of Topography (Swisstopo), Traffic (BAV), Statistics (BFS), Tax Administration (ESTV), and Environment (BAFU). ArcGIS 10.1 is used for the calculation of all spatial variables.

It is common in the hedonic pricing literature to include multiple house characteristics. Looking at other Swiss studies, these include building age, floor size, number of floors, the condition of the dwelling, and whether there is a garage, terrace/balcony or cellar. In this study, the data at the national scale are a collection of data of all municipalities, cantons etc. This means that variables that are (not) available at the smaller scale are also (not) available at the national level. Due to the limited data availability in this study, house characteristics consist of the living space of the entire dwelling, the year of construction, and a dummy for the presence of a garden. Hence, most but not all house characteristics that have been included in previous studies are also covered here. Information about the number of rooms was also available, but highly correlated with living space. These two variables measure and reveal the same type of information, hence the high correlation coefficient of 0.8 and omission of the number of rooms from the analysis.

Physical neighborhood characteristics are important in a study in a country so diverse in geography such as Switzerland. To represent some of this diversity, we include for each house its level of elevation, slope, and aspect (in degrees °). The latter refers to the compass direction of the slope (e.g., facing north or west). Some of these variables have been included in other Swiss studies as well, such as a house’s slope [*Salvi*, 2007, 2008; *Löchl and Axhausen*, 2010; *Crespo and Grêt-Regamey*, 2013] and aspect [*Salvi*, 2007, 2008]. In a

Table 2. Descriptive Statistics of the Variables Used in the Hedonic Price Model

Variable	Unit	Mean	SD	Min.	Max.	Data Source
Dependent variable						
Price	CHF	662,129.2	387,326.6	20,000	17,000,000	*Comparis* [2005/10]
House characteristics						
Living space	m^2	143.2	54.5	12	495	*Comparis* [2005/10]
Year of construction	year	1979	40.21	1400	2010	*Comparis* [2005/10]
Garden	dummy			0	1	*Comparis* [2005/10]
Neighborhood characteristics						
Elevation	m	510.32	195.07	196.04	2,056.15	*Swisstopo* [2003], DHM25©2003[a]
Slope	percent	9.03	9.45	0	102.65	*Swisstopo* [2003], DHM25©2003
Aspect	°	176.79	106.89	-1[b]	359.997[c]	*Swisstopo* [2013a], ALTI3D©2013
Distance to railway station	m	1250.22	1,236.16	5.33	23,861.27	*Swisstopo* [2011a], TLM©2011
Distance to bus	m	221.56	174.02	0	2,745.91	*BAV* [2014]
Distance to highway	m	2,543	2,993	0.06	29,510	*Swisstopo* [2011a], TLM©2011
Distance to school	m	401.98	412.91	1	11,724.77	*BFS* [2011/12]
Distance to CBD	m	11,711.23	10,207.4	0.08	137,572.8	*BFS* [2011a], GEOSTAT
Household income	CHF per year	43,144.44	11,949.55	18,807	221,234	*ESTV* [2005/10]
Population density	Number of persons per ha	45.93	43.30	0[d]	2,738	*BFS* [2011b], STATPOP2011
26 cantons	dummy			0	1	*Comparis* [2005/10]
Year 2005–2010	dummy			0	1	*Comparis* [2005/10]
Environmental characteristics						
Distance to park	m	478.92	445.26	11	7,363.32	*BFS* [2004/09], Arealstatistik 2004/09
Water abundance	percent in 1 km radius	3.08	7.24	0.0000	65.97	*Swisstopo* [2011b], VEC200©2011 *Swisstopo* [2013b], TLM©2013
Distance to lake	M	15,113.73	13,656.33	50	70,183.9	*Swisstopo* [2011b], VEC200©2011
Distance to large river	m within a 10 km radius	1732.0	1669.78	0.1	10,000	*Swisstopo* [2011b], VEC200©2011
Distance to small river	m within a 10 km radius	830.60	755.90	0.013	10,000	*Swisstopo* [2011b], VEC200©2011
Distance to bathing site	m	1,981.56	1,795.79	4.94	30,383.69	Google map of swim locations[e]
WWTP	m	2662	1637.97	29.73	16,660	*Maurer and Herlyn* [2006]

[a]All data from Swisstopo are reproduced with permission of Swisstopo (Art.30 GeoIV): 5704000000/JA100119.
[b]The minimum aspect of -1 corresponds in the GIS software to a flat area.
[c]The maximum aspect in the data is 359.997° and lies just below the maximum of 360°.
[d]The data source only considers densities of more than three people per ha. An observation that lies in a region with less than three people per ha is therefore recognized as zero.
[e]http://www.badi-info.ch/schwimmbad-karten.html.

few studies carried out in smaller regions (cantons) based on substantially less observations, lake or mountain views have been included [*Löchl*, 2007; *Baranzini et al.*, 2010]. Due to the large number of observations and the laborious procedure to generate such data and information, these variables were not included in this study. Other socioeconomic neighborhood variables include distances, measured in meters, from each house to the nearest railway station, bus stop, highway, school, and central business district (CBD) that employs at least 200 people. Under schools, we consider primary, secondary, and technical schools. This selection of variables is common in the existing literature [*Löchl*, 2007; *Salvi*, 2008]. Other neighborhood characteristics that may be of value in hedonic price models are crime rate and education [*Goetzmann and Spiegel*, 1997; *Lynch and Rasmussen*, 2001]. This information was, however, not available at the national level.

While some Swiss studies have included additional socioeconomic characteristics such as the number of foreigners or the tax level [*Salvi*, 2008; *Löchl and Axhausen*, 2010; *Crespo and Grêt-Regamey*, 2013], others have excluded socioeconomic characteristics altogether [*Banfi et al.*, 2007; *Schaerer et al.*, 2007]. At the national level, information about annual taxable income at the municipal level (in CHF) and population density (per hectare) was available and therefore included. Across the country, annual gross household income of municipalities ranges between CHF 18,807 and CHF 221,234. A comparison of average annual income aggregated across municipalities between cantons shows that the canton of Geneva has the highest average annual income of CHF 72,621, which is significantly different from the other cantons and corresponds with the highest average house price per canton. The canton of Jura has the lowest average annual income of CHF 34,234. The lowest house price was found in the canton of Wallis, where average annual income is only 2.5% higher than in the canton of Jura.

Dummy variables are created for each of the 26 cantons in Switzerland in order to detect potential trends in house prices per canton. The dummy for the canton of Geneva is used as the baseline. Dummy variables indicating the year of house sales between 2005 and 2010 are furthermore included in order to account for potential temporal trends in house prices. The year 2005 is used as the baseline.

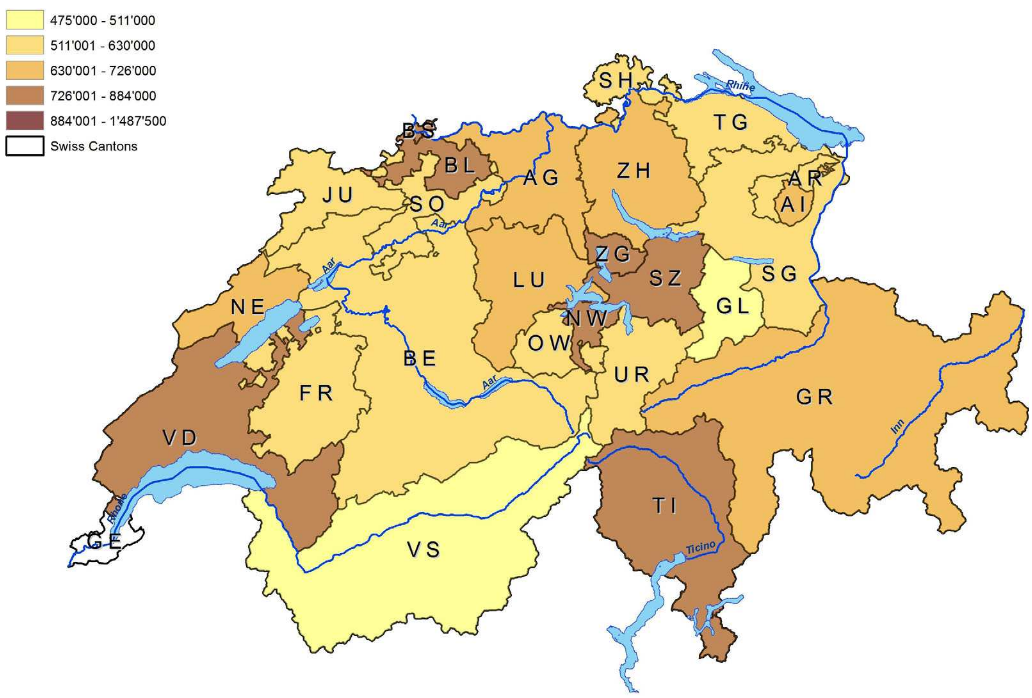

Figure 1. Map of Switzerland with the average and rounded house prices per canton.

Finally, environmental characteristics include the share of area covered by water in a radius of 1 km around each house, as well as Euclidean distances (in m) to the nearest park, official bathing site, lake, large river, and small river. We thereby separate the commonly used variable for the distance to water into different types of water bodies. The nondistance variable water abundance is a new variable compared to existing studies that focus primarily on distance, and includes both the area cover of standing and running water. It has been shown in e.g., *Muller* [2009] that the omission of variables related to water view and waterfront possibly leads to specification bias. View variables have been included in previous Swiss studies, which were carried out at a city or canton scale, and have been found to have a significant positive relationship with house prices [*Löchl*, 2007; *Löchl and Axhausen*, 2010; *Baranzini and Schaerer*, 2011]. At the national level, however, information about water views of houses is not available. Parks include public parks, sport parks, golf courses, camping sites, and garden allotments. The distance to the nearest lake takes into consideration lakes with a minimum surface of 2 km^2 and includes no limit on the maximum distance, because larger lakes are expected to have a more important effect on house prices. For the distance to the nearest river, a maximum radius of 10 km is used in order to reduce computation time. Beyond this distance, no effect on house prices is expected. In addition, a distinction is made between two river sizes, based on classes that were introduced by *BAFU* [2000] and *Swisstopo* [2014] for the purpose of making a distinction between large and small rivers. In this study, we distinguish between medium to large rivers and smaller streams and creeks. This distinction is based on classes, ranging between 4 and 10, which were introduced by *BAFU* [2000] and *Swisstopo* [2014, p. 61] with the purpose of making a visual distinction between large (important) and small (less important) rivers. In this study, classes 4–7 are aggregated under medium to large rivers and classes 8–10 fall under smaller streams and creeks. Another environmental characteristic is the distance (in m) to the nearest wastewater treatment plant (WWTP). This is included as a disamenity, because the proximity is expected to affect public perception of water quality due to the discharge of effluents. In addition, WWTP's may produce an unpleasant odor and also negatively impact house prices in that way. The distance to the nearest WWTP has, to our knowledge, not been incorporated in previous hedonic pricing studies in Switzerland or anywhere else.

The effects of socioeconomic and distance variables were tested for nonlinearities. The natural log transformations of income and the distances to the nearest CBD, lake, and large river appeared to improve the fit of the model. This distance variable hence follows a ratio rather than an absolute change in distance.

4. Results

4.1. Linear Regression Models

The results of the four linear models are presented in Table 3. All models are estimated in R version 3.1.0. In the first linear model, all structural house characteristics are highly significant ($p < 0.001$) and positive. Houses with an additional square meter in living space sell all else being equal (ceteris paribus) at a 0.63% higher price, which translates into 4171 CHF based on the national average house price. Similar results were found in *Löchl and Axhausen* [2010], who applied his model to the rental market in the canton of Zurich. A newer house by 1 year increases the average house price ceteris paribus by 0.15%, which is also similar to the findings in *Löchl and Axhausen* [2010]. Other similar results outside Switzerland are presented for instance in *Sander and Polasky* [2009], *Price et al.* [2010], *Donovan and Butry* [2011], and *Sander and Haight* [2012]. The presence of a garden has the largest impact and yields on average a 3.87% higher house price.

With respect to the physical neighborhood characteristics, both the elevation and slope of a house are statistically significant. Their contribution to higher house prices are 0.02% for an additional meter in elevation and 0.36% for a 1% increase in slope. The latter finding of a positive slope coefficient in the whole of Switzerland corresponds to the case studies carried out in Zurich and presented in *Salvi* [2008] and *Crespo and Grêt-Regamey* [2013]. These two studies observe, however, a greater price increase of approximately 2% per 1% increase in slope. A positive coefficient for elevation was also found in the United States by *Sander and Polasky* [2009]. The compass direction of the slope (aspect) is insignificant and this corresponds to the results reported in *Salvi* [2008]. Other neighborhood characteristics such as the distance to the nearest highway, school, and CBD are also statistically significant and have a negative effect on house prices. Note that the distance to the nearest CBD, as well as income, are log-transformed. These transformations increase the R^2 significantly by 1.1%. Alternatively, including the linear and squared terms of these variables (as well as a combination of the two) leads to an insignificant zero percent change in house prices. We therefore include the natural log transformation of these two variables in the final model. The distance-decay to the nearest railway station, highway, school, and CBD indicates that house prices decrease when they are located further away from these amenities. This is conform the expectation that households are willing to pay more to live closer to transportation junctions, shops, and work [*Löchl*, 2007; *Sander and Polasky*, 2009; *Sander and Haight*, 2012]. The increase in house prices is 0.06% for living 100 m closer to the nearest railway station, 0.07% for living 100 m closer to the nearest highway, and 0.11% for living 100 m closer to the nearest school. For a 10% reduction in the distance to the nearest CBD house prices increase, on average and all else being equal, with 0.03%. Only the distance to the nearest bus stop has a significant positive effect. Living 100 m closer to a bus stop results ceteris paribus in a 0.49% decrease in house prices. Proximity to the nearest railway station is statistically insignificant.

With respect to the socioeconomic neighborhood characteristics, the significant positive relationship between a neighborhood's income level and house prices is as expected. Households with higher incomes tend to live in richer neighborhoods and buy more expensive houses. A 10% higher income level contributes, on average and all else being equal, to a 0.6% higher level in house prices. In the canton of Zurich [*Löchl*, 2007], this relationship is similar to the country level. Population density has a negative sign, indicating that a more densely populated area has a negative impact on house prices, similar to the results found in *Crespo and Grêt-Regamey* [2013]. An increase of one person per hectare results ceteris paribus in a 0.06% drop in the average house price. The negative relationship between house prices and both the distance to the nearest CBD and population density is in line with *Löchl and Axhausen* [2010], who found this for the canton of Zurich. Note that the drop in house prices, as a consequence of a higher population density can signal the impact of noise disamenity on house prices. In this case, the negative effect of moving further away from the nearest CBD on house prices could be interpreted as contradictory if also this variable would be associated with noise and traffic. This is however not explicitly measured here and the distance-decay to the nearest CBD is therefore interpreted to reflect the associated increasing inconvenience of doing groceries etcetera. All canton dummies are significant and negatively related to the baseline canton Geneva, because house prices in this canton are highest. Comparing the other cantons with each other, we find that on average coefficients differ substantially. Basel-Stadt has a coefficient estimate that deviates most from the rest and is on average 70% lower than the coefficients for the rest of the cantons. The smallest difference is found between Nidwalden and Aargau. Since the data set covers the 6 year time period 2005–2010, these years are included as dummies to pick up any inflationary trends, with 2005 as the baseline. It can be

Table 3. Linear Regression Models

	Linear Model 1: Green Space	Linear Model 2: Water Abundance	Linear Model 3: Water Bodies	Linear Model 4: Recreational Amenity and Disamenity
Intercept	0.923 (0.060)***	0.923 (0.059)***	1.036 (0.060)***	1.077 (0.060)***
House characteristics				
Living space	6.287 (0.019)***	6.299 (0.019)***	6.299 (0.019)***	6.310 (0.019)***
Year of construction	1.468 (0.025)***	1.488 (0.025)***	1.480 (0.025)***	1.486 (0.025)***
Garden	0.038 (0.003)***	0.039 (0.003)***	0.039 (0.003)***	0.039 (0.003)***
Neighborhood characteristics				
Elevation	0.192 (0.009)***	0.216 (0.009)***	0.207 (0.009)***	0.185 (0.009)***
Slope	3.615 (0.117)***	3.472 (0.117)***	3.357 (0.117)***	3.320 (0.117)***
Aspect	0.015 (0.009)	0.016 (0.009)	0.022 (0.009)*	0.022 (0.009)*
Distance to railway station	−0.006 (0.001)***	−0.004 (0.001)***	−0.005 (0.001)***	−0.002 (0.001)*
Distance to bus	0.049 (0.006)***	0.054 (0.006)***	0.058 (0.006)***	0.063 (0.006)***
Distance to highway	−0.007 (0.000)***	−0.007 (0.000)***	−0.007 (0.000)***	−0.007 (0.000)***
Distance to school	−0.011 (0.003)***	−0.014 (0.003)***	−0.014 (0.003)***	−0.012 (0.003)***
LN(Distance to CBD)	−0.025 (0.001)***	−0.027 (0.001)***	−0.027 (0.001)***	−0.022 (0.001)***
Socioeconomic characteristics				
LN(Household income)	0.576 (0.006)***	0.563 (0.006)***	0.545 (0.006)***	0.537 (0.006)***
Population density	−0.637 (0.026)***	−0.624 (0.026)***	−0.638 (0.026)***	−0.658 (0.026)***
Cantons				
Zurich	−0.497 (0.024)***	−0.504 (0.024)***	−0.489 (0.024)***	−0.507 (0.024)***
Bern	−0.582 (0.024)***	−0.596 (0.024)***	−0.581 (0.024)***	−0.593 (0.024)***
Luzern	−0.522 (0.024)***	−0.539 (0.024)***	−0.538 (0.024)***	−0.548 (0.024)***
Uri	−0.493 (0.030)***	−0.507 (0.030)***	−0.496 (0.030)***	−0.452 (0.030)***
Schwyz	−0.500 (0.024)***	−0.530 (0.024)***	−0.534 (0.024)***	−0.537 (0.024)***
Obwalden	−0.508 (0.027)***	−0.530 (0.027)***	−0.513 (0.027)***	−0.536 (0.027)***
Nidwalden	−0.515 (0.027)***	−0.553 (0.027)***	−0.560 (0.027)***	−0.568 (0.027)***
Glarus	−0.705 (0.028)***	−0.711 (0.028)***	−0.702 (0.027)***	−0.735 (0.028)***
Zug	−0.544 (0.027)***	−0.559 (0.027)***	−0.559 (0.027)***	−0.568 (0.027)***
Fribourg	−0.617 (0.025)***	−0.633 (0.025)***	−0.635 (0.025)***	−0.630 (0.025)***
Solothurn	−0.631 (0.024)***	−0.639 (0.024)***	−0.595 (0.024)***	−0.603 (0.024)***
Basel-Stadt	−0.317 (0.025)***	−0.317 (0.025)***	−0.255 (0.025)***	−0.277 (0.025)***
Basel-Landschaft	−0.402 (0.024)***	−0.401 (0.024)***	−0.346 (0.024)***	−0.365 (0.024)***
Schaffhausen	−0.667 (0.025)***	−0.675 (0.025)***	−0.643 (0.025)***	−0.664 (0.025)***
Appenzell Ausserrhoden	−0.832 (0.025)***	−0.842 (0.025)***	−0.817 (0.025)***	−0.832 (0.025)***
Appenzell Innerhoden	−0.654 (0.031)***	−0.665 (0.031)***	−0.634 (0.031)***	−0.653 (0.031)***
St. Gallen	−0.635 (0.024)***	−0.647 (0.024)***	−0.628 (0.024)***	−0.643 (0.024)***
Graubünden	−0.465 (0.025)***	−0.485 (0.025)***	−0.429 (0.025)***	−0.422 (0.025)***
Aargau	−0.555 (0.024)***	−0.562 (0.024)***	−0.530 (0.024)***	−0.545 (0.024)***
Ticino	−0.402 (0.025)***	−0.411 (0.025)***	−0.432 (0.025)***	−0.443 (0.025)***
Vaud	−0.443 (0.025)***	−0.447 (0.025)***	−0.455 (0.025)***	−0.453 (0.025)***
Vallais	−0.764 (0.027)***	−0.777 (0.027)***	−0.738 (0.027)***	−0.751 (0.027)***
Neuchâtel	−0.648 (0.030)***	−0.672 (0.030)***	−0.667 (0.030)***	−0.655 (0.030)***
Jura	−0.814 (0.033)***	−0.823 (0.033)***	−0.776 (0.033)***	−0.770 (0.033)***
Thurgau	−0.675 (0.024)***	−0.691 (0.024)***	−0.682 (0.024)***	−0.692 (0.024)***
Years				
2006	0.001 (0.004)	0.002 (0.004)	0.003 (0.004)	0.003 (0.004)
2007	−0.003 (0.004)	−0.002 (0.004)	−0.001 (0.004)	0.000 (0.004)
2008	0.010 (0.004)**	0.011 (0.004)**	0.013 (0.004)***	0.013 (0.004)***
2009	0.028 (0.004)***	0.029 (0.004)***	0.030 (0.004)***	0.031 (0.004)***
2010	0.043 (0.004)***	0.045 (0.004)***	0.046 (0.004)***	0.047 (0.004)***
Environmental characteristics				
Distance to park	−0.023 (0.003)***	−0.021 (0.003)***	−0.021 (0.003)***	−0.015 (0.003)***
Water abundance		2.584 (0.149)***	0.910 (0.182)***	0.629 (0.183)***
LN(distance to lake)			−0.022 (0.001)***	−0.021 (0.001)***
LN(Distance to large river)			0.004 (0.001)***	0.005 (0.001)***
Distance to small river			−0.003 (0.001)*	−0.003 (0.001)*
Distance to bathing site				−0.012 (0.001)***
Distance to WWTP				0.002 (0.001)***
R^2	0.640	0.641	0.642	0.644
Num. obs.	85,684	85,684	85,684	85,684
AIC	31,955	31,658	31,318	30,949
LogLikelihood	−15,931	−15,782	−15,609	−15,422
Df	46	47	50	52
Chisq		298.9***	345.9***	373.5***

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

observed that the years 2008, 2009, and 2010 are significantly different from this baseline year. More specifically, compared to 2005, house prices increase in 2008 by 1.01% and then with 2.84% and 4.39% in 2009 and 2010, respectively. This result is conform the findings presented in, for example, *Mukherjee and Schwabe* [2014]. Finally, with respect to green space, the distance to the nearest park is, as expected, significant and negative, indicating that as a house is located 100 m closer to the nearest park, its price increases on average and ceteris paribus by 0.20%. Similar findings are reported for instance in *Won Kim et al*. [2003] and *Sander and Polasky* [2009]. The variables included in the first model together explain 64.0% of the variation in the observed house prices.

The second linear model nests the first model and incorporates water abundance as additional explanatory variable. The significance levels and signs of the house and neighborhood characteristics remain the same compared to those in the previous model. The coefficient estimate capturing the relationship between house prices and parks remains the same as before, namely a house price increases on average 0.2% if it is located 100 m closer to a park. The estimate for water abundance also shows a significant positive impact on house prices: if water abundance increases by 1% in a 1 km radius around the house, its price increases ceteris paribus on average by 0.26%. This suggests that the presence of water in general is valued positively, but goes against the results presented in *Schaerer et al*. [2007], who found a negative impact for the share of surface water on house prices for the region of Zurich and an insignificant impact of the same variable for the region of Geneva. The variables in the second model explain 64.1% of the variation in house prices, which means that water abundance only adds 0.1% to the explanatory power of the first model. Based on the Likelihood Ratio test, also presented in Table 3, the second model nevertheless yields a significant improvement over the first model. A way to assess the explanatory power of each individual variable is to assess the delta R^2, which is also known as the squared semipartial correlation coefficient and measures the improvement or deterioration in the R^2 by adding or removing variables from a statistical model [*Schwab*, 2005]. It is thus a useful way to determine whether a variable has a substantial effect on an outcome. For more details regarding the calculation of the delta R^2, the interested reader is referred to *Schwab* [2005]. When deriving the delta R^2 for model two for the green space and water abundance variables, we find that the latter has a larger contribution to the model's explanatory power ($\delta R^2 = 0.0013$) than the distance to the nearest park ($\delta R^2 = 0.0003$). Both are, however, relatively low compared to other explanatory variables such as living space, which has the largest contribution ($\delta R^2 = 0.4540$), followed by income ($\delta R^2 = 0.0369$), and the year of construction ($\delta R^2 = 0.0146$).

In the third linear model, which nests model two, we focus on the different types of water bodies by also including distances to the nearest lake, large and small rivers. Compared to model two, significance levels and signs remain again unchanged, except for the aspect of the house that is now significant and positive. Looking at the water related variables in model 3, a 1% increase in water abundance around the house increases house prices on average by 0.09. The distance variables to the different water bodies have been tested for linear and nonlinear effects. We find that log transformed distances to the nearest lake and large river increase the explanatory power of the model (compared to the linear case) by 0.1%. By including these transformations, it is shown that houses that are located 10% further away from the nearest lake have a 0.02% lower price. Similar findings are reported in *Won Kim et al*. [2003] and *Sander and Polasky* [2009]. On the contrary, as we move 10% further away from the nearest large river, house prices increase with 0.004%. Although this is a relatively small price increase, this positive relationship may hint at the possible impact of flood risks on house prices [*Daniel et al*., 2007, 2009]. Switzerland is subject to riverine flooding on an annual basis [*Hausmann et al*., 2012], and the greatest flood catastrophe of the last 40 years took place in 2005. This catastrophic flood may possibly still exert a significant influence on our house sales prices located close to large rivers. A similar positive relationship between house prices and large rivers has been found in the Netherlands [*Daniel et al*., 2007, 2009]. For the distance to the nearest small river, no nonlinear effect is found and is therefore included as a linear variable. With every 100 m further away from the nearest small river, the house price drops with 0.03%. Model three explains 64.2% of the variation in house prices. This implies that the different water bodies add 0.1% to the explanatory power of the second model. The δR^2 shows that the structural house characteristics still have the largest relative contribution, but that out of all the environmental characteristics the distance to the nearest lake has the largest relative contribution to explaining house prices ($\delta R^2 = 0.0012$).

The fourth and final model nests the third model and focuses on the recreational benefits of living close to bathing sites and on the disamenity value associated with the presence of WWTPs. Compared to the

10.1002/2015WR017534

previous model, the signs of all variables remain unchanged. Nonlinear transformations of the distances to the nearest bathing site and WWTP do not improve the fit of the model. Applying a natural log transformation, the R^2 remains the same, as well as for the combined linear and squared distance term. The latter also shows a zero effect on price when the distance to the nearest bathing site changes. We therefore maintain the model with the untransformed distances to the nearest bathing site and WWTP and find that houses that are located 100 m further from a bathing site have on average a 0.12% lower price. Our results confirm the general perception that WWTPs are considered a disamenity given the positive relationship between the proximity of houses to the nearest WWTP. Houses that are located 100 m further away from the nearest WWTP sell on average and all else being equal at a 0.02% higher price. The final model explains 64.4% of the variation in house prices, with only 0.2% due to the inclusion of the distances to the nearest bathing site and WWTP. Comparing the δR^2, we find that the recreational function plays a more important role ($\delta R^2=0.0015$) than the disamenity represented by the WWTP ($\delta R^2 = 0.00005$). Still, these values are very low compared to the contribution of other house characteristics.

4.2. Robustness Checks

Although all cantons have a significant and negative relationship with house prices and house prices increase significantly between the years 2008 and 2010, canton-specific time trends may exist. To detect this, a canton-year fixed effect is included in the baseline model, model one, for each canton and each year. We find a time trend for half of the number of cantons that is more or less in line with the one at the national level. Namely, half of the number of cantons are significant and positive in either one or several years between 2008 and 2010. The absence of a time trend for the remaining cantons may be related to the large differences between cantons in terms of average house prices and numbers of house price observations. City fixed effects could in theory be used instead of canton-fixed effects. These city effects are however not further examined in this study, because the study focuses on the national level rather than the local level. Furthermore, each canton has multiple cities, which would only aggravate the inclusion of too many interaction terms, unless further arbitrary selection criteria would be applied, which falls outside the scope of this study. A robustness check on model one on the use of Euclidean distance to parks is carried out by replacing this with a road distance variable. The results show a significant and negative relationship with house prices, with no impact on the explanatory power of the model. This finding is similar to the use of the Euclidean distance to parks.

Also in model three, which incorporates water abundance as well as distances to different water bodies, the use of Euclidean distances to these water bodies is tested by replacing them with road distance variables. The only impact of using road distance is found in the distance to the nearest small river, which becomes insignificant. The explanatory power of the model remains unchanged. Another robustness check was carried out as to whether there is a lake, large river, or small river within 500 m around the house location. Including these three dummy variables in model three instead of the distance variables shows that house prices increase on average significantly when there is a lake within a radius of 500 m around the house. For small rivers however the opposite holds, namely house prices decrease when these types of water bodies are located in a radius of 500 m around the house. The dummy for the presence of a large river is insignificant. With also a relatively minor increase in explanatory power, these dummies are excluded from model three.

In model four, a test on the use of Euclidean distances to the nearest bathing site and WWTP shows that, replacing them with actual road distances, the increase in R^2 is minimal and not significant. Given the limited impact of road distance variables in each of the four models, and to stay in line with neighborhood-related distance variables, we maintain each model with water-related variables that are based on Euclidean distances.

The analysis of the relationship between house prices and water resources in the final model is furthermore expanded by incorporating a measure of water quality. The availability of sufficient data points for water quality, in relation to the number of house observations, is however very limited. With these limitations in mind, nevertheless a variable is created that provides a rough proxy for the chemical status of water, i.e., water quality. It is a point-source water pollution from WWTPs, estimated as the amount of wastewater (in m^3) to the discharge of the river. The amount of wastewater is calculated from the inhabitants connected to the WWTP [*BAFU*, 2008]. The relationship between house prices and water quality is, as expected, negative.

Table 4. Test Statistics of 4, 6, 8, 10, 12, and 14 Nearest Neighbor Weight Matrices

	4-NNW[a]	6-NNW	8-NNW	10-NNW	12-NNW	14-NNW
Moran's I statistic	0.531***	0.475***	0.434***	0.404***	0.380***	0.360***
Robust LMerr	8,512***	11,238***	13,324***	15,134***	16,859***	18,494***
Robust LMlag	2,185***	2,116***	1,896***	1,693***	1,535***	1,338***
Loglik	−8,998	−9,014	−9,232	−9,415	−9,544	−9,686
AIC	18,102	18,134	18,570	18,936	19,193	19,478
Pseudo R^2	0.694	0.694	0.692	0.691	0.690	0.689

[a]NNW stands for nearest neighbor weight matrix.
***$p < 0.001$.

However, the change in explanatory power is zero percent and insignificant. Based on this and given the limited number of data points, this proxy for water quality is considered sufficiently rough to be excluded from the final model.

Given the fact that the range of house prices varies greatly (between 20,000 CHF and 17,000,000 CHF), a final test is carried out, on model four, on the impact of excluding the 5 and 10% lowest and highest house price values. Compared to the unrestricted model, we find that most of the included variable signs and significance levels remain unchanged. Only the distances to the nearest railway station and WWTP are insignificant, where the latter is only insignificant when the 10% lowest and highest values are excluded. However, the absolute values of the coefficient estimates become generally smaller as we reduce the number of observations, as well as the R^2.

4.3. Spatial Hedonic Pricing Models

Although the full linear hedonic price model 4 in Table 3 incorporates various directly observable spatial characteristics to explain the variation in house prices, such as the geographical location of houses and their distances to several amenities, a Breusch-Pagan test indicates the presence of heteroskedasticity (BP test statistic = 6908, $p < 0.001$). This is not unexpected, because so far we have not considered any systematic unobservable spatial patterns in the house price observations. In order to account for the effect of one house price observation on another, a spatial weight matrix is constructed. Spatial weight matrices can be based on a distance-band for which a minimum distance is set, or they may be distance-based or boundary-based. Nearest neighbor weights are an example of distance-based weights. Based on centroid distances, the nearest neighbor option finds the k-nearest neighbors of each house price observation, where these neighbors influence the house price equally. Rook contiguity weights are an example of boundary-based weights that define areal units as neighbors if they share a common border. For technical details of the calculation of spatial weights, the interested reader is referred to *Anselin* [2003, 2005] and *Cressie* [2015]. Based on the choice of spatial weight matrix, the data can consequently be tested for spatial autocorrelation with a Moran's I test, i.e., whether and to what extent the data share boundaries. Significant clustering of the data may be an indication for the choice to incorporate spatial patterns of house price observations in the hedonic price model. Significant randomness in the data may be a reason to proceed with a nonspatial hedonic price model.

Several Swiss hedonic pricing studies have opted for a k-nearest neighbor weight matrix, because it is a convenient approach to deal with heterogeneity in the spatial distribution of data points [*Löchl*, 2007; *Salvi*, 2007, 2008; *Löchl and Axhausen*, 2010]. This is also the case at the national level, where heterogeneous data distributions can be explained by the fact that some cantons have many more inhabitants and house price observations than other cantons. We therefore tested the final model with 4, 6, 8, 10, 12, and 14 nearest neighbor weight matrices. It is uncommon in the hedonic pricing literature to use a number of neighbors that is much higher than this. Only in *Price et al*. [2010] tests were carried out ranging from the 2 nearest to the 100 nearest neighbors. They find that the 4 nearest neighbors perform optimally. In this study, all spatial weights are row-standardized, such that each weight can be considered as the fraction of all spatial effects of one observation on another. This is an intuitively attractive method [*Viton*, 2010] and therefore common practice in the literature [*Löchl*, 2007; *Salvi*, 2007; *Price et al*., 2010]. Scalar normalization is an alternative to this, and possibly more sophisticated as discussed in *Kelejian and Prucha* [2010], but has not yet found its implementation in the hedonic pricing literature and is therefore also not considered in this study.

Table 5. Spatial Error Models

	Spatial Error Model 1: Green Space	Spatial Error Model 2: Water Abundance	Spatial Error Model 3: Water Bodies	Spatial Error Model 4: Recreational Amenity and Disamenity
Intercept	1.340 (0.079)***	1.375 (0.080)***	1.486 (0.079)***	1.524 (0.079)***
House characteristics				
Living space	5.918 (0.019)***	5.917 (0.019)***	5.922 (0.019)***	5.930 (0.019)***
Year of construction	1.354 (0.025)***	1.359 (0.025)***	1.358 (0.025)***	1.360 (0.025)***
Garden	0.032 (0.002)***	0.032 (0.002)***	0.032 (0.002)***	0.033 (0.002)***
Neighborhood characteristics				
Elevation	0.195 (0.015)***	0.223 (0.016)***	0.211 (0.015)***	0.190 (0.015)***
Slope	3.336 (0.142)***	3.272 (0.143)***	3.188 (0.142)***	3.182 (0.142)***
Aspect	0.005 (0.009)	0.006 (0.009)	0.008 (0.009)	0.008 (0.009)
Distance to railway station	−0.006 (0.002)***	−0.004 (0.002)**	−0.005 (0.002)**	−0.002 (0.002)
Distance to bus	0.094 (0.008)***	0.098 (0.008)***	0.099 (0.008)***	0.100 (0.008)***
Distance to highway	−0.007 (0.001)***	−0.007 (0.001)***	−0.007 (0.001)***	−0.007 (0.001)***
Distance to school	−0.009 (0.004)*	−0.012 (0.004)**	−0.013 (0.004)**	−0.010 (0.004)**
LN(Distance to CBD)	−0.024 (0.003)***	−0.026 (0.003)***	−0.025 (0.003)***	−0.020 (0.003)***
Socioeconomic characteristics				
LN(Household income)	0.537 (0.010)***	0.522 (0.011)***	0.502 (0.011)***	0.496 (0.010)***
Population density	−0.525 (0.029)***	−0.518 (0.029)***	−0.527 (0.029)***	−0.537 (0.029)***
Cantons				
Zurich	−0.497 (0.045)***	−0.505 (0.045)***	−0.488 (0.044)***	−0.506 (0.044)***
Bern	−0.588 (0.045)***	−0.605 (0.046)***	−0.587 (0.045)***	−0.597 (0.044)***
Luzern	−0.523 (0.045)***	−0.543 (0.046)***	−0.541 (0.045)***	−0.550 (0.044)***
Uri	−0.512 (0.057)***	−0.529 (0.058)***	−0.513 (0.057)***	−0.469 (0.056)***
Schwyz	−0.486 (0.046)***	−0.521 (0.046)***	−0.525 (0.045)***	−0.528 (0.045)***
Obwalden	−0.539 (0.050)***	−0.566 (0.051)***	−0.541 (0.050)***	−0.563 (0.049)***
Nidwalden	−0.502 (0.052)***	−0.546 (0.053)***	−0.555 (0.051)***	−0.563 (0.051)***
Glarus	−0.711 (0.052)***	−0.718 (0.053)***	−0.704 (0.052)***	−0.734 (0.051)***
Zug	−0.548 (0.052)***	−0.567 (0.052)***	−0.566 (0.051)***	−0.574 (0.050)***
Fribourg	−0.617 (0.047)***	−0.634 (0.048)***	−0.637 (0.047)***	−0.631 (0.046)***
Solothurn	−0.635 (0.045)***	−0.645 (0.046)***	−0.592 (0.045)***	−0.600 (0.045)***
Basel-Stadt	−0.333 (0.047)***	−0.335 (0.047)***	−0.262 (0.047)***	−0.285 (0.046)***
Basel-Landschaft	−0.397 (0.045)***	−0.397 (0.046)***	−0.332 (0.045)***	−0.352 (0.044)***
Schaffhausen	−0.664 (0.047)***	−0.674 (0.048)***	−0.639 (0.047)***	−0.659 (0.046)***
Appenzell Ausserrhoden	−0.820 (0.048)***	−0.832 (0.049)***	−0.805 (0.048)***	−0.820 (0.047)***
Appenzell Innerhoden	−0.665 (0.058)***	−0.679 (0.059)***	−0.640 (0.058)***	−0.657 (0.057)***
St. Gallen	−0.639 (0.045)***	−0.654 (0.046)***	−0.630 (0.045)***	−0.644 (0.044)***
Graubünden	−0.486 (0.046)***	−0.511 (0.047)***	−0.442 (0.046)***	−0.435 (0.046)***
Aargau	−0.552 (0.045)***	−0.559 (0.045)***	−0.521 (0.045)***	−0.536 (0.044)***
Ticino	−0.396 (0.048)***	−0.409 (0.048)***	−0.432 (0.047)***	−0.442 (0.047)***
Vaud	−0.458 (0.048)***	−0.465 (0.048)***	−0.476 (0.047)***	−0.471 (0.047)***
Vallais	−0.763 (0.051)***	−0.779 (0.052)***	−0.735 (0.051)***	−0.746 (0.050)***
Neuchâtel	−0.650 (0.057)***	−0.679 (0.058)***	−0.681 (0.057)***	−0.666 (0.056)***
Jura	−0.788 (0.061)***	−0.798 (0.062)***	−0.749 (0.060)***	−0.742 (0.060)***
Thurgau	−0.670 (0.045)***	−0.689 (0.046)***	−0.679 (0.045)***	−0.687 (0.044)***
Years				
2006	0.000 (0.004)	0.000 (0.004)	0.000 (0.004)	0.001 (0.004)
2007	−0.004 (0.004)	−0.004 (0.003)	−0.003 (0.003)	−0.002 (0.004)
2008	0.008 (0.003)*	0.009 (0.003)**	0.011 (0.003)**	0.011 (0.003)**
2009	0.025 (0.004)***	0.025 (0.004)***	0.027 (0.004)***	0.027 (0.004)***
2010	0.048 (0.004)***	0.049 (0.004)***	0.050 (0.004)***	0.051 (0.004)***
Environmental characteristics				
Distance to park	−0.017 (0.004)***	−0.015 (0.004)***	−0.016 (0.004)***	−0.011 (0.004)**
Water abundance		2.904 (0.261)***	1.069 (0.314)***	0.841 (0.311)**
LN(distance to lake)			−0.025 (0.002)***	−0.024 (0.002)***
LN(Distance to large river)			0.009 (0.002)***	0.009 (0.002)***
Distance to small river			0.001 (0.003)	0.001 (0.003)
Distance to bathing site				−0.012 (0.001)***
Distance to WWTP				0.002 (0.001)
Pseudo R^2	0.691	0.691	0.692	0.692
Num. obs.	85,684	85,684	85,684	85,684
AIC	18,961	18,843	18,678	18,570
Log Likelihood	−9,433	−9,373	−9,288	−9,232
Df	46	47	50	52
Lambda statistic	0.535***	0.543***	0.532***	0.524***

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

A Moran's I test is carried out to test for spatial autocorrelation and shows in Table 4 that there is evidence of significant spatial autocorrelation and clustering (the Moran's I statistic ranges between 0.360 for the 14 nearest neighbors and 0.531 for the 4 nearest neighbors). The spatial patterns underlying house price observations therefore need to be incorporated in the hedonic pricing model. The Lagrange Multiplier test tells us whether this spatial structure should be incorporated in the dependent variable or in the error component of the model. For all nearest neighbor options, the outcomes of both the robust error test and the robust lag test are highly significant. Because it is difficult to select the most appropriate best fit model based on these nondistinct *p*-values, the spatial error model is chosen given that its robust error test statistic is highest in all nearest neighbor options (the Robust LMerr ranges between 8512 for the 4 nearest neighbors and 18,494 for the 14 nearest neighbors, $p < 0.001$; the Robust LMlag ranges between 1338 for the 14 nearest neighbors and 2185 for the 4 nearest neighbors) [*Anselin*, 2005]. Results of the spatial error models based on the different nearest neighbor weight matrices further show in Table 4 that between the 4 nearest neighbors and the 14 nearest neighbors there is relatively speaking very little difference between the Log-likelihood and AIC values of each model. Given these relatively small differences, we also find similar values for the pseudo R^2, which ranges between 0.689 and 0.694. Furthermore, with similar significance and signs, the impact of these different model specifications on coefficient estimates is very limited. To stay in line with the Swiss hedonic pricing literature [*Löchl*, 2007], we therefore choose to use here the 8 nearest neighbor weight matrix.

Rook contiguity weights are less often applied in the literature, but have also been tested and compared with the 8 nearest-neighbor model specification in this study. The latter provides statistically the best fit and is therefore used in the spatial error models (details about the rook contiguity matrix are provided in Appendix A of this paper).

Table 5 presents the results on the spatial error models. Compared to the four linear models, the significance levels and signs for most variables are similar in the spatial error models. In the third and fourth spatial error models, the distance to the nearest small river is insignificant. This is not unexpected as these are much less subject to flooding than large rivers. In the final spatial error model, we furthermore find insignificant distances to the nearest railway station and WWTP. Differences between most coefficients are relatively small. In the final model, the largest difference between coefficient estimates is found for the distance to the nearest large river, while no difference is found for the distances to the nearest highway and bathing site. In all four models, the variables explain 69% of the variation in house prices (measured now with the pseudo R^2), with each model showing less than 0.1% increase in explanatory power over the previous model.

Finally, a Breusch-Pagan test for the spatial error model shows that heteroskedasiticity remains significant (BP test statistic $= 4259$, $p < 0.001$). This indicates that, although the spatial model improves the model fit over the linear model, some spatial patterns in the spatial hedonic model remain unaccounted for.

5. Discussion and Conclusions

The impact of the global economic crisis on the housing market in Switzerland has been very limited and can be explained by a number of factors. The country has a well-developed house rental market, a low homeownership rate (37%), and conservative lending policies. In addition, house prices have been rising more in Switzerland than in other European countries because of the large influx of relatively highly qualified and wealthy migrants and it has experienced a strong increase in per capita income. The low homeownership rate and large rental sector are mainly due to the scarcity of land, explaining the high costs of housing, and the large foreign population. As a result, house prices have been stable throughout the global financial crisis [*Schneider and Karin*, 2015] and have been steadily increasing since 2009. Given the geographic constraints that Switzerland faces, i.e., lakes and mountains, the house planning system is lenient. This means that there is a strong incentive to permit development, in urban and rural areas, and there has been a large construction boom since 2009 [*Hilber*, 2014]. It is however unclear what the economic value is of different environmental amenities and whether these could be incorporated in more targeted geographic urban planning.

In this study, linear and spatial hedonic price models were estimated to explain the variation in house prices in Switzerland by including different characteristics related to water, as well as house, neighborhood, and socioeconomic characteristics. First a model was estimated that excluded water, but included green space. This contribution was then compared by including the variable water abundance. The following model zoomed in on different types of water bodies, measured as distances to the nearest lake, large, and small rivers. The final model focused on the relationship between house prices and the recreational value of water and the disamenity value, by including the distances to the nearest bathing site and WWTP, respectively. Robustness checks were carried out on potential nonlinearities in neighborhood and socioeconomic characteristics, as well in the water related distance variables. We furthermore tested for collinearity between variables, road distances versus Euclidean distances, the presence of water around each house location, a measure of water quality, and a housing set with less variation in house prices.

Our results suggest that with the inclusion of the distance to the nearest park, and without any of the water related variables, the first linear hedonic price model explains 64.0% of the variation in house prices. The inclusion of water abundance in the second model improves the explanatory power to 64.1%. This small improvement is due to the relatively large contribution of structural house characteristics. A δR^2 assessment of this model surprisingly shows that the contribution of water abundance of 0.13% is much larger than the 0.03%related to proximity to parks. Nevertheless, in our model the largest relative contribution of 49.1% comes from living space and income. This is followed by the year of construction with a contribution of 1.5%. In the third model, the distances to the different water bodies increase the explanatory power again with 0.1%. Also in this model we find that structural house characteristics have the largest relative contribution. However, out of all environmental characteristics, the distance to the nearest lake has with 0.12% the largest contribution. The fourth and final model shows that the relationship between house prices and the recreational value of water and the disamenity value represented by WWTPs are significant. The model explains 64.4% of the variation in house prices of which, in this 0.2% increase (compared to the previous model), the recreational function plays a more important role. Namely, the relative contribution of the distance to the nearest bathing site is 0.15%, while the distance to the nearest WWTP is 0.01%.

This incorporation of spatial effects in all spatial error models lead to an increase in the explanatory power (based on the pseudo R^2) to 69%, a higher log likelihood value and lower AIC. Each model shows less than 0.1% increase compared to the previous model. That means that the impact of adding more water related variables in the spatial models is limited, because the spatial effects pick up more explanatory power. Compared to other studies that also incorporated a number of water-related variables and were carried out at the canton or local level in Switzerland, the total explanatory power of 69% falls within the range of reported values. For example, *Löchl* [2007] explains 51% of the variation in house prices for the canton of Zurich, including view on the lake as the only water-related variable. *Schaerer et al*. [2007] report an R^2 of 60% for the region of Zurich and 65% for the region of Geneva. Their water related variables include view on the lake, distance to the lake, and the percentage of water area. With the view on the lake as their sole water-related variable, *Löchl and Axhausen* [2010] are able to explain 85% of the price variation. This is, however, largely due to the large number of incorporated household characteristics.

Looking at the contribution of each individual environmental variable to the model's explanatory power, this study shows that in the final model the largest contribution comes from the distance to the nearest bathing site. This variable also exceeds the importance of other distance variables in our study, including those related to neighborhood characteristics such as schools or shopping centers. The second largest contribution of environmental characteristics is the distance to the nearest lake. This corresponds to some extent with the findings reported in *Sander and Polasky* [2009], who show that of all their distance variables, proximity to lakes has the largest influence on house prices. Despite the improvement in model fit, with the incorporation of spatial patterns, we were unable to fully account for heteroskedasticity and part of the spatial autocorrelation remained unaccounted for.

The current study is an improvement compared to previous hedonic price models conducted in Switzerland by observing house sale prices rather than the house rental market, by covering data at national level for Switzerland as a whole rather than at canton or local (city) level, and by implementing both linear and spatial versions of the hedonic price model. Compared to the literature, we furthermore incorporate a variety of water variables related to the abundance of water, the proximity of different types and sizes of water bodies, as well as the recreational value of water and the disamenity value. The step-wise inclusion of these amenities enables us to study their relative contribution and find which ones are most valuable when setting house prices.

The housing market captures values from a multitude of structural house related characteristics that affect house prices, as well as the economic value of living in a particular location. With respect to location, this study shows that the housing market differentiates between several water related resources, including proximity to lakes, rivers of different sizes, bathing sites, and WWTPs. We find a statistically significant relationship between house prices and these environmental characteristics, showing for some a larger contribution to house prices than for others. As such, the housing development industry could make more geographically targeted planning activities in terms of these differently valued environmental amenities.

Appendix A: Rook Contiguity Weights

Rook contiguity weights use common boundaries to specify neighbors, i.e., a portion of the boundary of each observation is shared. Compared to the 8 nearest neighbors approach, contiguity weights have a number of neighbors that is not equal among the different observations. Based on the house price observations, the distribution of the number of neighbors in this study gives a minimum number of three neighbors and a maximum of 61. The mean number of neighbors is 11 with a standard deviation of 5.7.

Also with rook contiguity weights, there is significant presence of spatial autocorrelation (Moran's I statistic = 0.375, $p < 0.001$) and a spatial error model is applied based on its robust test statistic (Robust LMerr = 7517, Robust LMlag = 1445). With a significant value of the spatial autocorrelation coefficient ($\lambda = 0.54$, $p < 0.001$) and a relatively lower AIC (19,407), the spatial error model with rook contiguity weights is an improvement over the linear hedonic price model. The signs and values of the coefficients are almost all in line with the spatial error model with nearest neighbor weights. However, due to the increased number of neighbors, the distances to the nearest railway station and park have become insignificant. Eventually, based on the pseudo R^2, the model explains a similar 68.9% of the variation in house prices.

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