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Bubble Analysis of the Swiss Real Estate Market Using a Hedonic Index

Master Thesis

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Abstract

We generate real estate price indices that show the evolution of house and condominium prices in the various districts of Switzerland. The indices are constructed from a dataset of real estate transaction prices accompanied by a set of property characteristics using hedonic regression techniques, where the data comes from the Swiss real estate market between 2000 and the first half of 2015. The strength of the hedonic method is that it generates constant quality indices, which are not affected by changes in the overall quality of real estate properties transacted from quarter to quarter. This process is conducted independently in each of the 148 districts of Switzerland, for both houses and condominiums.

The construction of the hedonic index provides insights on which factors primarily drive real estate prices and how they differ across districts. The primary driver is naturally the size of the real estate property, but factors like quality of the neighborhood and the condition of the building are also highly positively correlated with the price.

Finally, using the Log-Periodic Power Law Singularity (LPPLS) bubble model on the time series of the price indices, a number of districts in Switzerland that exhibit strong signs of bubbles are identified. These are classified as the *critical districts*. There are also other districts with weaker bubble signs or where a bubble is likely to have already burst. These are classified as the *districts to watch*. It is important to monitor the price development in these districts, at the very least in order to verify these findings. Finally a few districts were a bubble definitely ended at some point in the past are also identified.

Contents

Chapter 1

Introduction

1.1 Significance of Real Estate Bubbles

1.1.1 Consequences of Real Estate Bubbles

Real estate bubbles can have a detrimental effect on the stability of the global financial system as well as on the overall economy. The bursting of housing bubbles in the US and globally in and around 2007 resulted in a credit crisis which is considered as the primary cause of the $2008 - 2009$ financial crisis according to Holt [2008]. The work of Jannsen [2009] suggests that real estate crises are often followed by recessions and present evidence that associate housing crises with a subsequent reduction in the GDP growth rate.

At the same time banks in particular have reason to monitor the real estate market for signs of bubble. Hott [2011] suggests that the following circular relationship exists. Banks' willingness to provide funds for real estate purchases depends on the creditworthiness of the buyers, which in turn depends on the level of real estate prices. Real estate prices are affected by the demand for housing which is influenced by the willingness of banks to provide funding. The author shows that a downward turn in the real estate market (which can be caused by the bursting of a real estate bubble) can lead to significant losses for the banks.

1.1.2 Current Situation in Switzerland

It is only natural that the Swiss National Bank (SNB) is interested in closely monitoring the development of real estate prices in Switzerland and in identifying signs of bubble. At the moment, the SNB publishes on a quarterly basis residential real estate price indices for the whole of Switzerland and annually for each of eight regions: Zurich area, Eastern Switzerland, Central Switzerland, Northwestern Switzerland, Berne area, Southern Switzerland, Lake Geneva area and Western Switzerland (SNB [2015]). In figure 1.1 one can see the evolution of some of these indices for the areas of Zurich and Lake Geneva, as well as for the whole of Switzerland, from 1970 until today (2015).

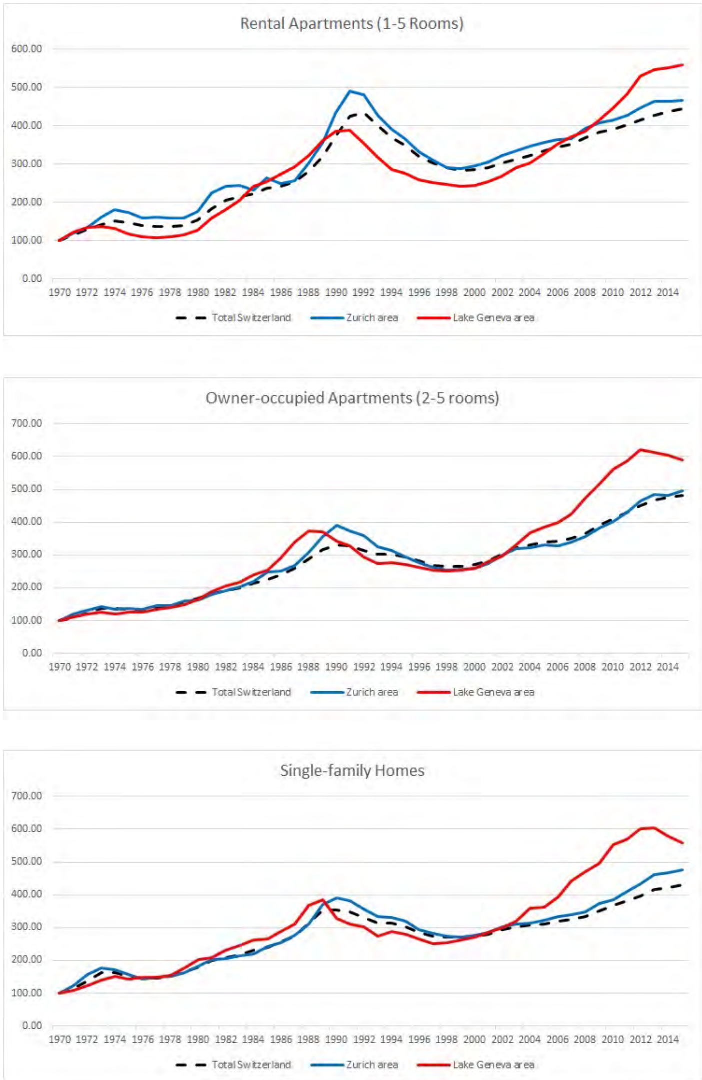


Figure 1.1: Evolution of various residential real estate price indices published by the SNB (1970 = 100)

Indices are provided for rental apartments, owner-occupied apartments and single-family homes. The calculations are performed by Wüest & Partner [1] and are based on asking prices with the sources being advertisements placed on print and internet media. In order to account for the heterogeneity of real estate properties, they are split into subgroups according to characteristics such as size, location, age or condition and a weighted average approach is used. Wüest & Partner additionally calculate other, transaction price based indices, using hedonic models.

Residential property prices in Switzerland have been upward trending over the past years. A recent report (UBS [2014]) suggests that the price increase is driven by the low level of interest rates, the increase in demand caused by immigration and by the overall growth of the Swiss economy. Prices however are still rising faster than wages, rents and consumer prices. This means that the risk of a market turn exists, either in the form of a correction or of a crash, typical of the bursting of a bubble.

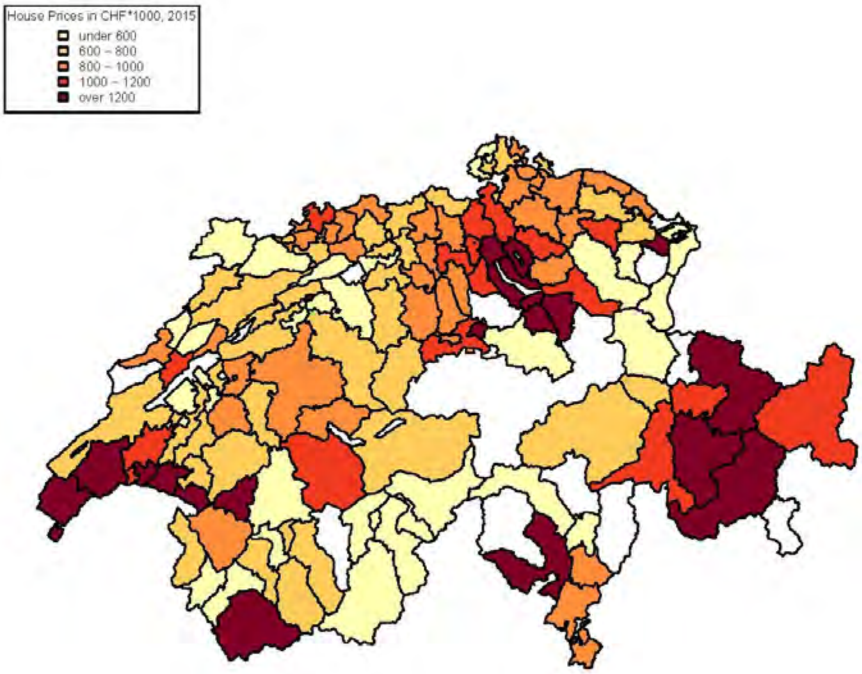
1.1.3 Current Price Level in Switzerland

In figure 1.2 one can see the current real estate price level across districts in Switzerland. The figures are based on median transaction prices from the Swiss Real Estate Datapool (SRED - see section 2.1) for the first half of 2015. The regions in white did not have any real estate transactions in the first half of 2015. As one can see, the most expensive districts are located in the cantons of Zurich, Geneva, Vaud and Graubünden, both for houses and for condominiums.

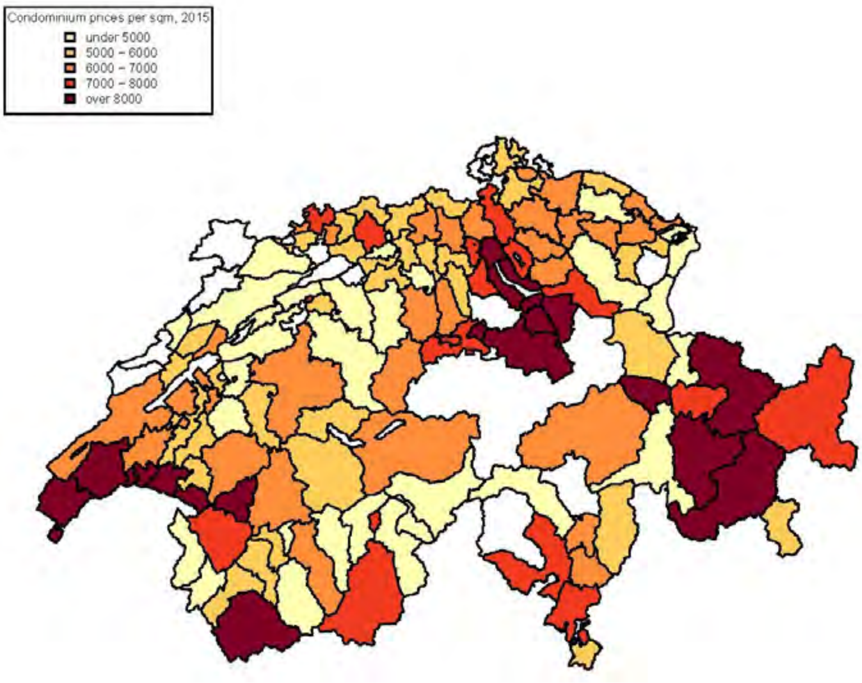
1.2 Previous Work and Motivation

In Ardila et al. [2013] Switzerland's residential real estate market was analyzed for signs of bubbles. The analysis was based on data collected by comparis.ch between 2005 and 2012 and consisted of asking prices. Properties were subdivided in three groups according to their size (number of rooms). Based on this data, price indices were computed for each subgroup in each of the 166 Swiss districts (there are only 148 since 1st January 2010 after some merging) by computing the median asking price and median asking price per square meter for houses and condominiums respectively. Afterwards, the Log-Periodic Power Law Singularity (LPPLS) (Johansen et al. [1999]) model was applied to the time series of the price indices to diagnose the risk of real estate bubbles. The LPPLS bubble model is explained in section 1.4.1 later. The result was that as of 2012$Q4$, 11 critical districts exhibiting signs of bubbles were identified and 7 more where the bubbles appeared to have already burst.

[1] `https://www.wuestundpartner.com/`



(a) Houses



(b) Condominiums

Figure 1.2: Median transaction prices in the first half of 2015 (in CHF×1000) based on SRED data

Also in Ardila et al. [2014] a diagnostic of real estate bubbles in USA and Switzerland was performed using a hybrid model that combined the LPPLS model with a diffusion index that was created from a number of macroeconomic variables. For Switzerland, the data covers the period between 1992 and 2013. As a price index, the national real housing index, as provided from the Bank of International Settlements, was used. The macroeconomic variables were obtained from the Swiss Federal Statistics Office and the SNB. The model diagnosed a housing bubble at the national level since 2012Q3.

The main goal is to improve on the work of Ardila et al. [2013] in two ways. First of all, by constructing the price indices using the hedonic method rather than taking median prices. The advantages of this approach are explained in detail in section 1.3 that follows. Secondly, our analysis is based on transaction prices, which describe the actual price level in the market more accurately than asking prices.

1.3 Real Estate Price Indices

A consistent and systematic method for constructing real estate price indices is necessary in order to be able to properly monitor real estate prices.

Using median prices over some period to estimate price indices is a rather simple approach, easily implemented and does not require much input data. However, since real estate properties are heterogeneous goods and the characteristics of houses sold can change from one period to another, a need for more sophisticated methods arises in order to control for differences in the overall quality of properties transacted over time (Eurostat [2013]).

Various methods have been developed and proposed. Below some of the most popular ones are described.

1.3.1 Repeat-Sales Indices

A popular approach for constructing a real estate price index is the repeat-sales method. This method uses data on properties that have been sold at least twice over the whole observation period. The method attempts to estimate changes in real estate prices over time by tracking the change in the sales price of the same property. This method, together with the hedonic approach which is described in detail in the next section, was applied already by Hoesli et al. [1997] to construct real estate price indices for the city of Geneva. An extension of this method, the *Weighted Repeat-Sales Method* was used by Jansen et al. [2008].

Formally, the following equation is estimated using a linear regression:

$$R = ln(P_2/P_1) = \sum_{t=1}^{T} \delta_t Dt + \epsilon \tag{1.1}$$

where P_2 is the price of the property at the time of the second sale, P_1 is the price of the property at the time of the first sale, R is the cumulative price appreciation between the two sales, D_t is a dummy variable equal to -1 for the period of the first sale, 1 for the period of the second sale and 0 otherwise, ϵ is the residual error of the estimate and δ_t are the estimated price indices for each period $t \in \{1, ...T\}$.

This method has the advantage of avoiding the problem of having to account for price differences in properties with different characteristics. At the same time, it requires very little input data: Transaction prices and dates, as well as a way to uniquely identify a property.

Nevertheless, there are several problems associated with this method. The main drawback is that it might be difficult to compile enough data to make accurate predictions, especially in a slow market. Also, properties that sell multiple times might not be representative of the overall population. Another issue is that a particular property's attributes can also change over time. Finally, as more data (transactions) become available in future time periods, they can alter the estimates of past price indices. This can happen if part of the new data is on properties that have transacted exactly once in the past.

1.3.2 Hedonic Indices

Another popular method for calculating price indices while taking into account the heterogeneity of real estate properties is the hedonic method, whose theoretical foundation was developed by Rosen [1974]. This method considers each property as a set of attributes. These attributes can be qualitative or quantitative characteristics of the property itself or locational characteristics of the property's neighborhood. The idea is to regress the sales price on these attributes and estimate the marginal contribution of each attribute to the price.

There are two approaches for estimating the evolution of price indices over time. In the first case, the following model is estimated for each time period t.

$$P = a + \sum_{k=1}^{K} \beta_k X_k + \epsilon \tag{1.2}$$

P is the sales price, X_k is a set of k of explanatory variables (property attributes) and ϵ is the property specific residual error value, normally distributed and with zero mean.

In order to get the price index, a benchmark property needs to be defined as a set of standard characteristics X_k^*. The value of this benchmark property is estimated for each period t by $P_t = a_t + \sum_{k=1}^{K} \beta_{kt} X_k^*$

Alternatively, it is possible to estimate one regression for all periods using time dummy variables:

$$P = a + \sum_{k=1}^{K} \beta_k X_k + \sum_{t=1}^{T} \delta_t D_t + \epsilon \tag{1.3}$$

where D_t is a dummy variable equal to 1 if the transaction took place in period t and 0 otherwise. The price index in this case is given by $P_t = a_t + \sum_{k=1}^{K} \beta_{kt} X_k^* + \delta_t$. An important difference is that the latter approach does not allow the mean and variance of the error term to vary among different periods.

The main advantage of hedonic models is that by decomposing a property to a set of structural and environmental characteristics, one can control for the natural heterogeneity of real estate properties since the value of each property is estimated by summing up the marginal contribution of a set of homogeneous attributes. Thus, this method is very robust to the potential change in the overall quality of real estate properties over time or new trends in the type of properties being bought and sold, phenomena that could be misinterpreted as changes in price levels by a more naive model. Bourassa et al. [2013] show how hedonic price indices can differ from median price indices due to data heterogeneity.

A natural drawback of the hedonic method is that it requires a very extensive data set, which includes the transaction price and the entire set of characteristics for each property. Such data sets are often not available or suffer from issues such as missing attributes or sample selection, both of which can impact the accuracy of the results.

Another drawback is that there is no consensus regarding the proper functional form of the hedonic regression model. Thus for a particular dataset the functional form can be misspecified, leading to biased parameter estimators.

A further issue with hedonic regression is the presence of spatial effects in real estate data (Anselin [1988a]). Those effects are spatial autocorrelation (1), also known as spatial dependence and spatial heterogeneity (2). Spatial autocorrelation refers to the fact that an attribute measured in a particular location is correlated to the same attribute measured nearby. Spatial heterogeneity is present when the effects of some attributes (on price) are not constant but vary across space. These spatial effects are often not fully explained by the included explanatory variables. If the model is estimated using a simple OLS regression and these spatial effects are ignored, it can lead to underestimated standard errors. If one of the goals is to assess the significance of various coefficients then spatial autocorrelation can lead to incorrect conclusions due to overestimated t-scores. However, it should be noted that the coefficients themselves are not affected by the presence of spatial effects.

Various methods have been developed to account for spatial autocorrelation and heterogeneity in the real estate market, some of which are described below.

Spatial Autoregressive Models (SAR)

Spatial autoregressive modeling, based on maximum-likelihood estimation, is perhaps the most popular approach to counter spatial autocorrelation. This method was first proposed by Anselin [1988b]. Three such models are tested by Kissling and Carl [2008], their difference lying on where the spatial dependence is believed to be present. As far as hedonic real estate price indices are concerned, this method was applied by Löchl and Axhausen [2010] to model hedonic residential rents.

1. **The SARlag model**

   The SAR lagged model assumes that the autoregressive process occurs only in the response variable and takes the following form:

   $$P = \rho \mathbf{W} P + \beta \mathbf{X} + \epsilon \tag{1.4}$$

   where P is the vector of transaction prices, ρ is the spatial autoregression coefficient, β is the the vector of regression coefficients, $\mathbf{X}$ is the matrix of observations on the independent variables, ϵ is a vector of independent and identically distributed error terms and finally $\mathbf{W}$ is a $N \times N$ spatial weight matrix, chosen by the user, where N is the sample size.

2. **The SARerr model**

   The SAR error model assumes that the autoregressive process is found only in the error term and takes the following form:

   $$\begin{aligned} P &= \beta \mathbf{X} + u \\ u &= \lambda \mathbf{W} u + \epsilon \end{aligned} \tag{1.5}$$

   where λ is the spatial autoregression coefficient, u is a vector of independent and identically distributed error terms and $\mathbf{W}$ is again the spatial weight matrix.

3. **The SARmix model**

   The SAR mixed model assumes that the spatial autocorrelation affects both the response and the explanatory variables and takes the following form:

   $$P = \rho \mathbf{W} P + \beta \mathbf{X} + \gamma \mathbf{W} \mathbf{X} + \epsilon \tag{1.6}$$

where γ describes the autoregression coefficient of the spatially lagged explanatory variables ($\mathbf{WX}$).

Which of the three models works best depends on the kind of spatial heterogeneity inherent in the data. One has to try and see which model best captures the spatial effects.

Geographically Weighted Regression (GWR)

Another extension of the OLS method is GWR, which was introduced by Fotheringham et al. [2002]. The method allows parameter estimates to vary geographically, thus estimating a different model for each data point. Compared to the SAR methods it can address not only spatial autocorrelation, but also spatial heterogeneity. The drawback is that it is computationally much more time-consuming. Essentially, GWR performs a series of local regressions. In its simplest form, a GWR model is expressed by the following equation

$$P_i = \alpha(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{k,i} + \epsilon_i \tag{1.7}$$

, where P_i is the i_{th} observation of the price (dependent variable), $x_{k,i}$ is the corresponding k_{th} explanatory variable, ϵ_i is the Gaussian error term, $\alpha(u_i, v_i)$ and $\beta_k(u_i, v_i)$ are the intercept and regression coefficient of the k_{th} explanatory variable estimated for local regression i and finally (u_i, v_i) are the location coordinates of the i_{th} observation.

In order to estimate a set of regression coefficients at each data point, GWR uses a weighted least squares approach, where observations are weighted according to their distance to this point. For data point i the estimation takes the following form:

$$\beta_i = (\mathbf{X}^T\mathbf{W}_i\mathbf{X})^{-1}\mathbf{X}^T\mathbf{W}_i\mathbf{P} \tag{1.8}$$

, where $\mathbf{X}$ is the $N \times K$ matrix of explanatory variables and $\mathbf{W}_i$ is a diagonal distance decay matrix customized for the location of i. The choice of a method for constructing the distance decay matrices lies with the user. First, a kernel function type must be selected. Popular options are a Gaussian kernel, $w_{ij} = exp(-d_{ij}^2/\theta^2)$ and a bi-square kernel:

$$w_{ij} = \begin{cases} (1 - d_{ij}^2/\theta)^2, & d_{ij} < \theta \\ 0, & d_{ij} > \theta \end{cases} \tag{1.9}$$

, where w_{ij} is the weight of observation j for estimating the coefficients at location i, d_{ij} is the (normally Euclidean) distance between i and j and θ is the bandwith size which can be either fixed for all locations or adaptive, $\theta_{i(k)}$ which is defined as the distance of the k_{th} nearest neighbor. Again the user must choose the method believed to be more appropriate. In either case, the optimal bandwith size θ or the optimal value of k is selected by optimizing some selection criterion such as the AIC (Akaike Information Criterion) Measure or the cross-validation (CV) score. The GWR approach was also tested by Löchl and Axhausen [2010]. An extension of GWR, the *Mixed-GWR* allows some of the variables to remain global. This method was used by Ricardo Crespo [2013] to construct a hedonic house price index.

1.4 Detecting Real Estate Bubbles

A housing price index provides information about the level of real estate prices relative to some reference point in time. Traditional methods for detecting real estate bubbles use the price index in combination with some other piece of information. Real estate bubble indicators are often based on metrics such as price to rent, price to household income, housing price to consumer price ratios and others (Holzhey [2013]). Macroeconomics factors are also often included.

For this thesis the bubble detection model used looks only at the development of real estate prices themselves and tries to identify price dynamics that indicate the existence of a bubble. The model is described below.

1.4.1 The Log-Periodic Power Law Singularity (LPPLS) Bubble Model

The Log-Periodic Power Law Singularity model was proposed by Johansen et al. [1999] as a way to (a) identify bubbles and (b) estimate the critical time where a regime change (end of a bubble) will occur. Below follows a summary of the model introduced in that paper.

A bubble is defined as a transient, super-exponential growth resulting from positive feedback loops and coupled with oscillations whose frequency is increasing over time. The oscillations occur under the assumption of a hierarchical organization of the market with two groups of agents: rational investors and 'noise' agents with bounded rationality who tend to exhibit herding behavior. This herding behavior is responsible for the positive feedback loops, while the oscillations are a result of the tension between the two groups of agents.

In this model the bursting of the bubble signals a regime change, where the price starts following different dynamics. This may not necessarily be a crash in the traditional sense, meaning a swift correction. It is also possible that the crash never occurs. This is a necessary component of the model as, in order for the bubble to exist, agents should continue to invest and earn compensation for the risk of a crash through the price increase generated by the bubble. Thus, the probability of the crash occurring must be strictly smaller than 1. The model is described in some detail below.

The market is assumed to consist of only one speculative asset that pays no dividend and has a price of $p(t)$ at time t. If t_0 denotes some initial time, then $p(t_0) = 0$, since the asset pays no dividends and $p(t)$ can be interpreted as the price in excess of the asset's fundamental value. In general the following hypothesis holds as a consequence of rational expectations:

$$\forall t^{'} > t \quad E_t \left[p(t^{'}) \right] = p(t) \tag{1.10}$$

The probability of the crash is assumed to be exogenous. The crash itself is modeled by a jump process j which is equal to 0 before the crash and 1 afterward. Also let $Q(t)$ be the cumulative distribution function of the time of the crash and $q(t) = dQ/dt$ the probability density function. Then $h(t) = q(t)/\left[1 - Q(t)\right]$ is the hazard rate: the probability per unit of time that the crash will happen in the next instance if it hasn't already happened.

Under the simplifying assumption that in case of the crash the price drops by a fixed percentage $\kappa \in (0, 1)$ then the price dynamics before the crash are described by:

$$dp = \mu(t)p(t)dt - \kappa p(t)dj \tag{1.11}$$

where $\mu(t)$ is a time-dependent drift. Under the condition $E_t\left[dp\right] = 0$, we get $\mu(t) = \kappa h(t)$. Solving this differential equation we get

$$log \left[\frac{p(t)}{p(t_0} \right] = \kappa \int_{t_0}^{t} h(t^{'})dt^{'} \quad \text{before the crash} \tag{1.12}$$

Therefore, the higher the probability of the crash the faster the price increases, to compensate investors for holding an asset that might crash. Even though this may seem counter-intuitive at first, it is consistent with rational expectations.

The agents (traders) are assumed to form a network through which they influence each other *locally*. Thus, each agent's opinion is influenced by two forces: (a) The opinion of his k nearest neighbors in the network, which he tends to imitate and (b) an idiosyncratic signal that he alone receives. Force (b) tends to create disorder, as in normal times, while when force (a) tends to create order that might lead to the bursting of a bubble when it leads to a coordinated action where everyone is placing 'sell' orders. Overall each agent is in one of two states, such as buy/sell (or bullish/bearish).

Johansen et al. [1999] also introduce two parameters which govern the tendency towards imitation or order versus idiosyncratic behavior. Furthermore, it is assumed that the agents form a hierarchical diamond lattice. Such a network is constructed in the following way: Starting with 2 agents linked to each other, replace the link with a diamond where the original traders are sitting on opposite sides and there are 2 new agents added to the network, which now contains 4 links. Continue in the same way, replacing each of the 4 links with a diamond. After p iterations there are $\frac{2}{3}(2+4^p)$ agents and a total of 4^p links. Most agents are only linked to 2 neighbors. The 2 'initial' agents have 2^p connections and everyone else in-between. This model is considered a more realistic approximation of the network of interconnections and communications between financial agents in the market.

Under the assumptions above Johansen et al. [1999] show that there exists a critical time t_c where for $t < t_c$ the following equations describe the evolution of the hazard rate as well as the price.

$$h(t) \approx B_0(t_c-t)^{-\alpha} + B_1(t_c-t)^{-\alpha} cos\left[\omega log(t_c-t)+\psi\right] \tag{1.13}$$

$$log\left[p(t)\right] \approx log\left[p_c\right] - \frac{\kappa}{\beta}\left\{B_0(t_c-t)^{\beta} + B_1(t_c-t)^{\beta}\cos\left[\omega log(t_c-t)+\phi\right]\right\} \tag{1.14}$$

where $\alpha \in (0,1)$, $\beta = 1-\alpha$, p_c is the price at the critical time (assuming no crash has happened beforehand), $\frac{\omega}{2\pi}$ is the log-frequency of the accelerating oscillations and ψ and ϕ are phase constants.

It is important to note the following:

- α (and therefore also β) has to be between 0 and 1 as otherwise the price would go to infinity as t approaches t_c.
- The critical time t_c is not the time of the crash, but the mode of the distribution of the crash time, meaning the most likely time that the crash will happen. It is possible, but not likely, that the crash happens before $t = t_c$. There is also a positive residual probability of reaching the t_c without a crash. This is crucial for the model as explained earlier.
- Any model that includes a group of noise trades influenced by neighbors with local imitation propagating spontaneously, crashes being caused by global cooperation of these noise traders, with prices related to system properties and system parameters evolving over time would display similar characteristics: A price increase following a power law in the neighborhood of a critical time.

The model described above can be used in the following way to detect financial bubbles: Given a time series of log-prices, equation 1.14 needs to be fitted with the time-series. There are 7 parameters that need to be estimated. Three linear ($A \equiv log(p_c), B \equiv \frac{-\kappa B_0}{\beta}, C \equiv \frac{-\kappa B_1}{\beta}$) and four non-linear ($\beta, t_c, \omega, \phi$), subject to some constraints that have already be mentioned (such as $\beta \in (0,1)$) and some additional ones that were derived empirically. For example, once such constraint is that $6 \leq \omega \leq 13$ which makes sure that the log-periodic oscillations are neither too fast nor too slow.

To determine these 7 parameters the least-squares method can be used. However solving such a non-linear minimization problem is anything but trivial due to the presence of various local minima. Nevertheless, a transformation is possible that significantly reduces the complexity of this minimization problem. As a first step, the linear parameters can be slaved to the non-linear ones. Therefore, if $S(A, B, C, \beta, t_c, \omega, \phi)$ is the function that needs to be minimized the following holds:

$$\min_{A,B,C,\beta,t_c,\omega,\phi} S(A, B, C, \beta, t_c, \omega, \phi) \equiv \min_{\beta,t_c,\omega,\phi} S_1(\beta, t_c, \omega, \phi) \tag{1.15}$$

where

$$S_1(\beta, t_c, \omega, \phi) = \min_{A,B,C} S(A, B, C, \beta, t_c, \omega, \phi) \tag{1.16}$$

Finally, Filimonov and Sornette [2013] showed that a further transformation is possible, reducing the number of non-linear parameters from 4 to 3 and having 4 linear parameters instead. This is achieved by re-writing equation 1.14 as follows:

$$log\,[p(t)] \approx A + B(t_c - t)^\beta + C_1(t_c - t)^\beta \cos\left[\omega log(t_c - t)\right] + C_2(t_c - t)^\beta \sin\left[\omega log(t_c - t)\right] \tag{1.17}$$

where $C_1 = C \cos\phi$ and $C_2 = C \sin\phi$. Similarly to before, it is possible to slave the 4 linear parameters to the 3 non-linear ones. The above process significantly reduces the complexity of the non-linear optimization problem. For this work, an implementation of the fitting process as described by Filimonov and Sornette [2013] was used.

Chapter 2

A Hedonic Real Estate Price Index

2.1 The Data Source

The Swiss Real Estate Datapool (SRED[1]) is an non-profit organization that provided us access to a large set of Swiss real estate transaction data that include the transaction price and various property and locational attributes. This dataset was compiled with the collaboration of 3 large Swiss banks - members of SRED (UBS, Credit Suisse and ZKB) and allows the possibility to construct a real estate price index based on the hedonic method. Hence, the purpose of this thesis is to analyze the Swiss real estate market for signs of bubble using hedonic-based price indices which can more accurately reflect the price level than indices based on median asking prices.

2.2 Data Used

The data used to construct the hedonic index was downloaded from SRED and contain real estate transactions in Switzerland for the period spanning from $2000Q1$ until $2015Q2$, a total of 62 quarters. The first three quarters (until $2000Q3$) had significantly fewer observations than the rest and were not taken into account. In particular, all three quarters had fewer than 2000 observations in total, while the minimum number of observations in any of the following quarters was 2381 ($2002Q1$).

Therefore the time window for our analysis spans from $2000Q4$ until $2015Q2$, for a total of 59 quarters. Table 2.1 lists the relevant fields contained in the SRED Data.

The SRED data contains 220‘012 observations in total, each of them belonging in one of 148 different districts (or *Bezirk*). There are 95‘916 trans-

[1] `http://www.sred.ch/`

Attribute	Value/Description
OBJEKT_ART_CODE	1: Single-family homes, 2: Condominiums
BAUJAHR	Year on which property was built
EFH_ART_CODE	(For single-family homes only) 1: Detached or 2: Attached (to other property)
PLZ_CODIERT	Postal code
BFS_BEZIRK_ID	District identifier
BFS_BEZIRK_NAME	District
BFS_KANTON_ID	Canton identifier $(1-26)$
BFS_KANTON_NAME	Canton
BFS_MSREGION_ID	MS Region identifier $(1-106)$
BFS_MSREGION_NAME	MS Region
BFS_GEMEINDETYP9_ID	Area type identifier $(1-9)$
BFS_GEMEINDETYP9_NAME	Area type: Agrarian, Mixed, Suburban, Periurban, High-income, Rural, Industrial, Touristic, City-Center
QUARTAL_EIGENTUM	Year & Quarter of the transaction
KAUFPREIS	Transaction price
KUBATUR_CHAR	Property volume (in m^3) for single-family homes
NETTOWOHNFLAECHE_CHAR	Net living area (in m^2) for condominiums
ANZAHL_ZIMMER_CHAR	Number of rooms
ANZAHL_NASSZELLEN_CHAR	Number of bathrooms
ANZAHL_GARAGENPLATZ_CHAR	Number of garage places
MIKROLAGE_CODE	Micro-location (neighborhood) ranking, between 1 (bad) and 4 (great)
QUALITAET_CODE	General Property quality ranking $(1-4)$
GEBAEUDE_ZUSTAND_CODE	Building condition ranking $(1-4)$
ERST_ZWEIT_DOMIZIL_CODE	1: Primary residence or 2: Secondary residence

Table 2.1: SRED attributes

actions of single-family homes and 124‘096 of condominiums. The region with the highest total number of condominium transactions is the Canton of Geneva (8‘266) and of houses Bern-Mitteland(4‘345). The fewest observations are located in the district of Bernina for houses and in Unterklettgau for condominiums with only 15 and 5 observations respectively across the whole dataset.

On average there are 25 observations for each district-quarter combination, 14 condominiums and 11 houses. However there is a significant number of cases where some districts have no transactions at all on some quarters. Table 2.2 below contains some descriptive statistics.

	(a) Observations Per District			(b) Observations Per Quarter		
Property Type	**Min**	**Max**	**Avg**	**Min**	**Max**	**Avg**
Houses	15(Bernina)	4‘345(Bern-Mitteland)	648	938(2014$Q1$)	2‘786(2006$Q3$)	1‘626
Condominiums	5(Unterklettgau)	8266(Geneva)	838	1‘164(2001$Q1$)	3‘512(2006$Q4$)	2‘103

Table 2.2: Observations per district & quarter

One can also see where the majority of observations are located in figures 2.1 and 2.2.

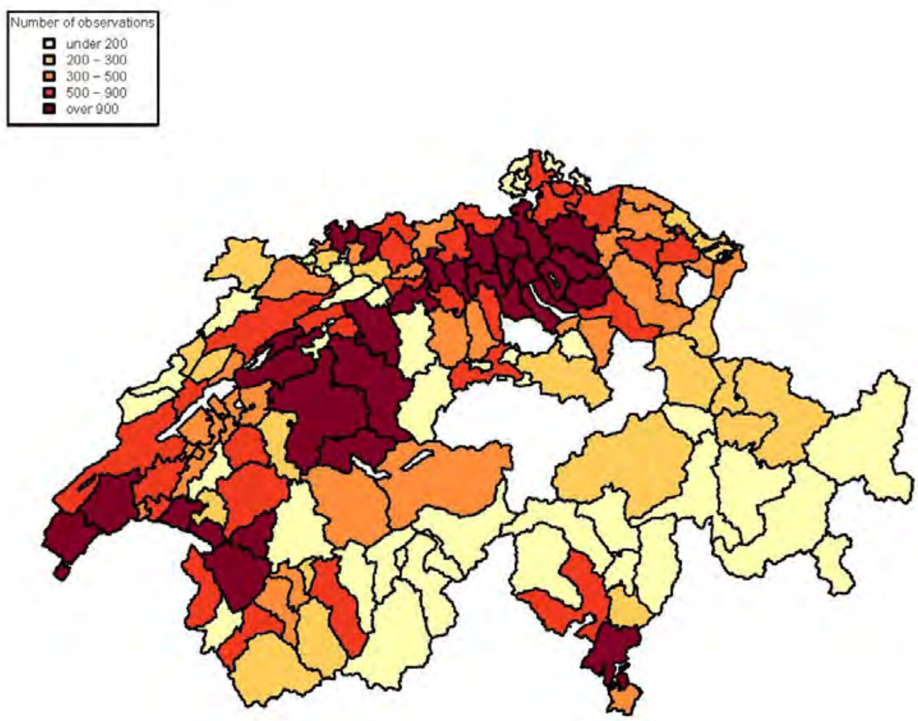


Figure 2.1: Number of observations of house transactions across districts between 2000$Q4$ and 2015$Q2$

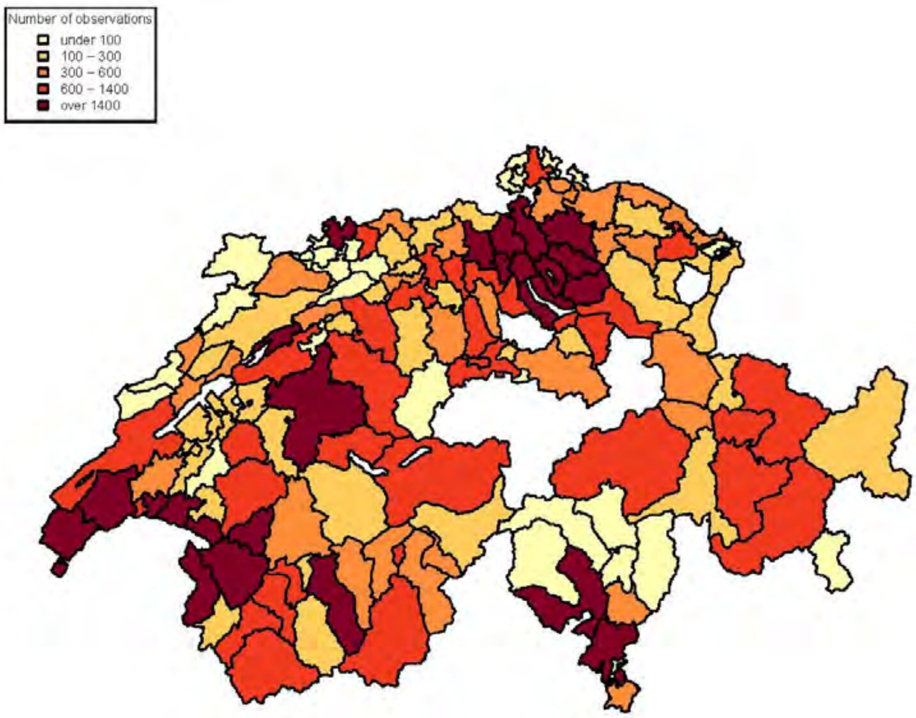


Figure 2.2: Number of observations of condominium transactions across districts between 2000$Q4$ and 2015$Q2$

The main goal of this thesis is to construct two time-series of price indices for each district, one for houses and one for condominiums, based on a hedonic model. The model to be used should be the same for all districts. The outcome then shall be examined in aggregate in order to identify trends that are present in all or most of the districts. Such trends can be related to the evolution of the price dynamics or to the effect of the various property attributes on price. At the same time a nation-wide index will also be generated. Finally, each time series will be examined independently for signs of bubble.

Another thing worth mentioning is that, for each property, location information is provided on ZIP code level. This is important since some of the advanced spatial analysis methods described in the previous chapter require the calculation of a weight matrix based on distances between pairs of properties. Without the exact location information, some simplifying approximation will be necessary.

2.3 Choosing the Appropriate Model

A number of decisions need to be made with regard to which hedonic model to use and its details. These issues were addressed one by one using the transaction data for the districts of Geneva and Zurich-City as test cases. The data was initially partitioned in two subsets, single-family homes (houses) and condominiums, which were treated independently. Initially, the simple OLS regression method was applied for the first steps towards choosing the appropriate model. Once the greatest part of the model was specified, more advanced regression techniques were also tested. The whole analysis was performed in the software environment *R*.[2]

The dependent variable, transaction price (*Kaufpreis*), was regressed on the set of variables shown in table 2.3.

With the exception of property size, every other characteristic is described by a group of dummy variables, one for each possible value it can have except for the one chosen as the base case. For the variables describing the property's age, the base case was chosen to be the period $1901 - 1970$ as it was the most common one in the dataset. For the same reason the base case for the area type was chosen to be the city center (AREA_ZEN). With regard to the number of bathrooms, number of garages and the three qualitative scores, the worst possible value was chosen as base case. The rationale is that the coefficients corresponding to the dummy variables will describe the incremental effect of an improvement in these characteristics (more bathrooms, more garages or better scores) on the property's value.

The number of rooms (*Anzahl_Zimmer_Char*) was purposely left out as one would expect a high degree of multicollinearity to net living area (or volume for houses). Specifically, the correlation coefficient between net living area and number of rooms was found to be 0.78. For houses, the correlation coefficient between volume and number of rooms is 0.59.

The explanatory variables can be categorized as (i) structural variables: net living area or volume, detached/attached property, building age and others (ii) locational variables such as micro-location quality score or area type variables and (iii) time dummy variables.

The three qualitative scores, *Mikrolage_Code*, *Qualitaet_Code* and *Gebaeude_Zustand_Code*, were computed by those who provide the transaction data to the SRED dataset (the banks) based on a number of relevant structural and/or locational attributes. Unfortunately, each bank that contributes data to SRED estimates these scores on their own, which means that there is not one single method that is consistently applied.

[2] `https://www.r-project.org/`

Variable	**Description**
NETTOWOHNFLAECHE_CHAR	Net living area in m^2
KUBATUR_CHAR	Volume in m^3
IS_DETACHED	Binary (dummy) variable for single-family homes
BUILT_BEF1900 BUILT_71TO80 BUILT_81TO90 BUILT_91TO00 BUILT_AFT2000	Binary variables for BAUJAHR. 1901-1970 is the base case
AREA_SUB AREA_RE AREA_PERI AREA_TOUR AREA_IND AREA_PEND AREA_MIX AREA_AGR	Binary variables for area type. City-center (AREA_ZEN) is the base case
BATHROOM2 BATHROOM3 BATHROOM4	Binary variables for number of bathrooms. 1 bathroom is the base case
GARAGE1 GARAGE2 GARAGE3	Binary variables for number of garages. 0 is the base case
LOC_AVG LOC_GOOD LOC_GREAT	Binary variables for micro-location ranking. 'Bad' is the base case
QUAL_AVG QUAL_GOOD QUAL_GREAT	Binary variables for quality ranking. 'Bad' is the base case
BUILD_AVG BUILD_GOOD BUILD_GREAT	Binary variables for building condition ranking. 'Bad' is the base case
FIRST	Binary variable for primary versus secondary residence
Q2-Q59	Binary variables for quarter of the transaction. Q2 is 2001Q1 and Q59 is 2015Q2. 2000Q4 is the base case

Table 2.3: List of independent variables used in the regressions

2.3.1 Functional Form and Choice of Dependent Variable

There is no general consensus regarding the appropriate functional form of the hedonic equation. The majority of the independent variables are dummy ones, but still a choice needed to be made about the dependent variable (transaction price) and the metric variable that measures property size: volume (m^3) for houses and net living area(m^2) for condominiums.

The following functional forms were tested: linear-linear, linear-log, log-linear and log-log. In the end the log-log model was chosen as it led to better overall model fit, as measured by both the R-squared and the adjusted R-squared measures. Both measures were higher in all four cases tested (houses and condominiumss in Zurich and Geneva).

This was expected, at least for the dependent variable, as a change in one property or locational attribute, all else equal, should have an impact on the transaction price that is dependent on the price level.

Finally, an attempt to use $price/m^2$ or $price/m^3$ respectively as the dependent variables was made. However this led to a significantly lower model fit so the idea was promtly discarded. The table below shows the goodness-of-fit results for condominiums in the district of Geneva. The situation is similar for the other three test cases.

Case	Lin.	Log-Lin.	Lin.-Log	Log-Log	Log-Log, pr./m^2
R^2	0.7585	0.8242	0.7375	0.8442	0.6835
Adj.R^2	0.756	0.8224	0.7348	0.8426	0.6802

Table 2.4: Different model fits for condominiums in Geneva

2.3.2 Houses and Condominiums as Separate Datasets

If we had the same metric for all properties, for example if we had the net living area in m^2 for single-family homes, it would be possible to estimate just one hedonic equation, by combining the two datasets and using appropriate dummy variables to differentiate between the various property types (such as *IS_DETACHED_HOUSE* and *IS_ATTACHED_HOUSE* with *IS_CONDO* the base case). This would also help mitigate to some extent the issue of insufficient amount of data in some regions.

Another option would be to approximate the net living area for single-family homes based on the volume of the property. This would assume that a more or less linear relationship between the two values exists. However, we had no clear evidence supporting that. Most importantly though, even if an approximately linear relationship between volume and net living area does exist, the levels of the corresponding coefficients from the separate regressions suggest that the effect of property size on price is higher for condominiums that for single-family homes. This heterogeneity is also evident in other explanatory variables and would require a number of interaction terms to be included in the regression. Examples of this heterogeneity include the difference in the significance (and hence in the effect on price) of characteristics such as property age or number of parking spots between houses and condominiums. For evidence of this heterogeneity the reader is referred to the appendix (tables A.1, A.2, A.3 and A.4), where the full OLS regression results of the log-log model are shown. One can notice there that coefficients corresponding to the same explanatory variables for the same district differ a lot between houses and condominiums.

In the end, treating the two subsets separately seemed like a more sound approach.

2.3.3 Treatment of Time Period Information

As explained in the previous chapter, an alternative to including the time-period dummy variables ($Q2-Q59$) would be to run a separate regression for each time period. In theory, this approach has the advantage of being robust to a potential temporal heterogeneity in the data, as it allows parameter estimates to vary across time periods. In practice however the number of observations per quarter is simply insufficient for a regression equation to be properly estimated. Also, the contribution of the various property attributes to the price is unlikely to change from one quarter to anther.

We already mentioned earlier that for a significant number of district-quarter combinations we have 0 observations. This approach could only be applied in the largest districts (in terms of sample size), such as Geneva where, when it comes to condominiums, there are at least 86 observations in each quarter. However, even in the case Geneva, the price indices generated this way are quite 'noisy' as can be evidenced by graph 2.3.

2.3.4 Spatial Autocorrelation Tests

The analysis done so far was based on the outcomes of ordinary least squares (OLS) regressions. As mentioned earlier, real estate data often suffers from spatial dependence and heterogeneity, effects which are not fully taken into account by the locational variables included in the model. As a first step, the residuals of the OLS regression were tested for spatial autocorrelation and heteroskedasticity.

The main test performed was the calculation of the *Moran's I* value (Moran [1950]):

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \tag{2.1}$$

where $i, j \in 1, ..., N$ are both indexing observations from our dataset (real estate transactions), N is the total number of observations and x is the

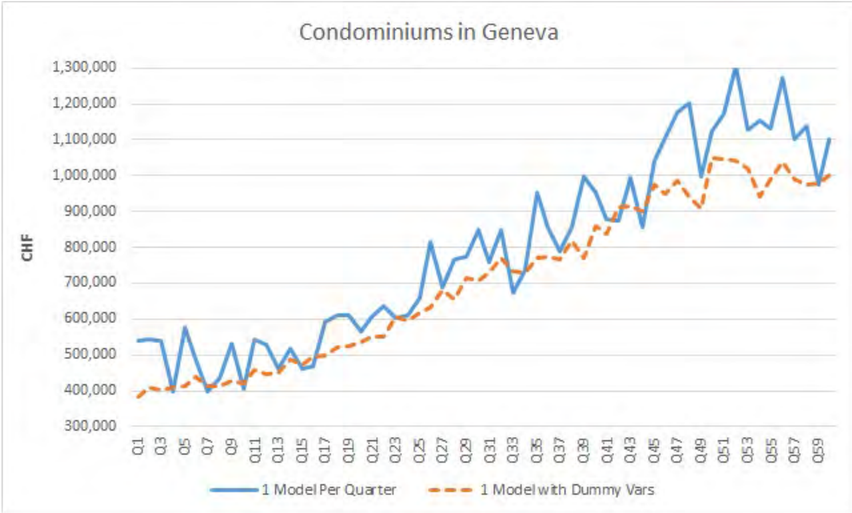


Figure 2.3: Hedonic index for condominiums in Geneva using one model per quarter versus quarterly dummy variables (prices in CHF)

variable of interest, in this case the residuals of the regression. Under the null hypothesis of no spatial autocorrelation,the expected value is $E(I) = \frac{-1}{N-1}$. A value of zero indicates a random spatial pattern. A value of $+1$ indicates perfect correlation and -1 perfect dispersion. The expected variance of the statistic is also known, thus it is possible to test the null hypothesis and calculate p-values.

To understand this statistic intuitively notice that when values for neighboring observations are either both larger or both smaller than the mean, then the cross-product $(x_i - \bar{x})(x_j - \bar{x})$ will be positive. The denominator serves to normalize the Moran's I value between -1 and $+1$. Therefore, if the values in the dataset tend to cluster spatially with high values close to other high values, then the Moran's I will be positive and tend towards $+1$ the stronger this phenomenon is.

We also performed the Lagrange multiplier test diagnostics (Anselin [1988a]). The idea behind them is the following: Consider the specification below

$$\begin{aligned} y = & \quad \rho W_1 y + \beta X + u \\ u = & \quad \lambda W_2 u + \epsilon \end{aligned} \tag{2.2}$$

,which is essentially a combination of the SARLag and SARErr models presented section 1.3.2. The spatial weight matrices W_1 and W_2 are allowed to be different to account for the case where the spatial autoregressive processes in the dependent variable and in the error terms are driven by different spatial structures.

The Lagrange multiplier test for a missing spatially lagged dependent variable (*LMLag*) tests the null hypothesis $H_0 : \rho = 0$. Similarly, the test for spatial autocorrelation of the error term (*LMErr*) tests whether $\lambda = 0$.

The are also the robust versions of the same two tests (*RLMLag* & *RLMErr*) that test for the one spatial effect in the possible presence of the other.

Construction of the Contiguity-Weighted Matrix

In order to perform the aforementioned tests a spatial weights matrix needs to be defined. For each location in the system, this matrix specifies which other locations affect the value in that location and are therefore its 'neighbors' (Anselin [1988b]). Every neighbor gets a non-zero weight w_{ij} based on some scheme. Ideally the weights matrix should be constructed in such a way that it properly represents the spatial dependence structure of the data. Often however matrices that are just empirically convenient are used (Anselin [2002]).

With regard to specifying the weights the two main approaches are to use either inverse distances, perhaps raised to some power, or binary weights, often divided by the number of neighbors so that the sum of weights per row is equal to 1. This procedure is called row-standardization. With regard to specifying the neighbors there are various approaches such as:

1. Spatially contiguous neighbors
2. Fixed bandwidth (neighbors within some fixed distance d)
3. k nearest neighbors (so bandwidth is different on each location)

In our case, the fact that exact locations are not provided, but only ZIP codes, severely restricts the possibilities. The only feasible approach is to consider observations within the same ZIP code as neighbors and the rest as non-neighbors. Taking observations of adjacent ZIP code areas as neighbors as well would be problematic as there are districts that have as few as 6 ZIP codes and where, given their adjacency, this method would lead to locations having a neighbor relationship with more than half of the dataset in the district.

Therefore the weights matrix was constructed as follows:

$$w_{ij} = \begin{cases} (1/\sum_j w_{ij}, & i, j \text{ in same ZIP code} \\ 0, & i, j \text{ in different ZIP codes} \end{cases} \tag{2.3}$$

,where i and j are both indexing the set of observations. Dividing by $\sum_j w_{ij}$ achieves row-standardization. This way the sum of weights of all the neighbors is equal to 1 for all observations, thus the significance of the neighbors as opposed to the characteristics of the property itself is the same for all properties during the model estimation.

Test Results

Below, in tables 2.5 and 2.6, are the calculations of *Moran's I* and the Lagrange Multiplier test results for the OLS regression on our test case datasets.

Case	Observed Moran's I	Expectation	Variance
ZH_Condos	0.239	$-4.27 \cdot 10^{-4}$	$1.61 \cdot 10^{-6}$
ZH_Houses	0.122	$-1.39 \cdot 10^{-3}$	$2.5 \cdot 10^{-5}$
GE_Condos	0.101	$-8.72 \cdot 10^{-4}$	$1.6 \cdot 10^{-6}$
GE_Houses	0.088	$-1.53 \cdot 10^{-3}$	$5.4 \cdot 10^{-6}$

Table 2.5: Moran's I scores for OLS. They all correspond to a p-value of 0

Case	LMlag	LMerr	RLMlag	RLMerr
ZH_Condos	2'966.81	30'740.57	697.56	28'471.32
ZH_Houses	386.22	535.58	181.55	330.91
GE_Condos	1'007.34	5'504.90	159.01	4'656.56
GE_Houses	493.90	1'267.28	98.89	872.27

Table 2.6: LM test Scores for OLS. They all correspond to a p-value of 0

The results indicate that spatial autocorrelation and heterogeneity are present and significant in all four cases. Ideally, apart from calculation of the price index, a secondary goal is to assess the significance of each characteristic that contributes to a property's value. In order to have more reliable *t*-statistics, it is best to address the issue of spatial autocorrelation. Some of the methods presented in the section 1.3.2 are subsequently tested.

2.3.5 Spatial Autoregressive Methods

All three methods presented earlier were tested (SARLag, SARErr, SARMix). The spatial weights matrix used was the one defined in equation 2.3. The full regression results for all three methods, as well as for the OLS method, are available in the appendix (tables A.1 - A.16).

The outcome of *Moran's I* calculation for the SAR models can be seen in 2.7 below.

Out of the three, we see that the SAR lagged model did not really solve the issue of spatial autocorrelation. Another issue inherent with this model is the assumption that the estimated price of some observation depends on the observed transaction price of nearby properties does not account for the potentially different time periods that these transactions occurred.

Both the SARErr and the SARMix model seem to successfully solve the issue of autocorrelation. Comparing the two models in terms of goodness of

	SARLag		SARErr		SARMix	
DataSet	Moran I	p-value	Moran I	p-value	Moran I	p-value
ZH_Condos	0.0895	0.000	$-2.49 \cdot 10^{-4}$	0.515	$-4.54 \cdot 10^{-4}$	0.999
ZH_Houses	0.0137	0.003	$5.21 \cdot 10^{-4}$	0.405	$-1.48 \cdot 10^{-2}$	0.997
GE_Condos	0.038	0.000	$-5.05 \cdot 10^{-4}$	0.611	$-6.16 \cdot 10^{-3}$	0.999
GE_Houses	0.025	0.000	$-1.28 \cdot 10^{-3}$	0.666	$-1.32 \cdot 10^{-2}$	1.000

Table 2.7: Moran's I for SAR models. Small p-values indicate that the hypothesis of no spatial autocorrelation is rejected

fit based on Akaike's Information Criterion (AIC), Log-Likelihood (LL) and the Sum of Squared Errors (SSE) we notice in table 2.8 that the SARMix model appears to have a slightly better overall fit (for AIC smaller value means better fit). However the overall difference between the two models is very small.

		SARErr			SARMix		
DataSet	**N**(#Obs)	AIC	LL	SSE	AIC	LL	SSE
ZH_Condos	5‘054	−2‘278.04	1‘223.02	176.58	−2‘427.09	1‘378.54	160.32
ZH_Houses	1‘376	108.16	29.92	76.24	91.39	119.31	68.13
GE_Condos	8‘266	−1‘390.05	784.03	388.02	−1‘561.58	954.79	374.35
GE_Houses	4‘299	−276.99	228.50	225.49	−416.86	384.43	210.47

Table 2.8: Goodness of fit for SARErr and SARMix models. Regression with N observations and $k = 89$ independent variables for houses (88 for condominiums)

Another point worth examining is the significance of the coefficients of the explanatory variables. Here the SARMix model fares worse than SARErr as it has several more explanatory variables that are not statistically significant. As spatial autocorrelation is not present in either model, this appears to be some weakness of the SARMix model in this particular setting.

Another limitation of the SARMix model is that due to the existence of the lagged explanatory variables there is no straightforward interpretation for estimating a price index. Besides, the majority of lagged explanatory variables also appears not to be significant. Finally, the estimated coefficients of some of the explanatory variables have values of very high magnitude, with a proportionally high standard error. This is another issue that could affect the price estimation. For the full SARMix regression results the reader can refer to tables A.13 - A.16 in the appendix.

The GWR method also described in section 1.3.2 cannot be applied in our dataset due to the unavailability of the exact property locations. The series of local regressions using a weighted least squares approach fails when a group of observations, all located in the same ZIP code area, appear to have a distance of 0.

In the end, it was decided that the SAR Error Model is the most appropriate one to use for the construction of the price indices. When tested for the districts of Zurich and Geneva there was essentially no spatial autocorrelation observable in its residuals. Furthermore, the model fit was quite satisfactory based on the computed criteria. Finally, the issue of non-significant explanatory variables is only minor for this model.

Quite interestingly, the estimated price indices for Zurich and Geneva from the SARErr model are almost identical from quarter to quarter with those we would get by using a simple OLS regression, as we can see in the graphs below.

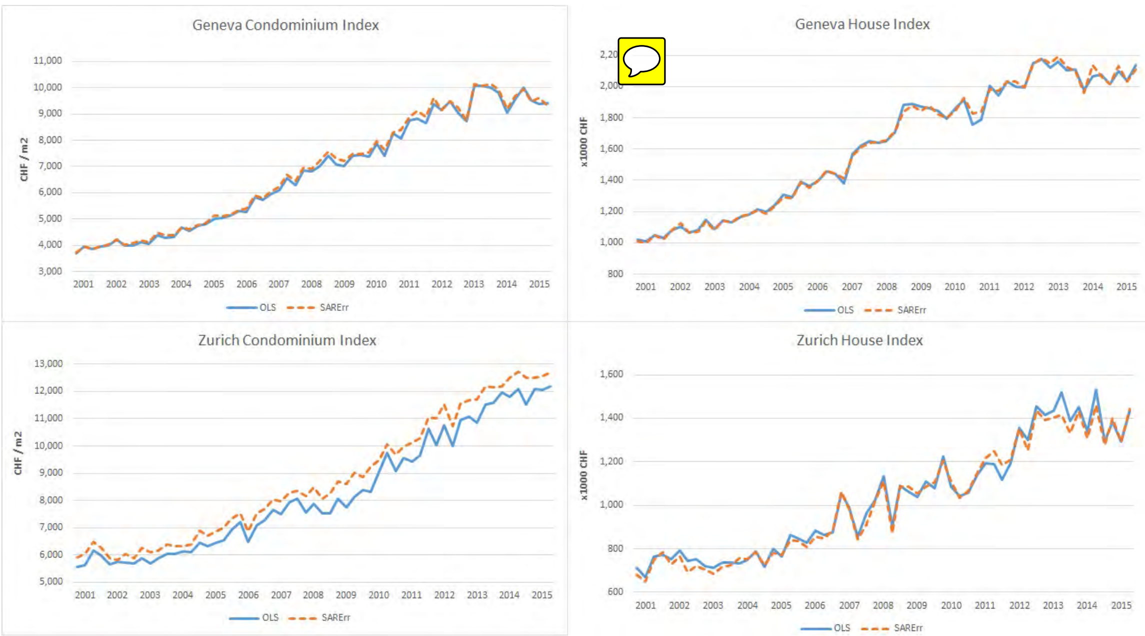


Figure 2.4: Comparison of price indices using OLS and SARErr

This, although expected as spatial autocorrelation does not bias the OLS coefficient estimates, is an important remark. A simple OLS regression is computationally much faster than the spatial autoregressive methods. As long as the primary focus is on constructing a price index and not testing the significance of each individual coefficient, the OLS method is a viable alternative. This is particularly useful when constructing the nation-wide index where, due to the sample size, the spatial autoregressive methods are inapplicable.

2.4 Constructing the Index

Now that the preferred method has been established, the next step is to apply it to as many of the 148 districts as possible. As it will become evident later, this will not be possible for some of the districts due to poor data availability.

2.4.1 The Method

Here is a quick recap of the chosen method.

The regression

The dependent variable is the transaction price. The natural logarithm of this variable will be regressed against the natural logarithm of the volume for houses and net living area for condominiums, the variable that measures the size of the property. On top of that, the 88 dummy variables listed in table 2.3 (87 for condominiums) will also be included in the regression. The regression method applied will be the Spatial Autoregressive Error (*SARErr*) method, described by the set of equations (1.5).

The Weight Matrix

The SARErr method requires a contiguity matrix. This is constructed as follows: Two observations are considered neighbors if they belong in the same ZIP code. Non-neighbors get a weight of 0. For each observation i, the weight of its neighbors is equal to $\frac{1}{N(i)}$, where $N(i)$ is the number of neighbors of observation i. This ensures that the weight matrix is *row-standardized*, meaning that the sum of weights of each row is equal to 1. In case an observation has no neighbors, the weights of 0 are substituted by $1/N$, where N is the total number of observations for that district, thus ensuring that the row-standardization remains in effect.

Price Index Estimation

The evolution of the price index time series can be determined exclusively from the 58 coefficients of the dummy variables $Q2 - Q59$. What the regression essentially achieves through the first 31 variables is to account for price differences due to different property or locational characteristics and isolate the effect of the time period in those 58 dummy variables. Thus, if b_n is the coefficient corresponding to quarter n and if we set the price index for $Q1$ as $p_1 = 1$, then $p_n = e^{b_n}$.

However, the hedonic price indices should ideally be comparable to other price indices, derived for example from average or median prices. Therefore, the initial level of the index should be meaningful as an indicator of price level. To achieve that, an 'average' house and an 'average' condominium were defined for each district by taking the median value for each of the attributes described in table 2.9 below.

Attribute	**Description**
Size	volume or net living area
Is_detached	only for houses
# of Bathrooms	$1, 2, 3$ or 4+
# of Garages	$0, 1, 2$ or 3+
Baujahr	6 periods
Area Type	9 types
Loc. Score	Bad, average, good or great
Qual. Score	Bad, average, good or great
Build. Score	Bad, average, good or great

Table 2.9: List of attributes used in defining the average property

This set of characteristics define the *average* house and condominium for each district. It is possible that no property with these exact characteristics exists in the data set, but this is besides the point. What matters is that the estimated value of the same property is calculated across time and this is one of the strengths of hedonic price indices: They are constant-quality price indices where price changes are result of changes in the market prices of the various characteristics and not in changes of the characteristics themselves.

Using the appropriate coefficients, one estimates the price of the 'average property' at $Q1$ as p_1. Then, similar to before, $p_n = p_1 \times e^{b_n}$.

Finally, the condominium price indices were converted to CHF/m^2, by dividing each index with the size of the corresponding average property. It is quite common to report condominium prices in CHF/m^2 and this makes our index more directly comparable to those from other studies.

2.4.2 Minimum Requirements for Districts

Regression analysis is quite sensitive to the size of the data sample. Small sample sizes relative to the number of independent variables can lead to high error variances due to small number of degrees of freedom. In the context of the hedonic real-estate index this translates to 'noisy' price time-series. Obviously the sample size has to be larger than the number of unknown parameters, otherwise it is not even possible to perform the regression, but there is no universally accepted guideline or even a rule of thumb for what is the minimum acceptable ratio of observations to unknown parameters.

Overall, qualified districts were required to meet the following set of quantitative criteria.

1. The district should have at least 1 observation for each of the 59 quarters. Out of the 148 districts, this rule alone excluded 73 districts for houses and 72 for condominiums.
2. The district should have at least 300 observations in total. With 89 unknown variables this corresponds to slightly more than 3 observations per parameter to be estimated. It also corresponds to an average of at least 5 observations per quarter. Adding this rule excluded just another 1 district for houses and 3 for condominiums.

In the end there are 75 qualified districts for houses and 72 for condominiums. One could argue that for some of these qualified districts still do not have sufficient data to generate reliable results. Estimating a coefficient that is potentially based on only $1-2$ observations for a particular quarter might lead to significant amount of noise entering the price time-series, hindering the process of monitoring the evolution of the price level. Therefore special attention was paid to 53 and 56 out of the 75 and 72 districts respectively that do not meet the much stricter condition of at least 5 observations per quarter for all 59 quarters.

2.5 The Results

There is a number of points of interest to examine in the outcome of the hedonic regression, which are analyzed below.

2.5.1 Significance of Coefficients

First of all it is important to gather information with regard to the statistical significance of the various coefficients. This provides a first overview of whether the model used is correctly specified. At the same time it provides information about which factors primarily drive real estate prices in the various districts of Switzerland. The following analysis is based on the p-values corresponding to the various coefficients. Unless mentioned otherwise, statistical significance is evaluated at the 95% confidence level.

Property Size

The single most important attribute for determining the price level is obviously the size of the property (volume or net living area). As expected, the coefficients are highly positive and statistically significant even at the highest significance levels for every single district. Also, judging from the values of the coefficients, relative to those corresponding to other explanatory variables, property size is also the most economically significant attribute when it comes to determining a property's value. To see this more clearly one can refer to figures 2.5 and 2.6 in the next section.

Property Age

Moving on to the age of the property, when it comes to condominiums the effect on price does not appear to be significant for properties built at any time prior to 1981. Indeed the coefficients corresponding to the periods *Before* 1900 and 1971−1980 (1901−1970 is the base case) are not statistically significant even at the 99% level for almost two thirds of the districts and they are positive just as often as they are negative. When it comes to newer properties, there is definitely a positive correlation between the year they were built and the price as evidenced by the fact that the corresponding coefficients are almost always positive. Also the coefficients corresponding to the period 1981 − 1990 are statistically significant at the 95% level or more than two thirds of the districts and even more so for the period *After* 2000 where they are always significant.

For houses, the situation is slightly different. Here the correlation between the period a house was built and its price is evident for all periods. The coefficients corresponding to the period *Before* 1900 are negative for almost all districts and the rest are all positive. These coefficients are also statistically significant at the 95% in the majority of districts.

Area Type

The area type appears to be the least significant piece of information when it comes to estimating a property's price. First of all, out of the 9 different area types only a subset of them can be found in each district. There are some area types that only exist in a handful of districts.

Furthermore, whether the overall area is classified as suburban, touristic, city center or any other type does not reveal much information about the neighborhood of the property. For example every property within the city of Zurich is classified as being located in a city center (AREA_ZEN) even if it is actually located quite far from the center of the city. Information about the micro-location is more relevant instead.

Overall, the corresponding coefficients, for both houses and condominiums do not appear to be statistically significant for more than half of the districts, at the 95% level.

Number of Bathrooms

For both houses and condominiums a second bathroom appears to be positively correlated with price and this correlation is statistically significant for the majority of districts. Of course this also holds true for properties with 3 bathrooms, when comparing with the base case of 1 bathroom. However, it is more interesting to observe whether a third or fourth bathroom adds significantly to the estimated value of the property when comparing with two bathrooms. Effectively we want to check whether the corresponding coefficients are significantly different from each other. To compute the appropriate statistic the regression model needs to be slightly adjusted.

The test showed that adding a third or a fourth bathroom does not have a significant impact on the property price for either houses or condominiums.

Number of Garages

When it comes to condominiums, one or more parking spots have a statistically significant impact to the value of the property. Performing a test similarly to above for bathrooms one can also notice that having two or more garages does not have a statistically significant effect on the condominium's value when compared to having exactly one garage.

For houses the situation is quite different. It appears that the number of garages (whether $0, 1, 2$ or more) does not significantly affect the price in the majority of districts, as most of the corresponding coefficients are not statistically significant even at the 99% level. A possible explanation for this slight paradox is that, as opposed to condominiums which are located predominantly in rather densely populated areas with limited parking availability, single-family homes are more often found in locations where parking space is normally not an issue.

Micro-location, Quality & Building Condition Scores

For all these 3 qualitative score indices a similar pattern is observed. The coefficients corresponding to a score of 2, which means *Average* are not statistically significant at the 95% level in more than half of the districts, implying that a score of *Average* versus *Bad* (the base case) in any of these three attributes often does not significantly affect the value of the property according to our hedonic model. On the other hand, when examining the coefficients corresponding to a score of 3 or 4, which stand for *Good* and *Great* respectively, these are positive and statistically significant for the vast majority of districts. The above holds true for houses as well as for condominiums and for all 3 attributes, although in general the quality and the building condition scores appear to be overall slightly more significant than the micro-location score when it comes to explaining the property's price.

Primary Residence

Whether the property is the primary or a secondary residence is not a factor that significantly affects the price in most districts. Both for houses and for condominiums, the corresponding coefficient is not statistically significant in the majority of districts.

Time Period Coefficients

By observing the coefficients corresponding to $Q2 - Q59$ one can observe some nation-wide trends of the real estate price level. One thing that is noticeable is that the coefficients corresponding to the first 15 quarters for condominiums and 20 for houses are not statistically different from 0 in the majority of districts. This implies that between 2001 and 2005 (2006 for houses) real estate prices across Switzerland were relatively stagnant. This behavior changes in later quarters when coefficients become more significant statistically, indicating that in later years the prices have clearly departed from their 2000 levels. This trend will also be confirmed later, when a nation-wide price index is created.

Table 2.10 below summarizes the above analysis with regard to the statistical significance of the various coefficients.

Attribute	**Significance of Corresponding Coef (at 95% level)**
Property Size	Highly significant for both houses and condominiums
Property Age	Significant for houses. For condominiums only when built after 1980
Area Type	Only Area_Re (high-income) has significant corresponding coefficients
Number of Bathrooms	Statistical significance between 1 and 2 bathrooms. Not between 2 and 3+
Number of Garages	Statistical significance between 0 and 1 garages. Not between 1 and 2+
Qualitative Scores	Statistical significance between scores of 'Good' or 'Great' versus 'Bad', not so much for 'Average' vs 'Bad'
Primary Residence	Generally not statistically significant for either houses or condominiums
Time Period	Coefficients corresponding to periods up to 2005 were mostly not statistically significant. This changes in later periods as prices clearly depart form the levels they had at 2001

Table 2.10: Summary of statistical significance of various regression coefficients across districts at the 95% confidence level

2.5.2 Homogeneity of Coefficients

Another issue of importance is whether the various coefficients are homogeneous across districts. In other words, it is interesting to examine the spatial heterogeneity from district to district by looking at how much each coefficient varies across districts.

One can already deduce from the analysis above that most of the coefficients are not homogeneous across districts. There are various factors that appear to significantly affect the price in some of the districts but are irrelevant in others. Some of those factors also vary between having positive or negative influence on the price across districts. The graphs in figures 2.5 and 2.6 show a better view of how various coefficients vary across districts. For some select explanatory variables, the bars show the full range of values that the corresponding coefficients take across districts with different shades for each quartile. The situation depicted in these graphs also agrees with the analysis of section 2.5.1 above.

Even the coefficients corresponding to the property size which, as mentioned earlier, are consistently significant across all districts, can vary a lot between districts. Specifically, the coefficient corresponding to a house's volume varies between 0.360 and 0.737 and the one corresponding to an apartment's surface size from 0.694 to 1.059, with standard deviations of 0.0826 and 0.0618 respectively as one can see in table 2.11 below. To put this into perspective, for an average-sized house of $800m^3$ or an average-sized condominium of $100m^2$, a increase in the corresponding coefficient of one standard deviation, would increase the estimated property value by as much as 74% and 51% for houses and condominiums respectively.

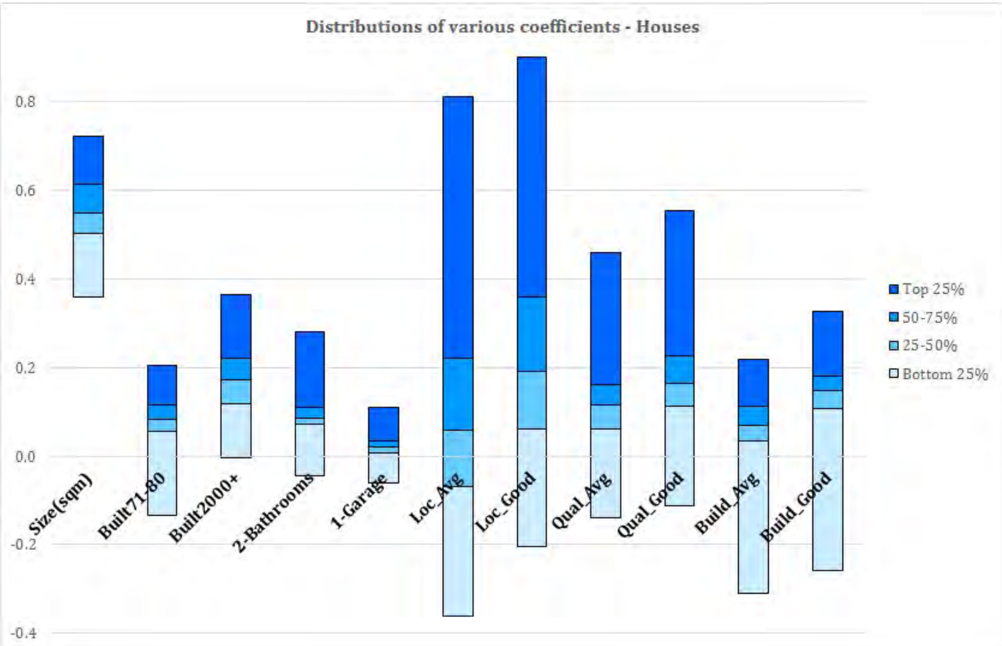


Figure 2.5: Distribution of coefficients of select explanatory variables for houses

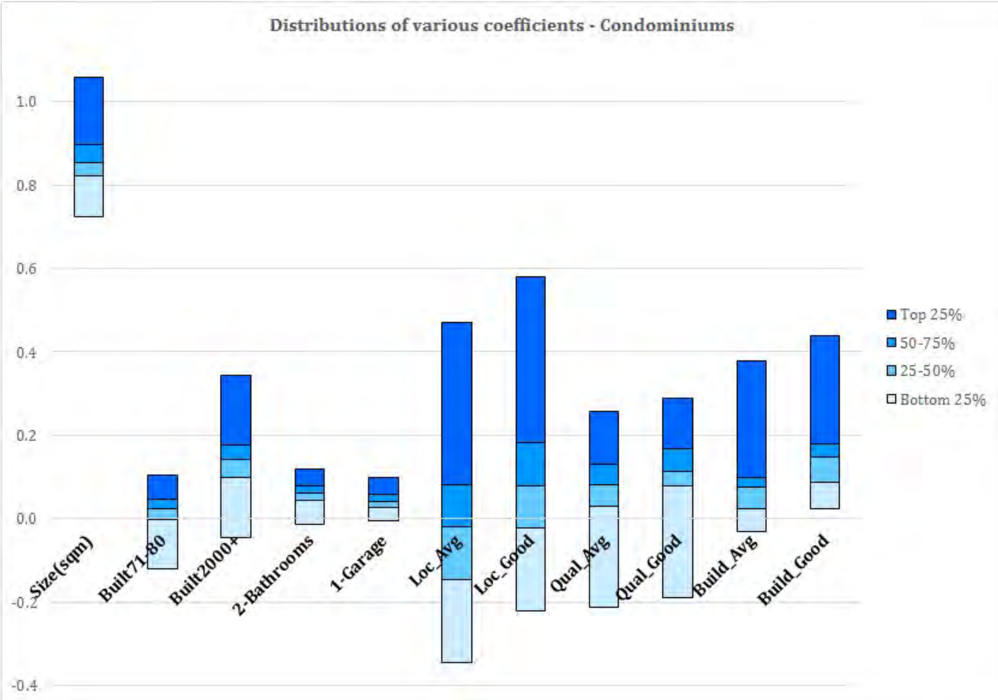


Figure 2.6: Distribution of coefficients of select explanatory variables for condominiums

Attribute	Min value of Coef.	Max value of Coef.	Std Dev
KUBATUR (Houses)	0.36	0.737	0.0826
NETTOWOHNFLAECHE (Condos)	0.694	1.059	0.0618

Table 2.11: Variability across districts of coefficients corresponding to property size

The situation is similar when examining the coefficients corresponding to the time periods $Q2 - Q59$. Those coefficients vary even more wildly across districts, especially for the second part of the overall time window ($Q30$ and onwards), indicating that the real estate price movements across the country have been anything but uniform.

This can also be witnessed in figures 3.1 and 3.2 in the next chapter and also in figures A.1 to A.8 in the appendix where one can see that the real estate price dynamics vary a lot from district to district.

2.5.3 Model Fit

As a measure of model fit, the Akaike's Information Criterion (AIC) was calculated for each regression. However AIC by itself cannot tell anything about the quality of the fit in an absolute sense. Instead it can only be used for comparing the relative quality of different models. Therefore it was compared to the AIC value of the standard OLS regression model. Remember that a lower AIC score indicates a better fit. Comparing the two scores, for both houses and condominiums, one comes to the following conclusions.

1. There is only a handful of districts where the AIC value of the SARErr model is marginally higher than that of the OLS model. The difference is very small and these are all districts with a small sample size which works against model fit anyway.

2. In the majority of districts, the AIC score indicates that the SARErr model has a fit that is between slightly and significantly better than the corresponding OLS model.

3. There is an observable correlation between sample size and the relative performance of the two models in terms of fit. The bigger the sample size the greater the difference between the two AIC scores for the same district. In the largest districts such as Geneva, City of Zurich, Bern-Mitteland, Nyon and Uster one observes the greatest differences.

The tables with all the AIC scores can be found in the appendix (tables A.17 and A.18).

2.5.4 Residual Spatial Autocorrelation

The *Moran test* was performed on the residuals of each regression. The value of *Moran's I* ranged between -0.033 and 0.007. As mentioned earlier, the closer this value is to 0 the less likely it is that spatial autocorrelation is present in the residuals. The fact that there is no evidence of spatial autocorrelation is also confirmed by the calculated $p-$values, as the smallest is 0.21.

The full results of the Moran test can also be found in the appendix (table A.19).

2.6 Comparison to Other Indices

In this section the hedonic price indices are compared to simpler indices generated by taking the median prices from each quarter (median price per square meter for condominiums). They are also compared to indices generated from the comparis.ch dataset and are based on asking prices. This helps illustrate a number of differences that arise due to the application of different methods and the use of different datasets.

2.6.1 Comparison to Median Transaction Prices

A comparison of the hedonic price indices with the corresponding median prices per quarter can show the advantages of the hedonic method over the more simplistic approach. Although in all cases the trend of the price levels is similar, the hedonic method generates a much 'smoother' time series, as it is not sensitive the changes in the overall quality of properties transacted from quarter to quarter. This becomes even more apparent for districts with small sample size where the noise caused in the median price index by the varying housing quality from period to period can even overshadow the overall upward trend in price levels, making it hard to detect.

Another potential source of difference has to do with the way the initial price (at $Q1$) is computed for the hedonic index. This price depends on the definition of the average properties for each district. Remember that these average properties are defined as a combination of the median values of each individual attribute. In some extreme cases this can lead to an 'average' property that is actually significantly better (or worse) than average. When this happens, the hedonic price index will be constantly above (or below) the corresponding median price index, although the spread should remain rather constant over time.

Below is a graphical representation of the situations described above for some select districts.

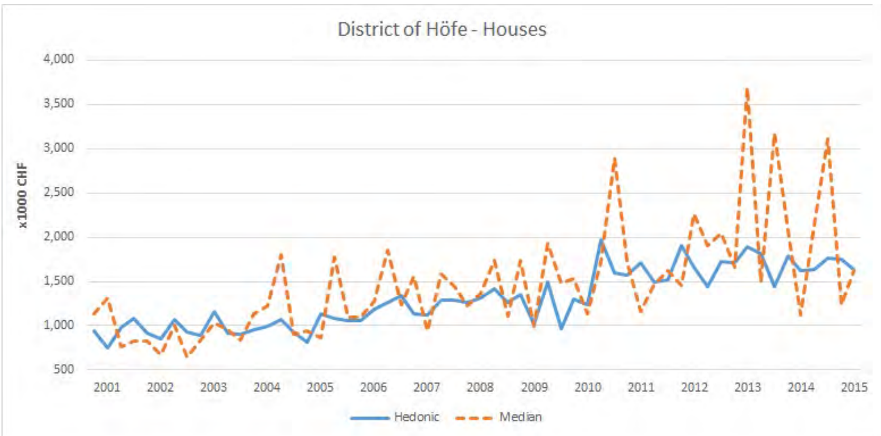


Figure 2.7: Housing price indices for district Höfe

Höfe (figure 2.7) is one of the districts with the lowest number of houses transactions, just 344 observations in total. On the one hand, the median price index contains oscillations so wide that detecting the true changes in the price level is really hard. On the other hand, the hedonic index is much less noisy and it is therefore easier to track the price increase.

The district of Zug (figure 2.8) is one of the largest in terms of sample size for condominiums. In this case the trend in the overall price level is

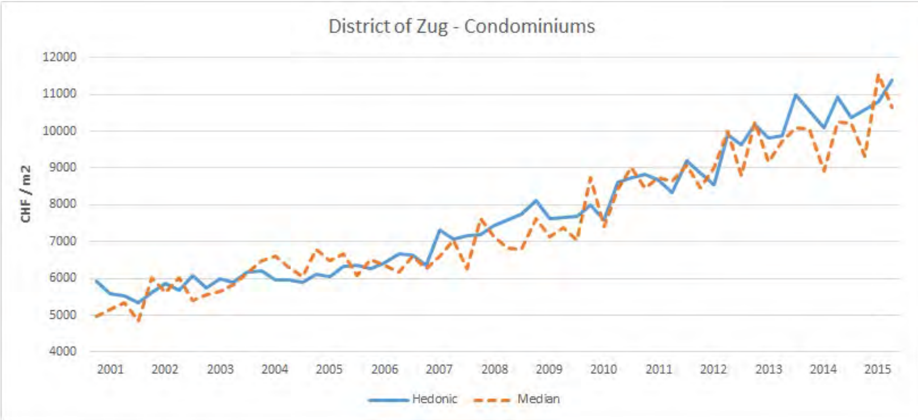


Figure 2.8: Condominium price indices for district Zug

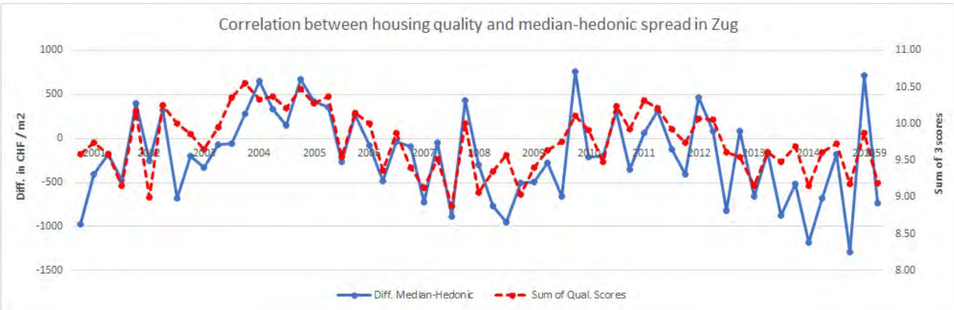


Figure 2.9: Median-hedonic spread vs property quality in Zug

easily identifiable in both cases. The variability in the spread between the two indices is caused by changes in the average quality of condominiums sold from quarter to quarter. To better understand how these patterns are related, one can look at figure 2.9.

The solid line shows the spread between the median price per square meter and the value of the corresponding hedonic index. The dashed line is the sum of the average values of the 3 scores that characterize micro-location, property quality and building condition, each ranging between 1 (bad) and 4 (great). It serves as an indicator of the average quality of condominiums sold in each quarter. One can see that there is an almost perfect correlation between these two time series.

Finally, Meilen (figure 2.10) is one of the districts where the 'average condominium' turned out to be of rather higher quality than average. It has a score of *Great* for both building condition and property quality, 2 parking spots and the area type is classified as *high-income*. As a consequence, the hedonic price index appears constantly at an overall higher level than the median prices.

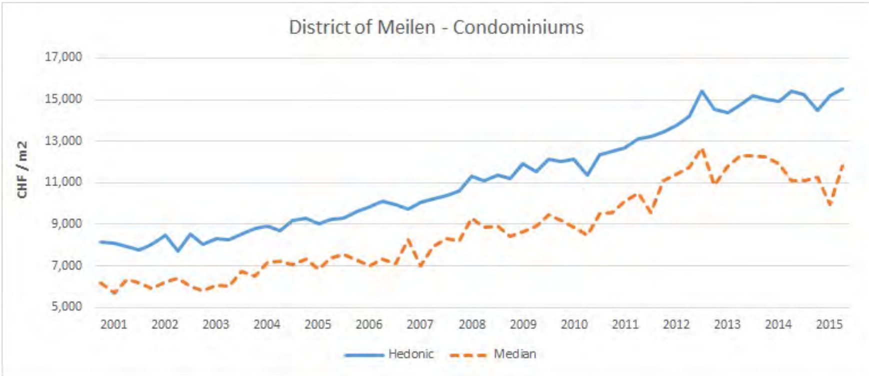


Figure 2.10: Condominium price indices for district Meilen

2.6.2 Comparison to Asking Prices from comparis.ch

Additionally, the SRED price indices (both hedonic and median) were also compared to the ones generated from the comparis.ch dataset of ask prices, the one used in Ardila et al. [2013], but augmented with more recent data. The comparison period spans from 2005$Q1$ to 2015$Q2$ as earlier data is not available from comparis.

The goal was to identify trends in the spread between ask and transaction prices. Due to the reasons described already in section 2.6.1, the hedonic price indices were not suitable for this task. Instead the median price indices from the SRED dataset were compared to the corresponding median price indices from the comparis.ch dataset. The fact that both are computed using the same method restricts the potential sources of difference to one of the following three reasons.

1. Differences due to the fact that they are computed out of different datasets. Each dataset contains some properties that the other doesn't.

2. Noise inherent in the indices, particularly for those districts where the sample size is rather small. As sample sizes get larger, prices on each quarter are approximately normally distributed and therefore the median price is a quite accurate indicator of the overall price level.

3. The actual spread between ask and transaction prices. This is the only 'true' price difference and the one that is of interest.

It turns out that there is no consistent interpretation of the spread between the two price indices. One would at least expect that two time series describing two real estate price indices for the same district would turn out to be co-integrated. To investigate this, the differences between the median prices from the SRED dataset and those from comparis.ch (so that at least the methodology is the same) were tested both for stationarity, using the *Kwiatkowski-Phillips-Schmidt-Shin* (KPSS) test (Kwiatkowski et al. [1992]) and for unit root, using the *Augemented Dickey-Fuller* test (Said and Dickey [1984]). Also, to minimize the effect of noise, only the largest districts in terms of number of transactions were examined, 35 in total for condominiums and 19 for houses.

Unfortunately, the tests did not turn out to be particularly insightful. For both houses and condominiums there was a small subset of districts for which the unit root hypothesis was rejected and an equally small number of districts for which the stationarity hypothesis was rejected. For the majority of districts, none of the hypotheses could be safely rejected and thus no conclusion could be made. Repeating the test for various linear combinations of the differences of the two time series led to very similar results.

A summery of the results can be seen in table 2.12 below. Two examples are also shown in figures 2.11 and 2.12 below, one of a district where the median prices from SRED and comparis.ch appear to be co-integrated (the unit root hypothesis was rejected) and one where they do not (the stationarity hypothesis was rejected).

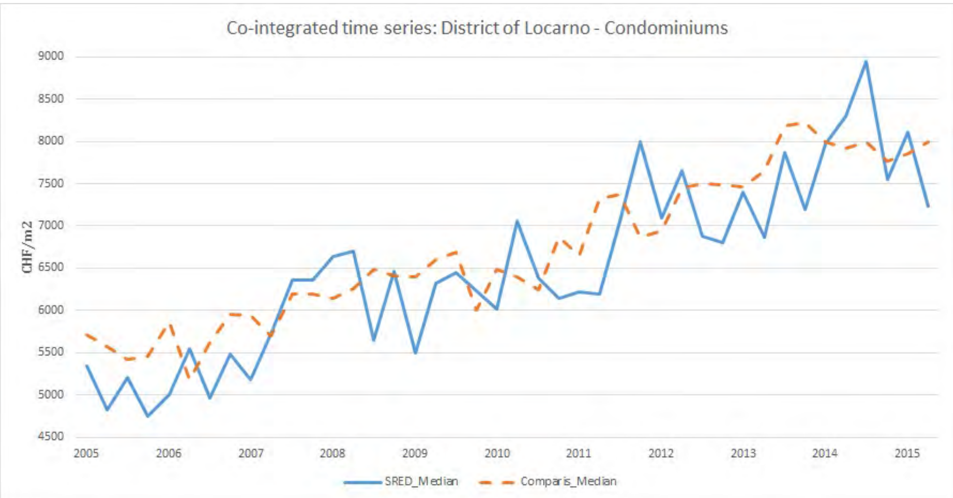


Figure 2.11: An example of two co-integrated time series: SRED median and comparis.ch median condominium prices in the district of Locarno

In the end, no conclusion can be safely drawn from the tests performed. The only inference that can be made from the direct comparison of the two datasets is that the median transaction prices from the SRED dataset are generally slightly lower than the median ask prices from the comparis.ch dataset, as one would probably expect in a seller's market where prices have been trending upwards.

To avoid confusion due to the differences in price levels between various

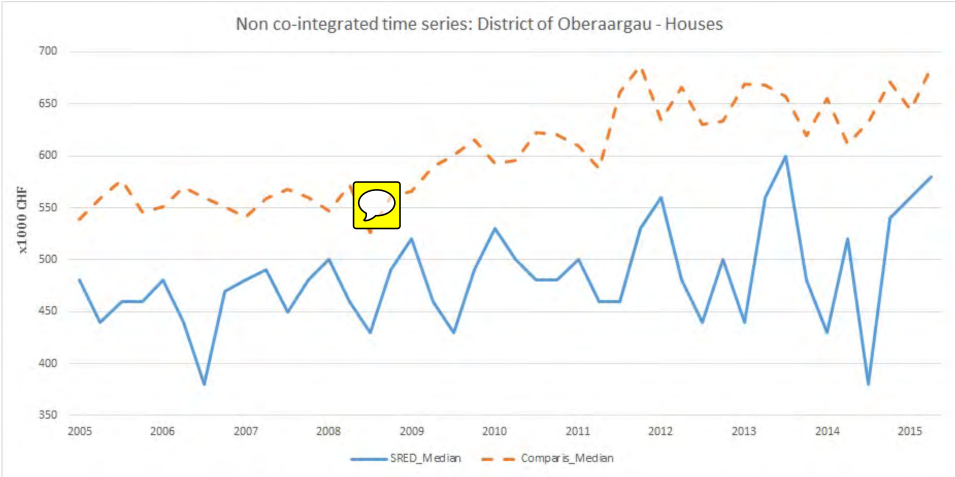


Figure 2.12: An example of two non co-integrated time series: SRED median versus comparis.ch median house prices in the district of Oberaargau

Test Result	Houses	Condominiums
Unit Root Rejected (95%)	2	3
Stationarity Rejected (95%)	2	5
No conclusion (95%)	15	27
Total	19	35

Table 2.12: Summary of results from unit root and stationarity tests for the differences between SRED and comparis.ch median prices

indices, in the following sections relative indices will be used, where $2007Q1$ will act as base period and all indices will be equal to 100 at that time. Since the focus of the following sections is identification of bubbles and this is done by applying the LPPLS method where only the relative price increases from period to period are relevant, this approach will facilitate comparison between different indices.

2.7 National Indices

It is useful to compute two national real estate price indices, one for houses and one for condominiums. They can be used to identify nation-wide trends in real estate prices and also for comparability with other national indices.

Unfortunately, the spatial autoregressive methods are unable to handle large sample sizes and therefore cannot be applied for the calculation of the national indices. Instead, there are two alternative approaches which are described in the following sections and which, as it turns out, lead to very similar results.

2.7.1 Hedonic Indices with OLS Regression

The first approach is to calculate the hedonic indices based on the same model as for the districts, but using a simple OLS regression rather than one of the SAR methods. An OLS regression can be performed much faster and the sample sizes are not an issue in this case. The drawback is that OLS does not solve the issue of the significant spatial heterogeneity of the data. However, as was already mentioned, this should not affect the price index estimation process.

From the list of estimated coefficients, only the ones corresponding to $Q2 - Q59$ are required in order to get the evolution of the time series of the price indices relative to $Q1 = 2000Q4$. For reasons stated in the previous section, no 'average property' was estimated. Instead the price indices were computed relative to the base quarter ($2007Q1$) for which the price index was set to 100.

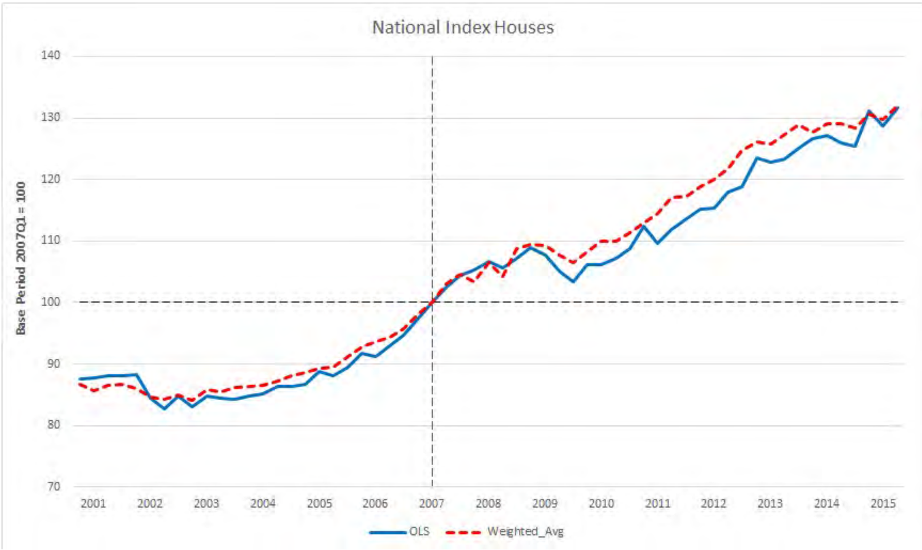
2.7.2 Weighted Average Approach

Since price index time series have already been calculated on district level, one could estimate a national index by taking a weighted average of the district-level indices with weights proportional to the number of observations per district. This method is simple and rather straightforward. It also has some similarities to the way the SNB national index is estimated, where a weighted average approach is also applied, but on different constituent local indices.

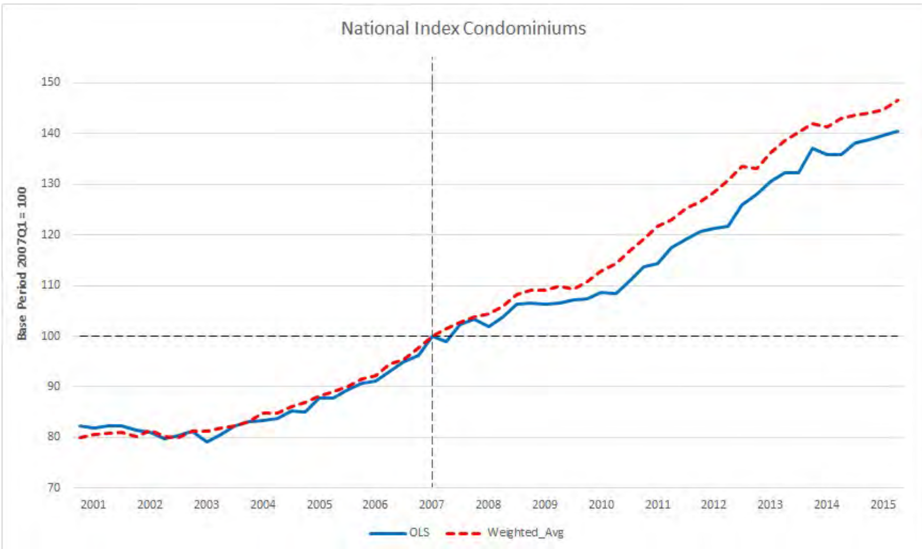
A drawback of this approach is that only districts for which a price index was calculated are taken into account for the national index. Thus, districts that did not have a sufficiently large sample size to generate a local price index, which is approximately half of the districts of Switzerland, are completely ignored.

Another issue is whether this weighted average should be calculated after each index is expressed in relative values (to the base period) or before. In the latter case, districts with overall higher prices will carry more weight. While this might sound natural, it also means that districts where the hedonic price index is artificially inflated due to the issues mentioned earlier will also carry more weight. Overall it seems a better choice to take the weighted average of the relative indices. This way the weight each district carries to the national index depends solely on its relative sample size.

In the end, it turns out that both approaches (of sections 2.7.1 and 2.7.2) lead to very similar price index calculations, as one can witness from the graphs in figure 2.13.



(a) Houses



(b) Condominiums

Figure 2.13: National price indices: comparison between national hedonic regression index and weighted average of district-level hedonic indices

2.8 Average Rates of Price Appreciation

Finally we look at the average rate of appreciation of real estate prices between 2000Q4 and 2015Q2 according to the calculated price indices.

From the analysis of section 2.5.2, we already know that the average rate of appreciation will vary significantly across districts. They also vary significantly between condominiums and houses.

Indeed in the French-speaking districts of Switzerland such as Geneva, Entremont, Lausanne and Riviera-Pays-d'Enhaut real estate prices for condominiums have been increasing on average by more than 1.55% per quarter which corresponds to an annualized increase of more than 6.35%. For houses the situation is somewhat different. Once again most districts from the French-speaking part have relatively high rates of price appreciation, but apart from Geneva, the highest rates are observed in Horgen, Zug and the city of Zurich. Still, the highest average rate of price appreciation is only 1.3% per quarter, somewhat less than for condominiums.

On the other hand, there are districts where real estate prices appear to increase at a very slow rate which, for condominiums, is as small as 0.26% per quarter. For houses there are even two districts where the rate is negative, implying that current prices are at a lower level than at the end of 2000!

Another observation is that prices in most districts were increasing at a significantly slower rate until approximately 2009. Indeed this can also be observed in the national price indices. Between 2000Q4 and 2009Q4 the average rate of price appreciation of the condominium price index is 0.76% per quarter and the one of the house price index 0.47% per quarter, while in the last 5.5 years they are 1.18% and 1.06% per quarter respectively.

For the full set of statistics the reader is referred to the appendix (table A.20).

Chapter 3

Bubble Analysis

Once the final price indices have been generated, they can be used to assess whether a speculative bubble is present in any of the districts and to predict the critical time. It is also possible to identify bubbles that have already ended in the past.

3.1 The Process

The identification of potential bubbles is done using the model described in section 1.4.1. The inputs are the price index time-series to be analyzed, the acceptable lower and upper bounds for each of the 7 parameters of equation (1.14) that describe the price dynamics of a bubble as well as a minimum and maximum window size (in periods) for which the fitting is attempted. The maximum window size corresponds to the overall length of the observation period. Then for smaller windows, a shifting window approach is used, where each subset of the time series, equal in length to the window size, is scanned separately in an attempt to fit the equation that describes bubble dynamics.

Any solution found meeting these constraints is called a *qualified fit* and is then examined further in order to assess its validity as a true bubble indicator.

3.2 Our Parameters

For our analysis, the LPPLS parameters from equation (1.14) of qualified fits were required to be within the following ranges:

- The exponent β between 0.1 and 0.9. In section 1.4.1 we already explained that β needs to be between 0 and 1. This slightly stricter restriction avoids cases where the exponent is too close to the upper or lower bound as they do not accurately reflect the desired price dynamics.

- The log-frequency ω between 4 and 16. This constraints the log-periodic oscillations to be neither too fast nor too slow for reasons described by Filimonov and Sornette [2013].

- The critical time t_c between 0.9 and 1.2, where 1 refers to the end of the observation window. This means that for a particular time window of analysis, the critical time must occur near the end of the window, in the near future or somewhere in-between.

- The minimum window size was set to 32 quarters and the maximum to 59, which is the whole available window of observations, from 2000Q4 to 2015Q2.

3.3 Analysis of the Results

Initially a very large number of qualified fits were found. Out of the 147 price time-series (72 for condominiums and 75 for houses), in 112 of them there was at least one potential fit. Therefore each of these districts had to be examined further to assess whether these fits are true potential indicators of a bubble or whether they are not of practical interest.

3.3.1 Acceptance Criteria

To assess the validity of each qualified fit the following, primarily qualitative, criteria where used:

1. **Sample size**: The calculated price index on a particular quarter depends on the observed transaction prices from that quarter relative to all other quarters, having accounted for potential differences in the various property attributes. When the number of observations on a particular quarter is small, this undermines the reliability of the calculated price indices. Therefore some qualified fits based on a price time-series generated from a small sample size were ignored. An example of an unacceptably small sample size is a time period of at least $7-8$ quarters that is part of the fitting window and has fewer than 5 observations per quarter on average.

2. **Noise**: Examples of noisy time series include those with oscillations of very high amplitude and/or frequent big jumps in the price, in both directions. When this happens, the LPPLS method often finds fits on the noise itself rather than on the true trend of the prices. This issue is often correlated with the small sample sizes discussed above.

3. **Price increase**: Not everything that fits the definition of a bubble according to section 1.4.1 is of interest in practice. In order for a bubble to be of actual concern, it must be accompanied by a significant overall increase in the price level. In some districts the price time-series resembled a super-exponential growth but the overall amplitude was rather small. This is often the case with qualified fits with a small value of the exponent β. In the end, price increases smaller than 4% per year on average over the window for which the fit was found were not considered significant enough to cause any concerns regarding the existence of a bubble of practical interest.

4. **Number of fits**: Quite often good fits appeared together in clusters with the predicted critical times concentrated together in a very small time window. Therefore individual stand-alone fits were scrutinized more.

5. **Critical times in the past**: Whenever a qualified fit predicted a critical time in the somewhat distant past (at least $6-7$ quarters before the present) then we have enough observations past the critical time to decide whether a regime change has indeed taken place or the prediction was wrong. In the latter case, the fits were classified as 'false positive'.

The first three criteria apply to the full set of qualified fits for a district as a whole, while the fourth and fifth have to do with individual fits.

3.3.2 Classification of Districts

Based on the above criteria, each district, both for condominiums and for houses, was classified in one of the following groups, in similar fashion to Ardila et al. [2013].:

- **Critical Districts**: These are districts with a significant number of qualified fits (at least 3) that predict a critical time at some point within the next 6 quarters. As mentioned earlier, having a rather large number of fits clustered together is generally a sign that strengthens the validity of these predictions. Critical times further in the future are not taken into account.

- **Districts to Watch**: Those are either districts for which there are just 1 or 2 predicted critical times in the near future or districts for which there is at least one potentially good fit at some point in one of most recent quarters. In the latter case there are not enough data points to assess whether a regime change has indeed taken place, therefore the price dynamics need to be observed carefully over the next few quarters.

- **District to Ignore**: These are all the districts that did not perform well with regard to the criteria mentioned earlier (sample size, noise, price increase), as well as districts for which predicted bubbles with critical times in the past were not realized since there was no change in the price dynamics past the critical time.

- **Bubble in the Past**: There is a number of districts where, although they are not of interest at present, a fit was found that indicated a bubble that burst at some point in the past and where the evolution of the price after the predicted critical time verified that a regime change did indeed take place. These findings are quite interesting, especially the bubbles that seem to have burst during the $2008 - 2010$ financial crisis. In the previous work of Ardila et al. [2013], where observations only started from $2005Q1$, such fits were impossible to identify.

3.3.3 The results

Overall, 2 critical districts, 8 districts to watch and 4 districts where bubbles have burst in the past were identified for houses. Another 6 critical districts, 22 districts to watch and 5 districts where bubbles have burst in the past were identified for condominiums. It is interesting that in the latest report based on comparis.ch data there were no critical districts at all. For houses there were only 5 districts classified as either 'to watch' or 'to monitor' and for condominiums 16.

Below are listed all the districts of interest where at least one LPPLS fit worth reporting was found, accompanied by a short description. A graphical representation of the LPPLS fits also follows.

Houses

Table 3.1 lists all the districts of interest for houses.

Condominiums

Tables 3.2, 3.3 and 3.4 show the critical districts, the districts to watch and the ones with bubbles in the past respectively for condominiums. The situation is quite different in comparison to houses. There are also more districts of interest. This is expected as we have already seen that real estate prices have been increasing more rapidly for condominiums than for houses.

Figures 3.1 and 3.2 display graphically the LPPLS fits for the critical districts mentioned above. Plots for the rest of the districts of interest (districts to watch and those with fits in the past) can be found in the appendix (figures A.1 - A.8).

District	Classification	Critical Time(s)	Comment	Status in Comparis Report
Bezirk Uster	Critical	2015-2016	Some fits with critical times at end of 2015 & beginning of 2016. Also possible that a regime change took place in 2014Q4.	Not included in the districts of interest
Bezirk Lenzburg	Critical	2015Q3-Q4	Multiple fits with critical times towards the end of 2015	District to monitor but not considered critical
Bezirk Bülach	To Watch	2014Q2	Potential regime change at 2014Q2. Monitor for a few quarters	Not included in the districts of interest
Bezirk Dielsdorf	To Watch	2015Q4	1 fit with critical time at the end of 2015	Not included in the districts of interest
Bezirk Pfaeffikon	To Watch	2014Q2	Potential regime change at 2014Q2. Monitor for a few quarters	Not included in the districts of interest
Bezirk Winterthur	To Watch	2014Q1	Potential regime change at 2014Q1. Monitor for a few quarters	Not included in the districts of interest
Verwaltungskreis Thun	To Watch	2014Q4	Potential regime change at 2014Q4. Monitor for a few quarters	Not included in the districts of interest
Bezirk Bremgarten	To Watch	2015Q1	Potential regime change at 2015Q1. Monitor for some quarters	Not included in the districts of interest
Bezirk Muri	To Watch	2015Q1	Potential regime change at 2015Q1. Monitor for some quarters	Not included in the districts of interest
Bezirk Rheinfelden	To Watch	2014Q4	Potential regime change at 2014Q4. Monitor for a few quarters	Not included in the districts of interest
Bezirk Hinwil	Past	2013Q3	Indication of bubble bursting at 2013Q3	District to monitor for possible regime change
Bezirk March	Past	2013Q2	Indication of bubble bursting at 2013Q2	Not included in the districts of interest
Distretto di Lugano	Past	2008Q2	Indication of bubble bursting at 2008Q2	Analysis based on comparis.ch dataset cannot identify bubbles this far in the past
District de la Riviera-Pays-d'Enhaut	Past	2008Q3	Indication of bubble bursting at 2008Q3	Analysis based on comparis.ch dataset cannot identify bubbles this far in the past

Table 3.1: Districts of interest for houses

District	Critical Time(s)	Comment	Status in Comparis Report
Bezirk Bülach	2015Q3-Q4	Multiple fits with critical times towards the end of 2015	District to watch: some bubble signals with critical times in the near future
Bezirk Pfaeffikon	2015Q3-Q4	Multiple fits with critical times towards the end of 2015	District to monitor but no bubble signals any more
Bezirk Uster	2015-2016	Fits with critical times between end of 2015 and beginning of 2016	District to monitor but no bubble signals any more
Bezirk Winterthur	2015Q2	Fits with critical times at present (end of 2015Q2)	Not included in the districts of interest
Verwaltungskreis Thun	2015Q3-Q4	Multiple fits with critical times towards the end of 2015	District to watch. A bubble signal but not very strong
Wahlkreis St. Gallen	2015-2016	Many fits with critical times between end of 2015 and beginning of 2016	Not included in the districts of interest

Table 3.2: Critical districts for condominiums

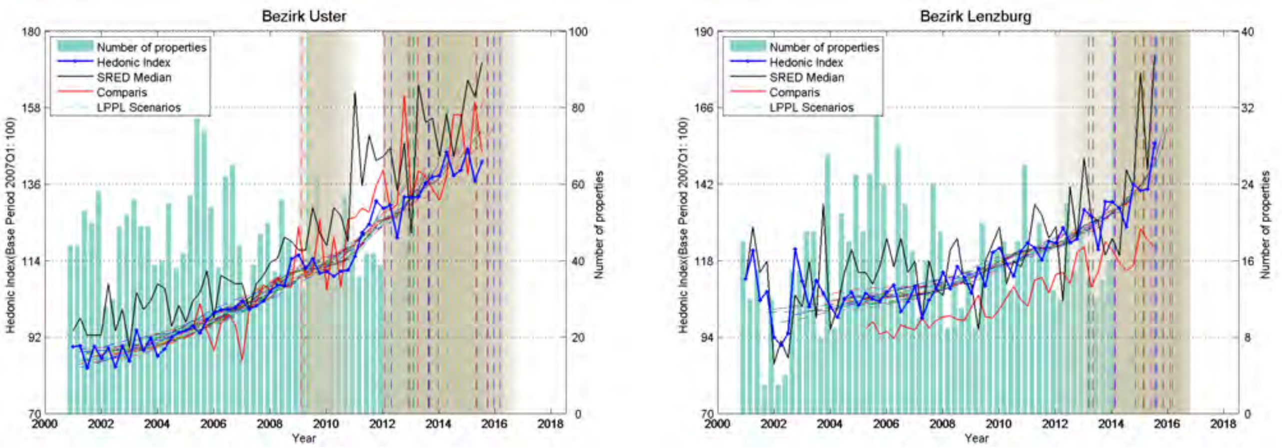
District	Critical Time(s)	Comment	Status in Comparis Report
Bezirk Affoltern	2016Q4	A few fits with critical times at late 2016	Not included in the districts of interest
Bezirk Dielsdorf	2014Q2	Potential regime change at 2014Q2. Monitor for a few quarters	Also monitored for potential regime change in the past
Bezirk Hinwil	2014Q4	Potential regime change at 2014Q4. Monitor for a few quarters	Also monitored for potential regime change in the past
Bezirk Dietikon	2013Q3	Potential regime change at 2013Q3. Monitor for a few quarters	Not included in the districts of interest
Bezirk Zuerich	2014Q2	Potential regime change at 2014Q2. Monitor for a few quarters	Not included in the districts of interest
Verwaltungskreis Bern-Mittelland	2015Q2	2 Fits with critical times at present (end of 2015Q2) and early 2016	Not included in the districts of interest
Wahlkreis Luzern-Land	2014Q1	Potential regime change at 2014Q1. Monitor for a few quarters	District to watch with some, not very strong, bubble signals
Wahlkreis Sursee	2014Q1	Potential regime change at 2014Q1. Monitor for a few quarters	District to watch with some, not very strong, bubble signals
Kanton Zug	2015Q2	1 fit with critical time at present (2015Q2). To monitor	Not included in the districts of interest
District de la Sarine	2016Q1	2 fits with critical times at the beginning of 2016	Not included in the districts of interest
Bezirk Arlesheim	2014Q4	Potential regime change at 2014Q4. Monitor for a few quarters	Not included in the districts of interest
Wahlkreis See-Gaster	2014Q2	Potential regime change at 2014Q2. Monitor for a few quarters	Also monitored for potential regime change in the past
Bezirk Albula	2015Q4	2 fits with critical times at the end of 2015	Not included in the districts of interest
Bezirk Prättigau-Davos	2015Q1	Potential regime change at 2015Q1. Monitor for some quarters	Not included in the districts of interest
Bezirk Surselva	2014-2015	Potential regime change at 2014Q3 or 2015Q1. Monitor for some quarters	Not included in the districts of interest
Bezirk Aarau	2014Q3	Potential regime change at 2014Q3. Monitor for a few quarters	District to watch with some, not very strong, bubble signals
Bezirk Baden	2014Q4	Potential regime change at 2014Q4. Monitor for a few quarters	Not included in the districts of interest
Bezirk Bremgarten	2015-2016	2 fits with critical times at end of 2015 & beginning of 2016	Not included in the districts of interest
District de Lausanne	2014Q3	Potential regime change at 2014Q3. Monitor for a few quarters	Not included in the districts of interest
District de l'Ouest Lausannois	2015Q1	Potential regime change at 2015Q1. Monitor for some quarters	Not included in the districts of interest
District de la Riviera-Pays-d'Enhaut	2014Q4	Potential regime change at 2014Q4. Monitor for a few quarters	Not included in the districts of interest
District de Sion	2014Q4	Potential regime change at 2014Q4. Monitor for a few quarters	Not included in the districts of interest

Table 3.3: Districts to watch for condominiums

District	Critical Time(s)	Comment	Status in Comparis Report
Bezirk Meilen	2012Q3	Indication of bubble bursting at 2012Q3	Not included in the districts of interest
Distretto di Locarno	2008Q4	Indication of bubble bursting at 2008Q4	Analysis based on comparis.ch dataset cannot identify bubbles this far in the past
District de Morges	2013Q4	Indication of bubble bursting at 2013Q4	Not included in the districts of interest
Canton de Geneve	2011Q4	Indication of bubble bursting at 2011Q4 (prediction was slightly off with critical time 2012Q1)	Analysis based on comparis.ch dataset cannot identify bubbles this far in the past
District de Nyon	2008Q3	Indication of bubble bursting at 2008Q3	Analysis based on comparis.ch dataset cannot identify bubbles this far in the past

Table 3.4: Districts with bubbles in the past for condominiums

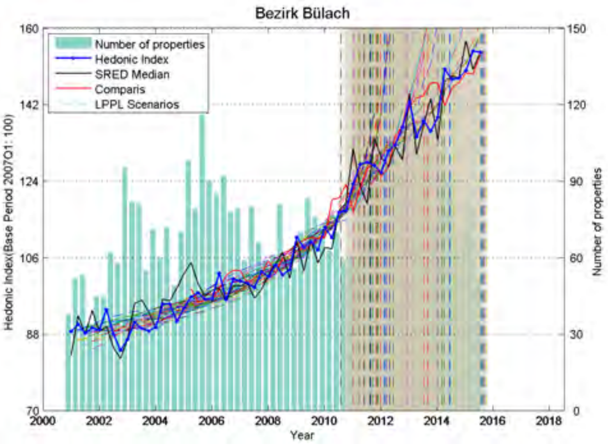
The thick solid line shows the hedonic price index. Two more solid lines are plotted, representing the SRED median and the comparis.ch median indices for the district. All indices are expressed in relative prices with the base quarter being 2007$Q1$ for which all price indices are equal to 100. The dotted lines show the price paths of the LPPLS fits and the vertical dotted lines correspond to the predicted critical times (one for each fit). Finally the volume of transactions per quarter is displayed in the form of vertical bars.



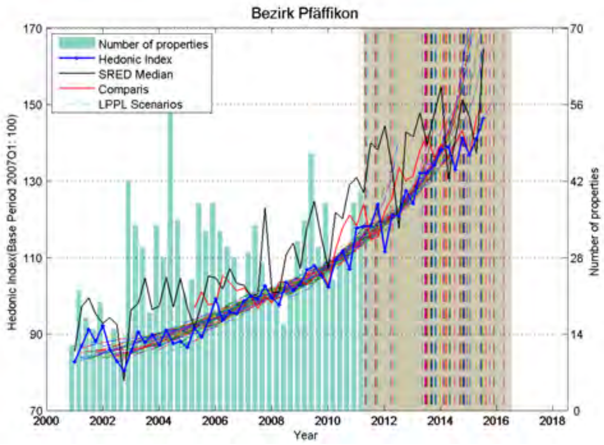
(a) Bezirk Uster

(b) Bezirk Lenzburg

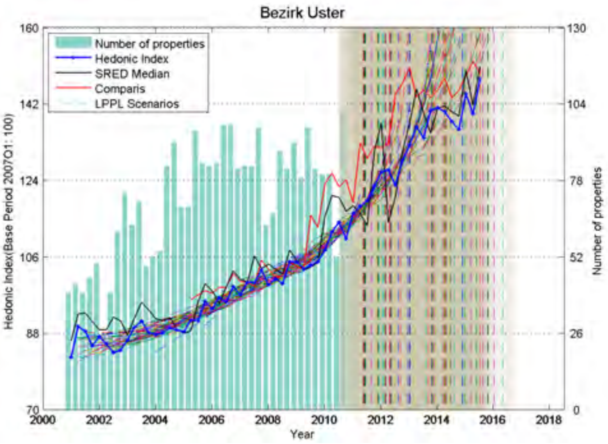
Figure 3.1: Critical districts for houses



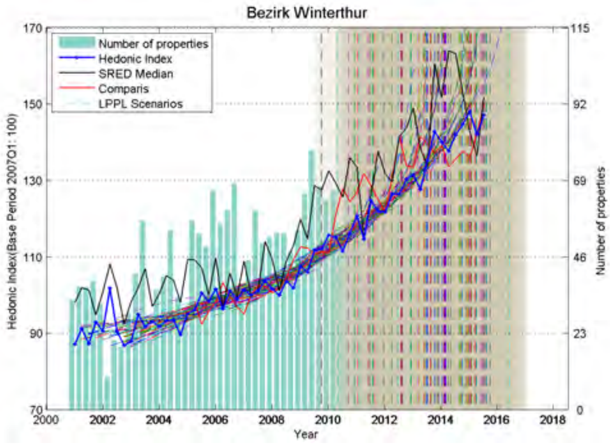
(a) Bezirk Bülach



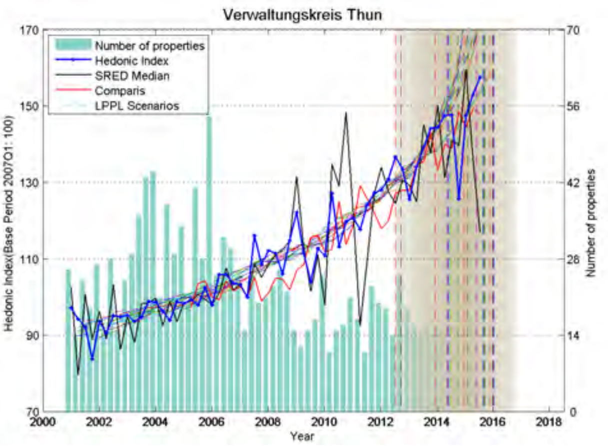
(b) Bezirk Pfaeffikon



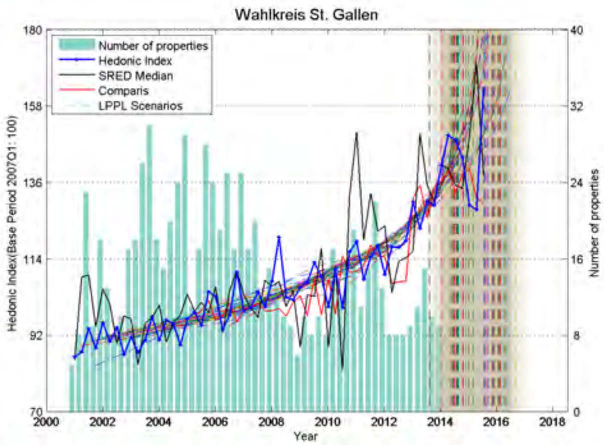
(c) Bezirk Uster



(d) Bezirk Winterthur



(e) Verwaltungskreis Thun



(f) Wahlskreis St. Gallen

Figure 3.2: Critical districts for condominiums

Chapter 4

Conclusions

Due to their robustness against changes in the overall quality of real estate properties transacted from quarter to quarter, the hedonic price indices differ significantly from the ones based on median prices, in a number of districts. Consequently the bubble signals also differ. In general, a bubble analysis based on the hedonic index generates not only different but also a significantly greater number of qualified fits. This can be at least partly attributed to the noise introduced in the median price time series by changes in the overall property quality, which interferes with the fitting process.

Overall, there is a small number of critical districts where a bubble is expected to burst within the next few quarters. These are the district of Lenzburg for Houses, the districts of Bülach, Pfäffikon, Winterthur, St. Gallen and Thun for condominiums and the district of Uster for both property types.

However, there is no cause for alarm. Given the strong economic environment in Switzerland (OECD [2015]), the very low interest rates and empirical evidence from real estate bubbles identified in the past few years, a crash is highly unlikely. Instead soft landing where prices become stagnant for a few quarters or a slight correction is more likely, similar to the price development in those districts were a bubble already burst in the last few years.

On top of the critical districts there is a significant number of districts to watch, in the majority of which a bubble might have burst recently. However, since there are not enough data points to verify the regime change, the evolution of prices in these districts needs to be monitored for a few more quarters. If a regime change is indeed verified, this would signal a potentially attractive market from a buyer's perspective, before prices start rising again.

Furthermore, data availability from as early as 2000Q4 allowed the LPPLS scanning process to identify bubbles that have burst sometime between 2008 and 2013 in a small number of districts. These findings are not only of theoretical interest but they also provide some empirical evidence concerning the market reaction after a real estate bubble bursts.

Another thing that must be stressed is that previous work based on asking prices from comparis.ch remains relevant. First of all it is not necessary that both asking and transaction prices move together at all times, so it is interesting to monitor the price evolution of both. Furthermore, as long as the SNB also publishes real estate indices based on median asking prices, they are still relevant for policy-makers which means that changes in these indices matter, whether they are caused by changes in the price level or by changes in the housing quality.

As a next step, it is important to continue this analysis as new data becomes available in the future, paying particular attention to the critical districts. Finally, it would be nice to have access to a larger dataset with better coverage on a broad number of districts. One way for this to happen is if some regional banks in Switzerland would participate in the datapool and share their real estate transaction data. This would allow us to generate price indices for more districts as well as to improve the accuracy of the current ones.

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Appendix A

Various Tables and Figures

Geneva Houses - OLS									
Variable	Estimate	Std. Error	t value	Pr(>|t|)	Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	8.0217	0.1450	55.3390	0.0000	Q15	0.1761	0.0330	5.3439	0.0000
log(KUBATUR_CHAR)	0.6544	0.0141	46.3189	0.0000	Q16	0.1615	0.0341	4.7309	0.0000
IS_DETACHED	0.1047	0.0088	11.9556	0.0000	Q17	0.1954	0.0329	5.9375	0.0000
BUILT_BEF1900	-0.0941	0.0191	-4.9369	0.0000	Q18	0.2476	0.0348	7.1064	0.0000
BUILT_71TO80	0.0404	0.0130	3.1011	0.0019	Q19	0.2381	0.0336	7.0907	0.0000
BUILT_81TO90	0.0590	0.0121	4.8669	0.0000	Q20	0.3090	0.0341	9.0526	0.0000
BUILT_91TO00	0.0626	0.0146	4.2778	0.0000	Q21	0.2884	0.0320	9.0109	0.0000
BUILT_AFT2000	0.0679	0.0156	4.3485	0.0000	Q22	0.3128	0.0350	8.9279	0.0000
AREA_SUB	-0.1030	0.0263	-3.9132	0.0001	Q23	0.3585	0.0340	10.5403	0.0000
AREA_RE	0.0388	0.0263	1.4727	0.1409	Q24	0.3463	0.0330	10.5062	0.0000
AREA_PERI	-0.1569	0.0288	-5.4443	0.0000	Q25	0.3023	0.0362	8.3444	0.0000
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	Q26	0.4304	0.0437	9.8545	0.0000
AREA_IND	#N/A	#N/A	#N/A	#N/A	Q27	0.4643	0.0362	12.8295	0.0000
AREA_PEND	-0.2034	0.0580	-3.5047	0.0005	Q28	0.4819	0.0374	12.8851	0.0000
AREA_MIX	-0.3057	0.0782	-3.9069	0.0001	Q29	0.4733	0.0373	12.6886	0.0000
AREA_AGR	#N/A	#N/A	#N/A	#N/A	Q30	0.4818	0.0422	11.4225	0.0000
BATHROOM2	0.1429	0.0191	7.4729	0.0000	Q31	0.5129	0.0392	13.0934	0.0000
BATHROOM3	0.2007	0.0206	9.7276	0.0000	Q32	0.6137	0.0397	15.4570	0.0000
BATHROOM4	0.2400	0.0260	9.2260	0.0000	Q33	0.6147	0.0433	14.1971	0.0000
GARAGE1	0.0230	0.0109	2.1103	0.0349	Q34	0.6058	0.0423	14.3152	0.0000
GARAGE2	0.0742	0.0105	7.0863	0.0000	Q35	0.6013	0.0427	14.0890	0.0000
GARAGE3	0.0745	0.0172	4.3237	0.0000	Q36	0.5915	0.0419	14.1141	0.0000
LOC_AVG	0.4638	0.0826	5.6181	0.0000	Q37	0.5653	0.0424	13.3303	0.0000
LOC_GOOD	0.5819	0.0824	7.0658	0.0000	Q38	0.6002	0.0451	13.3174	0.0000
LOC_GREAT	0.7186	0.0831	8.6514	0.0000	Q39	0.6314	0.0414	15.2553	0.0000
QUAL_AVG	0.0673	0.0409	1.6455	0.0999	Q40	0.5442	0.0380	14.3151	0.0000
QUAL_GOOD	0.1041	0.0418	2.4934	0.0127	Q41	0.5617	0.0401	14.0067	0.0000
QUAL_GREAT	0.1925	0.0415	4.6415	0.0000	Q42	0.6764	0.0437	15.4817	0.0000
BUILD_AVG	0.0516	0.0198	2.6102	0.0091	Q43	0.6445	0.0454	14.2036	0.0000
BUILD_GOOD	0.1168	0.0201	5.8234	0.0000	Q44	0.6886	0.0395	17.4509	0.0000
BUILD_GREAT	0.0990	0.0232	4.2707	0.0000	Q45	0.6716	0.0493	13.6266	0.0000
FIRST	0.2643	0.0677	3.9030	0.0001	Q46	0.6692	0.0449	14.8927	0.0000
Q2	-0.0123	0.0318	-0.3864	0.6992	Q47	0.7445	0.0398	18.7130	0.0000
Q3	0.0260	0.0324	0.8031	0.4220	Q48	0.7570	0.0478	15.8204	0.0000
Q4	0.0141	0.0311	0.4517	0.6515	Q49	0.7326	0.0427	17.1502	0.0000
Q5	0.0590	0.0321	1.8372	0.0662	Q50	0.7497	0.0468	16.0202	0.0000
Q6	0.0792	0.0379	2.0881	0.0368	Q51	0.7227	0.0443	16.3245	0.0000
Q7	0.0424	0.0364	1.1669	0.2433	Q52	0.7255	0.0448	16.1912	0.0000
Q8	0.0576	0.0356	1.6197	0.1054	Q53	0.6626	0.0471	14.0614	0.0000
Q9	0.1187	0.0360	3.2989	0.0010	Q54	0.7059	0.0487	14.4845	0.0000
Q10	0.0653	0.0370	1.7637	0.0779	Q55	0.7112	0.0468	15.2023	0.0000
Q11	0.1153	0.0345	3.3446	0.0008	Q56	0.6802	0.0437	15.5601	0.0000
Q12	0.1028	0.0346	2.9735	0.0030	Q57	0.7216	0.0465	15.5043	0.0000
Q13	0.1344	0.0359	3.7381	0.0002	Q58	0.6918	0.0455	15.2004	0.0000
Q14	0.1465	0.0354	4.1386	0.0000	Q59	0.7392	0.0466	15.8730	0.0000

Table A.1: Regression results for houses in Geneva with OLS method. Looking that the level and the statistical significance of the various estimates and comparing them with those of condominiums in the same district (table A.2) one can notice that the two datasets (houses and condominiums) are not quite homogeneous.

Geneva Condominiums - OLS									
Variable	Estimate	Std. Error	t value	Pr(>|t|)	Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	8.3974	0.1093	76.8253	0.0000	Q16	0.2514	0.0267	9.4082	0.0000
log(NETTOWOHNFLAECHE_CHAR)	0.9018	0.0091	98.5878	0.0000	Q17	0.2643	0.0267	9.8937	0.0000
BUILT_BEF1900	0.1056	0.0168	6.2871	0.0000	Q18	0.3017	0.0265	11.4030	0.0000
BUILT_71TO80	0.0531	0.0096	5.5440	0.0000	Q19	0.3120	0.0245	12.7126	0.0000
BUILT_81TO90	0.0537	0.0095	5.6519	0.0000	Q20	0.3310	0.0254	13.0110	0.0000
BUILT_91TO00	0.0539	0.0110	4.9001	0.0000	Q21	0.3594	0.0242	14.8648	0.0000
BUILT_AFT2000	-0.0386	0.0124	-3.1204	0.0018	Q22	0.3573	0.0285	12.5180	0.0000
AREA_SUB	-0.2155	0.0064	-33.8543	0.0000	Q23	0.4554	0.0255	17.8360	0.0000
AREA_RE	-0.0845	0.0087	-9.6761	0.0000	Q24	0.4359	0.0269	16.1888	0.0000
AREA_PERI	-0.2074	0.0150	-13.8387	0.0000	Q25	0.4765	0.0288	16.5574	0.0000
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	Q26	0.5009	0.0289	17.3588	0.0000
AREA_IND	#N/A	#N/A	#N/A	#N/A	Q27	0.5722	0.0294	19.4718	0.0000
AREA_PEND	-0.3367	0.0299	-11.2483	0.0000	Q28	0.5310	0.0284	18.6895	0.0000
AREA_MIX	-0.2950	0.0677	-4.3591	0.0000	Q29	0.6177	0.0274	22.5760	0.0000
AREA_AGR	#N/A	#N/A	#N/A	#N/A	Q30	0.6097	0.0307	19.8605	0.0000
BATHROOM2	0.1178	0.0084	14.1026	0.0000	Q31	0.6418	0.0300	21.3745	0.0000
BATHROOM3	0.1420	0.0128	11.1015	0.0000	Q32	0.6945	0.0296	23.4561	0.0000
BATHROOM4	0.1581	0.0279	5.6608	0.0000	Q33	0.6481	0.0297	21.7948	0.0000
GARAGE1	0.0701	0.0068	10.3100	0.0000	Q34	0.6399	0.0297	21.5508	0.0000
GARAGE2	0.1077	0.0089	12.0957	0.0000	Q35	0.6933	0.0311	22.2902	0.0000
GARAGE3	0.1894	0.0255	7.4152	0.0000	Q36	0.7003	0.0298	23.5123	0.0000
LOC_AVG	0.1598	0.0782	2.0426	0.0411	Q37	0.6915	0.0288	23.9824	0.0000
LOC_GOOD	0.2668	0.0781	3.4161	0.0006	Q38	0.7570	0.0300	25.2360	0.0000
LOC_GREAT	0.4080	0.0784	5.2015	0.0000	Q39	0.6955	0.0271	25.6281	0.0000
QUAL_AVG	0.0447	0.0423	1.0568	0.2906	Q40	0.8033	0.0293	27.4334	0.0000
QUAL_GOOD	0.0432	0.0425	1.0158	0.3097	Q41	0.7800	0.0283	27.6085	0.0000
QUAL_GREAT	0.2034	0.0426	4.7758	0.0000	Q42	0.8632	0.0311	27.7553	0.0000
BUILD_AVG	-0.0108	0.0149	-0.7214	0.4707	Q43	0.8689	0.0285	30.4967	0.0000
BUILD_GOOD	0.0549	0.0152	3.6034	0.0003	Q44	0.8501	0.0324	26.2597	0.0000
BUILD_GREAT	0.0706	0.0178	3.9730	0.0001	Q45	0.9299	0.0307	30.3012	0.0000
FIRST	-0.0245	0.0468	-0.5237	0.6005	Q46	0.9048	0.0301	30.0908	0.0000
Q2	0.0640	0.0287	2.2279	0.0259	Q47	0.9435	0.0308	30.6738	0.0000
Q3	0.0433	0.0275	1.5752	0.1153	Q48	0.8949	0.0314	28.5292	0.0000
Q4	0.0670	0.0269	2.4908	0.0128	Q49	0.8586	0.0299	28.7539	0.0000
Q5	0.0728	0.0264	2.7566	0.0059	Q50	1.0031	0.0318	31.5579	0.0000
Q6	0.1326	0.0300	4.4189	0.0000	Q51	1.0013	0.0309	32.4289	0.0000
Q7	0.0751	0.0282	2.6668	0.0077	Q52	0.9968	0.0320	31.1158	0.0000
Q8	0.0744	0.0277	2.6808	0.0074	Q53	0.9757	0.0293	33.3319	0.0000
Q9	0.1073	0.0264	4.0597	0.0000	Q54	0.8967	0.0319	28.1213	0.0000
Q10	0.0941	0.0273	3.4521	0.0006	Q55	0.9475	0.0325	29.1773	0.0000
Q11	0.1722	0.0270	6.3669	0.0000	Q56	0.9946	0.0313	31.7980	0.0000
Q12	0.1505	0.0260	5.7972	0.0000	Q57	0.9460	0.0298	31.7607	0.0000
Q13	0.1548	0.0255	6.0744	0.0000	Q58	0.9303	0.0295	31.5063	0.0000
Q14	0.2350	0.0260	9.0313	0.0000	Q59	0.9342	0.0291	32.1058	0.0000
Q15	0.2089	0.0250	8.3702	0.0000					

Table A.2: Regression results for condominiums in Geneva with OLS method. Seen together with table A.1 one can notice that the two datasets (houses and condominiums) are not quite homogeneous.

Zurich Houses - OLS									
Variable	Estimate	Std. Error	t value	Pr(>|t|)	Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	8.2426	0.1792	45.9865	0.0000	Q15	0.1032	0.0674	1.5303	0.1262
log(KUBATUR_CHAR)	0.7433	0.0274	27.1610	0.0000	Q16	0.0093	0.0727	0.1284	0.8979
IS_DETACHED	0.0435	0.0160	2.7111	0.0068	Q17	0.1145	0.0737	1.5535	0.1205
BUILT_BEF1900	-0.0977	0.0323	-3.0271	0.0025	Q18	0.0721	0.0706	1.0209	0.3075
BUILT_71TO80	-0.0952	0.0543	-1.7542	0.0796	Q19	0.1918	0.0659	2.9131	0.0036
BUILT_81TO90	-0.0240	0.0462	-0.5186	0.6041	Q20	0.1761	0.0666	2.6452	0.0083
BUILT_91TO00	0.0442	0.0414	1.0690	0.2853	Q21	0.1521	0.0686	2.2167	0.0268
BUILT_AFT2000	0.0154	0.0500	0.3081	0.7581	Q22	0.2149	0.0754	2.8508	0.0044
AREA_SUB	#N/A	#N/A	#N/A	#N/A	Q23	0.1930	0.0669	2.8860	0.0040
AREA_RE	#N/A	#N/A	#N/A	#N/A	Q24	0.2055	0.0698	2.9438	0.0033
AREA_PERI	#N/A	#N/A	#N/A	#N/A	Q25	0.3930	0.0829	4.7407	0.0000
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	Q26	0.3301	0.0795	4.1531	0.0000
AREA_IND	#N/A	#N/A	#N/A	#N/A	Q27	0.1834	0.0795	2.3057	0.0213
AREA_PEND	#N/A	#N/A	#N/A	#N/A	Q28	0.3003	0.0746	4.0226	0.0001
AREA_MIX	#N/A	#N/A	#N/A	#N/A	Q29	0.3617	0.0784	4.6163	0.0000
AREA_AGR	#N/A	#N/A	#N/A	#N/A	Q30	0.4651	0.0753	6.1759	0.0000
BATHROOM2	0.0920	0.0234	3.9380	0.0001	Q31	0.2366	0.0823	2.8757	0.0041
BATHROOM3	0.1469	0.0286	5.1331	0.0000	Q32	0.4242	0.0723	5.8684	0.0000
BATHROOM4	0.1801	0.0507	3.5521	0.0004	Q33	0.3982	0.0811	4.9104	0.0000
GARAGE1	0.0161	0.0177	0.9061	0.3650	Q34	0.3763	0.0926	4.0656	0.0001
GARAGE2	0.0484	0.0265	1.8244	0.0683	Q35	0.4432	0.0899	4.9281	0.0000
GARAGE3	0.0990	0.0592	1.6720	0.0948	Q36	0.4146	0.0733	5.6570	0.0000
LOC_AVG	0.0302	0.0402	0.7519	0.4523	Q37	0.5415	0.0732	7.3980	0.0000
LOC_GOOD	0.1936	0.0392	4.9385	0.0000	Q38	0.4210	0.0859	4.9011	0.0000
LOC_GREAT	0.3700	0.0434	8.5283	0.0000	Q39	0.3801	0.0796	4.7780	0.0000
QUAL_AVG	0.0504	0.0294	1.7139	0.0868	Q40	0.3977	0.0825	4.8215	0.0000
QUAL_GOOD	0.1110	0.0346	3.2109	0.0014	Q41	0.4674	0.0700	6.6734	0.0000
QUAL_GREAT	0.2732	0.0377	7.2412	0.0000	Q42	0.5158	0.0949	5.4334	0.0000
BUILD_AVG	0.0625	0.0242	2.5850	0.0098	Q43	0.5118	0.0803	6.3704	0.0000
BUILD_GOOD	0.1233	0.0267	4.6201	0.0000	Q44	0.4505	0.0986	4.5669	0.0000
BUILD_GREAT	0.0584	0.0445	1.3118	0.1898	Q45	0.5161	0.0776	6.6540	0.0000
FIRST	#N/A	#N/A	#N/A	#N/A	Q46	0.6437	0.0795	8.1002	0.0000
Q2	-0.0610	0.0792	-0.7699	0.4415	Q47	0.6035	0.0699	8.6281	0.0000
Q3	0.0730	0.0812	0.8991	0.3687	Q48	0.7157	0.0813	8.8059	0.0000
Q4	0.0799	0.0666	1.1992	0.2307	Q49	0.6883	0.0810	8.4954	0.0000
Q5	0.0528	0.0711	0.7428	0.4577	Q50	0.7002	0.0921	7.6044	0.0000
Q6	0.1068	0.0899	1.1876	0.2352	Q51	0.7582	0.0726	10.4366	0.0000
Q7	0.0439	0.0762	0.5761	0.5647	Q52	0.6680	0.0837	7.9799	0.0000
Q8	0.0565	0.0674	0.8382	0.4021	Q53	0.7108	0.0724	9.8179	0.0000
Q9	0.0108	0.0714	0.1516	0.8795	Q54	0.6312	0.1030	6.1289	0.0000
Q10	-0.0003	0.0795	-0.0036	0.9971	Q55	0.7657	0.0802	9.5531	0.0000
Q11	0.0325	0.0685	0.4751	0.6348	Q56	0.5953	0.0787	7.5694	0.0000
Q12	0.0351	0.0745	0.4703	0.6382	Q57	0.6643	0.0797	8.3314	0.0000
Q13	0.0260	0.0686	0.3794	0.7044	Q58	0.5962	0.0791	7.5349	0.0000
Q14	0.0480	0.0711	0.6754	0.4995	Q59	0.7003	0.0767	9.1298	0.0000

Table A.3: Regression results for houses in Zurich with OLS method. Looking that the level and the statistical significance of the various estimates and comparing them with those of condominiums in the same district (table A.4) one can notice that the two datasets (houses and condominiums) are not quite homogeneous.

Zurich Condominiums - OLS

Variable	Estimate	Std. Error	t value	Pr(>|t|)	Variable	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	8.3187	0.0813	102.3070	0.0000	Q16	0.1484	0.0365	4.0714	0.0000
log(NETTOWOHNFLAECHE_CHAR)	0.9547	0.0131	73.0739	0.0000	Q17	0.1255	0.0372	3.3772	0.0007
BUILT_BEF1900	0.0790	0.0176	4.5014	0.0000	Q18	0.1481	0.0345	4.2958	0.0000
BUILT_71TO80	-0.0711	0.0143	-4.9798	0.0000	Q19	0.1608	0.0328	4.9058	0.0000
BUILT_81TO90	-0.0004	0.0155	-0.0247	0.9803	Q20	0.2173	0.0343	6.3345	0.0000
BUILT_91TO00	0.0002	0.0141	0.0149	0.9881	Q21	0.2592	0.0332	7.8096	0.0000
BUILT_AFT2000	-0.0182	0.0149	-1.2242	0.2209	Q22	0.1538	0.0354	4.3438	0.0000
AREA_SUB	#N/A	#N/A	#N/A	#N/A	Q23	0.2385	0.0338	7.0465	0.0000
AREA_RE	#N/A	#N/A	#N/A	#N/A	Q24	0.2684	0.0358	7.4953	0.0000
AREA_PERI	#N/A	#N/A	#N/A	#N/A	Q25	0.3160	0.0347	9.1007	0.0000
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	Q26	0.2977	0.0352	8.4507	0.0000
AREA_IND	#N/A	#N/A	#N/A	#N/A	Q27	0.3546	0.0372	9.5304	0.0000
AREA_PEND	#N/A	#N/A	#N/A	#N/A	Q28	0.3722	0.0377	9.8791	0.0000
AREA_MIX	#N/A	#N/A	#N/A	#N/A	Q29	0.3036	0.0369	8.2384	0.0000
AREA_AGR	#N/A	#N/A	#N/A	#N/A	Q30	0.3449	0.0362	9.5153	0.0000
BATHROOM2	0.0419	0.0099	4.2249	0.0000	Q31	0.3008	0.0355	8.4665	0.0000
BATHROOM3	0.0823	0.0188	4.3713	0.0000	Q32	0.3015	0.0338	8.9118	0.0000
BATHROOM4	0.0566	0.0580	0.9756	0.3293	Q33	0.3713	0.0349	10.6504	0.0000
GARAGE1	-0.0208	0.0084	-2.4723	0.0135	Q34	0.3306	0.0344	9.5983	0.0000
GARAGE2	0.0580	0.0121	4.7790	0.0000	Q35	0.3802	0.0334	11.3897	0.0000
GARAGE3	0.1229	0.0414	2.9709	0.0030	Q36	0.4090	0.0325	12.6031	0.0000
LOC_AVG	0.0934	0.0166	5.6381	0.0000	Q37	0.3999	0.0356	11.2412	0.0000
LOC_GOOD	0.2488	0.0165	15.0990	0.0000	Q38	0.4900	0.0358	13.6982	0.0000
LOC_GREAT	0.4063	0.0181	22.5075	0.0000	Q39	0.5582	0.0371	15.0579	0.0000
QUAL_AVG	0.0859	0.0236	3.6341	0.0003	Q40	0.4899	0.0342	14.3260	0.0000
QUAL_GOOD	0.1677	0.0243	6.8865	0.0000	Q41	0.5409	0.0354	15.2876	0.0000
QUAL_GREAT	0.3090	0.0245	12.6049	0.0000	Q42	0.5269	0.0382	13.7868	0.0000
BUILD_AVG	0.0841	0.0205	4.0963	0.0000	Q43	0.5492	0.0362	15.1762	0.0000
BUILD_GOOD	0.1313	0.0214	6.1446	0.0000	Q44	0.6473	0.0387	16.7394	0.0000
BUILD_GREAT	0.1695	0.0242	7.0072	0.0000	Q45	0.5894	0.0377	15.6218	0.0000
FIRST	-0.0707	0.0487	-1.4526	0.1464	Q46	0.6573	0.0396	16.6177	0.0000
Q2	0.0099	0.0414	0.2400	0.8104	Q47	0.5869	0.0389	15.0686	0.0000
Q3	0.1032	0.0383	2.6962	0.0070	Q48	0.6765	0.0413	16.3681	0.0000
Q4	0.0717	0.0371	1.9344	0.0531	Q49	0.6874	0.0365	18.8106	0.0000
Q5	0.0161	0.0378	0.4260	0.6701	Q50	0.6679	0.0342	19.5173	0.0000
Q6	0.0302	0.0436	0.6921	0.4889	Q51	0.7273	0.0364	19.9697	0.0000
Q7	0.0264	0.0393	0.6726	0.5013	Q52	0.7336	0.0401	18.3087	0.0000
Q8	0.0188	0.0373	0.5038	0.6144	Q53	0.7638	0.0329	23.2476	0.0000
Q9	0.0549	0.0336	1.6346	0.1022	Q54	0.7511	0.0385	19.5111	0.0000
Q10	0.0210	0.0403	0.5226	0.6013	Q55	0.7753	0.0378	20.5082	0.0000
Q11	0.0527	0.0333	1.5818	0.1138	Q56	0.7282	0.0362	20.1357	0.0000
Q12	0.0789	0.0348	2.2649	0.0236	Q57	0.7749	0.0350	22.1304	0.0000
Q13	0.0792	0.0347	2.2795	0.0227	Q58	0.7725	0.0356	21.7238	0.0000
Q14	0.0942	0.0420	2.2439	0.0249	Q59	0.7843	0.0355	22.1012	0.0000
Q15	0.0912	0.0363	2.5101	0.0121					

Table A.4: Regression results for condominiums in Zurich with OLS method. Seen together with table A.3 one can notice that the two datasets (houses and condominiums) are not quite homogeneous.

Geneva Houses - SARLag									
Variable	Estimate	Std. Error	z value	Pr(>|z|)	Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	2.8042	0.3276	8.5613	0.0000	Q16	0.1610	0.0328	4.9133	0.0000
log(KUBATUR_CHAR)	0.6295	0.0137	45.9921	0.0000	Q17	0.1967	0.0316	6.2296	0.0000
IS_DETACHED	0.0988	0.0084	11.7568	0.0000	Q18	0.2415	0.0334	7.2235	0.0000
BUILT_BEF1900	-0.0803	0.0183	-4.3879	0.0000	Q19	0.2412	0.0322	7.4860	0.0000
BUILT_71TO80	0.0395	0.0125	3.1639	0.0016	Q20	0.3024	0.0328	9.2309	0.0000
BUILT_81TO90	0.0563	0.0116	4.8408	0.0000	Q21	0.2922	0.0307	9.5154	0.0000
BUILT_91TO00	0.0523	0.0141	3.7197	0.0002	Q22	0.3154	0.0336	9.3850	0.0000
BUILT_AFT2000	0.0666	0.0150	4.4475	0.0000	Q23	0.3633	0.0326	11.1320	0.0000
AREA_SUB	-0.0815	0.0253	-3.2215	0.0013	Q24	0.3496	0.0316	11.0544	0.0000
AREA_RE	-0.0385	0.0257	-1.4979	0.1342	Q25	0.3186	0.0348	9.1680	0.0000
AREA_PERI	-0.1092	0.0278	-3.9285	0.0001	Q26	0.4283	0.0419	10.2196	0.0000
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	Q27	0.4587	0.0347	13.2061	0.0000
AREA_IND	#N/A	#N/A	#N/A	#N/A	Q28	0.4851	0.0359	13.5199	0.0000
AREA_PEND	-0.1982	0.0557	-3.5597	0.0004	Q29	0.4699	0.0358	13.1258	0.0000
AREA_MIX	-0.1789	0.0755	-2.3703	0.0178	Q30	0.4753	0.0405	11.7395	0.0000
AREA_AGR	#N/A	#N/A	#N/A	#N/A	Q31	0.5077	0.0376	13.5048	0.0000
BATHROOM2	0.1425	0.0183	7.7669	0.0000	Q32	0.5930	0.0381	15.5576	0.0000
BATHROOM3	0.1944	0.0198	9.8202	0.0000	Q33	0.6112	0.0415	14.7110	0.0000
BATHROOM4	0.2255	0.0250	9.0365	0.0000	Q34	0.5869	0.0406	14.4424	0.0000
GARAGE1	0.0259	0.0104	2.4832	0.0130	Q35	0.5996	0.0410	14.6394	0.0000
GARAGE2	0.0745	0.0101	7.4049	0.0000	Q36	0.5734	0.0402	14.2491	0.0000
GARAGE3	0.0752	0.0165	4.5463	0.0000	Q37	0.5665	0.0407	13.9222	0.0000
LOC_AVG	0.4639	0.0792	5.8565	0.0000	Q38	0.5906	0.0433	13.6554	0.0000
LOC_GOOD	0.5728	0.0790	7.2485	0.0000	Q39	0.6254	0.0397	15.7430	0.0000
LOC_GREAT	0.6964	0.0797	8.7358	0.0000	Q40	0.5594	0.0365	15.3349	0.0000
QUAL_AVG	0.0666	0.0392	1.6973	0.0896	Q41	0.5691	0.0385	14.7863	0.0000
QUAL_GOOD	0.1034	0.0401	2.5812	0.0098	Q42	0.6746	0.0419	16.0936	0.0000
QUAL_GREAT	0.1872	0.0398	4.7048	0.0000	Q43	0.6446	0.0435	14.8049	0.0000
BUILD_AVG	0.0495	0.0190	2.6093	0.0091	Q44	0.6831	0.0379	18.0389	0.0000
BUILD_GOOD	0.1161	0.0192	6.0313	0.0000	Q45	0.6905	0.0473	14.6005	0.0000
BUILD_GREAT	0.0970	0.0222	4.3606	0.0000	Q46	0.6744	0.0431	15.6431	0.0000
FIRST	0.3124	0.0650	4.8057	0.0000	Q47	0.7410	0.0382	19.4109	0.0000
Q2	-0.0202	0.0305	-0.6611	0.5085	Q48	0.7565	0.0459	16.4781	0.0000
Q3	0.0327	0.0311	1.0532	0.2923	Q49	0.7419	0.0410	18.1010	0.0000
Q4	0.0097	0.0299	0.3235	0.7463	Q50	0.7623	0.0449	16.9767	0.0000
Q5	0.0630	0.0308	2.0435	0.0410	Q51	0.7288	0.0425	17.1566	0.0000
Q6	0.0979	0.0364	2.6912	0.0071	Q52	0.7243	0.0430	16.8467	0.0000
Q7	0.0398	0.0349	1.1412	0.2538	Q53	0.6566	0.0452	14.5226	0.0000
Q8	0.0568	0.0341	1.6633	0.0963	Q54	0.7278	0.0468	15.5660	0.0000
Q9	0.1123	0.0345	3.2532	0.0011	Q55	0.7050	0.0449	15.7046	0.0000
Q10	0.0576	0.0355	1.6218	0.1048	Q56	0.6725	0.0420	16.0276	0.0000
Q11	0.1138	0.0331	3.4407	0.0006	Q57	0.7262	0.0447	16.2603	0.0000
Q12	0.1084	0.0332	3.2683	0.0011	Q58	0.6858	0.0437	15.7004	0.0000
Q13	0.1319	0.0345	3.8249	0.0001	Q59	0.7242	0.0447	16.2005	0.0000
Q14	0.1405	0.0340	4.1348	0.0000	Rho	0.3824			
Q15	0.1724	0.0316	5.4533	0.0000					

Table A.5: Regression results for houses in Geneva with SARLag method. This method didn't successfully adress the spatial autocorrelation in the data so the above regression results are not of much interest.

Geneva Condominiums - SARLag									
Variable	Estimate	Std. Error	z value	Pr(>|z|)	Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	3.4652	0.2280	15.1958	0.0000	Q16	0.2508	0.0258	9.7303	0.0000
log(NETTOWOHNFLAECHE_CHAR)	0.8973	0.0088	101.6916	0.0000	Q17	0.2667	0.0258	10.3529	0.0000
BUILT_BEF1900	0.1114	0.0162	6.8726	0.0000	Q18	0.3148	0.0255	12.3330	0.0000
BUILT_71TO80	0.0509	0.0092	5.5168	0.0000	Q19	0.3110	0.0237	13.1379	0.0000
BUILT_81TO90	0.0548	0.0092	5.9769	0.0000	Q20	0.3292	0.0245	13.4152	0.0000
BUILT_91TO00	0.0588	0.0106	5.5447	0.0000	Q21	0.3619	0.0233	15.5202	0.0000
BUILT_AFT2000	-0.0246	0.0119	-2.0631	0.0391	Q22	0.3706	0.0275	13.4595	0.0000
AREA_SUB	-0.1672	0.0065	-25.6147	0.0000	Q23	0.4551	0.0246	18.4778	0.0000
AREA_RE	-0.1503	0.0089	-16.9492	0.0000	Q24	0.4480	0.0260	17.2468	0.0000
AREA_PERI	-0.2109	0.0145	-14.5899	0.0000	Q25	0.4881	0.0278	17.5838	0.0000
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	Q26	0.5135	0.0278	18.4479	0.0000
AREA_IND	#N/A	#N/A	#N/A	#N/A	Q27	0.5797	0.0283	20.4523	0.0000
AREA_PEND	-0.3191	0.0289	-11.0462	0.0000	Q28	0.5467	0.0274	19.9447	0.0000
AREA_MIX	-0.4095	0.0654	-6.2581	0.0000	Q29	0.6307	0.0264	23.8871	0.0000
AREA_AGR	#N/A	#N/A	#N/A	#N/A	Q30	0.6093	0.0296	20.5760	0.0000
BATHROOM2	0.1123	0.0081	13.9432	0.0000	Q31	0.6441	0.0290	22.2388	0.0000
BATHROOM3	0.1343	0.0123	10.8896	0.0000	Q32	0.7013	0.0286	24.5594	0.0000
BATHROOM4	0.1486	0.0269	5.5168	0.0000	Q33	0.6668	0.0287	23.2426	0.0000
GARAGE1	0.0529	0.0066	7.9920	0.0000	Q34	0.6471	0.0286	22.5956	0.0000
GARAGE2	0.0862	0.0087	9.9563	0.0000	Q35	0.6983	0.0300	23.2759	0.0000
GARAGE3	0.1594	0.0247	6.4617	0.0000	Q36	0.6959	0.0287	24.2239	0.0000
LOC_AVG	0.1402	0.0755	1.8577	0.0632	Q37	0.6948	0.0278	24.9837	0.0000
LOC_GOOD	0.2327	0.0753	3.0892	0.0020	Q38	0.7598	0.0289	26.2586	0.0000
LOC_GREAT	0.3682	0.0757	4.8656	0.0000	Q39	0.6922	0.0262	26.4328	0.0000
QUAL_AVG	0.0361	0.0408	0.8853	0.3760	Q40	0.7934	0.0282	28.0863	0.0000
QUAL_GOOD	0.0331	0.0410	0.8063	0.4201	Q41	0.7843	0.0273	28.7755	0.0000
QUAL_GREAT	0.1881	0.0411	4.5785	0.0000	Q42	0.8632	0.0300	28.7741	0.0000
BUILD_AVG	-0.0164	0.0144	-1.1370	0.2556	Q43	0.8826	0.0275	32.1166	0.0000
BUILD_GOOD	0.0465	0.0147	3.1587	0.0016	Q44	0.8537	0.0312	27.3394	0.0000
BUILD_GREAT	0.0572	0.0171	3.3351	0.0009	Q45	0.9342	0.0296	31.5599	0.0000
FIRST	-0.0149	0.0451	-0.3308	0.7408	Q46	0.9010	0.0290	31.0669	0.0000
Q2	0.0590	0.0277	2.1310	0.0331	Q47	0.9351	0.0297	31.5173	0.0000
Q3	0.0340	0.0265	1.2837	0.1993	Q48	0.9018	0.0303	29.8067	0.0000
Q4	0.0547	0.0260	2.1046	0.0353	Q49	0.8538	0.0288	29.6453	0.0000
Q5	0.0740	0.0255	2.9068	0.0037	Q50	0.9971	0.0307	32.5206	0.0000
Q6	0.1313	0.0289	4.5381	0.0000	Q51	0.9857	0.0298	33.0861	0.0000
Q7	0.0807	0.0272	2.9694	0.0030	Q52	0.9896	0.0309	32.0234	0.0000
Q8	0.0884	0.0268	3.3022	0.0010	Q53	0.9680	0.0282	34.2789	0.0000
Q9	0.1084	0.0255	4.2517	0.0000	Q54	0.8961	0.0308	29.1363	0.0000
Q10	0.0986	0.0263	3.7509	0.0002	Q55	0.9399	0.0313	30.0031	0.0000
Q11	0.1851	0.0261	7.0977	0.0000	Q56	0.9751	0.0302	32.3074	0.0000
Q12	0.1615	0.0250	6.4512	0.0000	Q57	0.9290	0.0287	32.3250	0.0000
Q13	0.1596	0.0246	6.4929	0.0000	Q58	0.9149	0.0285	32.1149	0.0000
Q14	0.2435	0.0251	9.6985	0.0000	Q59	0.9207	0.0281	32.8021	0.0000
Q15	0.2110	0.0241	8.7650	0.0000	Rho	0.3707			

Table A.6: Regression results for condominiums in Geneva with SARLag method. This method didn't successfully adress the spatial autocorrelation in the data so the above regression results are not of much interest.

Zurich Houses - SARLag									
Variable	Estimate	Std. Error	z value	Pr(>|z|)	Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	3.1536	0.3491	9.0338	0.0000	Q16	0.0581	0.0648	0.8957	0.3704
log(KUBATUR_CHAR)	0.6088	0.0257	23.7073	0.0000	Q17	0.1339	0.0656	2.0402	0.0413
IS_DETACHED	0.0803	0.0144	5.5877	0.0000	Q18	0.1243	0.0630	1.9736	0.0484
BUILT_BEF1900	-0.1437	0.0288	-4.9910	0.0000	Q19	0.2084	0.0587	3.5513	0.0004
BUILT_71TO80	-0.1019	0.0483	-2.1070	0.0351	Q20	0.2093	0.0593	3.5274	0.0004
BUILT_81TO90	0.0211	0.0412	0.5110	0.6093	Q21	0.1702	0.0611	2.7834	0.0054
BUILT_91TO00	0.0109	0.0369	0.2950	0.7680	Q22	0.2254	0.0671	3.3570	0.0008
BUILT_AFT2000	0.0437	0.0446	0.9812	0.3265	Q23	0.2151	0.0596	3.6098	0.0003
AREA_SUB	#N/A	#N/A	#N/A	#N/A	Q24	0.2519	0.0622	4.0487	0.0001
AREA_RE	#N/A	#N/A	#N/A	#N/A	Q25	0.4411	0.0739	5.9698	0.0000
AREA_PERI	#N/A	#N/A	#N/A	#N/A	Q26	0.3574	0.0708	5.0479	0.0000
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	Q27	0.2131	0.0709	3.0075	0.0026
AREA_IND	#N/A	#N/A	#N/A	#N/A	Q28	0.2991	0.0665	4.4988	0.0000
AREA_PEND	#N/A	#N/A	#N/A	#N/A	Q29	0.4049	0.0698	5.7990	0.0000
AREA_MIX	#N/A	#N/A	#N/A	#N/A	Q30	0.4967	0.0671	7.4010	0.0000
AREA_AGR	#N/A	#N/A	#N/A	#N/A	Q31	0.2452	0.0733	3.3458	0.0008
BATHROOM2	0.0714	0.0208	3.4235	0.0006	Q32	0.4653	0.0644	7.2228	0.0000
BATHROOM3	0.1133	0.0256	4.4314	0.0000	Q33	0.4601	0.0723	6.3633	0.0000
BATHROOM4	0.1771	0.0452	3.9230	0.0001	Q34	0.4390	0.0825	5.3201	0.0000
GARAGE1	0.0301	0.0158	1.9014	0.0572	Q35	0.4857	0.0802	6.0596	0.0000
GARAGE2	0.0793	0.0237	3.3449	0.0008	Q36	0.4813	0.0654	7.3613	0.0000
GARAGE3	0.0958	0.0527	1.8160	0.0694	Q37	0.5673	0.0652	8.6984	0.0000
LOC_AVG	0.0137	0.0358	0.3828	0.7019	Q38	0.4768	0.0766	6.2280	0.0000
LOC_GOOD	0.1393	0.0351	3.9647	0.0001	Q39	0.4237	0.0709	5.9747	0.0000
LOC_GREAT	0.2757	0.0391	7.0426	0.0000	Q40	0.4567	0.0736	6.2089	0.0000
QUAL_AVG	0.0253	0.0262	0.9665	0.3338	Q41	0.5178	0.0624	8.2929	0.0000
QUAL_GOOD	0.0781	0.0308	2.5313	0.0114	Q42	0.5761	0.0846	6.8087	0.0000
QUAL_GREAT	0.2275	0.0337	6.7507	0.0000	Q43	0.6216	0.0719	8.6470	0.0000
BUILD_AVG	0.0867	0.0216	4.0224	0.0001	Q44	0.5568	0.0881	6.3225	0.0000
BUILD_GOOD	0.1326	0.0238	5.5747	0.0000	Q45	0.5616	0.0691	8.1250	0.0000
BUILD_GREAT	0.0879	0.0397	2.2151	0.0268	Q46	0.6909	0.0708	9.7546	0.0000
FIRST	#N/A	#N/A	#N/A	#N/A	Q47	0.6195	0.0623	9.9428	0.0000
Q2	-0.0676	0.0706	-0.9583	0.3379	Q48	0.7463	0.0724	10.3068	0.0000
Q3	0.0958	0.0723	1.3244	0.1854	Q49	0.7152	0.0722	9.9082	0.0000
Q4	0.1282	0.0594	2.1574	0.0310	Q50	0.7151	0.0820	8.7192	0.0000
Q5	0.0770	0.0633	1.2155	0.2242	Q51	0.7536	0.0647	11.6463	0.0000
Q6	0.1397	0.0801	1.7429	0.0814	Q52	0.6903	0.0746	9.2544	0.0000
Q7	0.0421	0.0679	0.6200	0.5352	Q53	0.7505	0.0645	11.6307	0.0000
Q8	0.0691	0.0600	1.1503	0.2500	Q54	0.6554	0.0917	7.1436	0.0000
Q9	0.0363	0.0636	0.5708	0.5681	Q55	0.7704	0.0714	10.7904	0.0000
Q10	0.0197	0.0709	0.2779	0.7811	Q56	0.6535	0.0702	9.3123	0.0000
Q11	0.0657	0.0611	1.0765	0.2817	Q57	0.7255	0.0711	10.2020	0.0000
Q12	0.0676	0.0664	1.0170	0.3092	Q58	0.6242	0.0705	8.8556	0.0000
Q13	0.1106	0.0613	1.8037	0.0713	Q59	0.7485	0.0684	10.9479	0.0000
Q14	0.0893	0.0634	1.4087	0.1589	Rho	0.4324			
Q15	0.1509	0.0601	2.5091	0.0121					

Table A.7: Regression results for houses in Zurich with SARLag method. This method didn't successfully adress the spatial autocorrelation in the data so the above regression results are not of much interest.

Zurich Condominiums - SARLag									
Variable	Estimate	Std. Error	z value	Pr(>|z|)	Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	1.0325	0.1605	6.4323	0.0000	Q16	0.1414	0.0312	4.5274	0.0000
log(NETTOWOHNFLAECHE_CHAR)	0.9085	0.0112	80.8763	0.0000	Q17	0.0935	0.0319	2.9355	0.0033
BUILT_BEF1900	0.0747	0.0150	4.9680	0.0000	Q18	0.1281	0.0295	4.3367	0.0000
BUILT_71TO80	-0.0199	0.0122	-1.6252	0.1041	Q19	0.1644	0.0281	5.8562	0.0000
BUILT_81TO90	0.0047	0.0133	0.3522	0.7247	Q20	0.2009	0.0294	6.8354	0.0000
BUILT_91TO00	0.0336	0.0121	2.7714	0.0056	Q21	0.2215	0.0285	7.7827	0.0000
BUILT_AFT2000	0.0291	0.0128	2.2808	0.0226	Q22	0.1432	0.0303	4.7221	0.0000
AREA_SUB	#N/A	#N/A	#N/A	#N/A	Q23	0.2265	0.0290	7.8117	0.0000
AREA_RE	#N/A	#N/A	#N/A	#N/A	Q24	0.2445	0.0307	7.9691	0.0000
AREA_PERI	#N/A	#N/A	#N/A	#N/A	Q25	0.3075	0.0297	10.3365	0.0000
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	Q26	0.2969	0.0302	9.8385	0.0000
AREA_IND	#N/A	#N/A	#N/A	#N/A	Q27	0.3462	0.0319	10.8606	0.0000
AREA_PEND	#N/A	#N/A	#N/A	#N/A	Q28	0.3339	0.0323	10.3394	0.0000
AREA_MIX	#N/A	#N/A	#N/A	#N/A	Q29	0.2978	0.0316	9.4296	0.0000
AREA_AGR	#N/A	#N/A	#N/A	#N/A	Q30	0.3272	0.0311	10.5307	0.0000
BATHROOM2	0.0502	0.0085	5.9145	0.0000	Q31	0.2889	0.0304	9.4910	0.0000
BATHROOM3	0.0826	0.0161	5.1187	0.0000	Q32	0.3100	0.0290	10.6952	0.0000
BATHROOM4	0.0573	0.0497	1.1519	0.2494	Q33	0.3694	0.0299	12.3689	0.0000
GARAGE1	-0.0057	0.0072	-0.7854	0.4322	Q34	0.3417	0.0295	11.5794	0.0000
GARAGE2	0.0583	0.0104	5.6048	0.0000	Q35	0.3767	0.0286	13.1668	0.0000
GARAGE3	0.1279	0.0354	3.6086	0.0003	Q36	0.3892	0.0278	13.9918	0.0000
LOC_AVG	0.0573	0.0142	4.0382	0.0001	Q37	0.4139	0.0305	13.5805	0.0000
LOC_GOOD	0.1696	0.0141	11.9891	0.0000	Q38	0.4569	0.0307	14.9025	0.0000
LOC_GREAT	0.2785	0.0156	17.8878	0.0000	Q39	0.5109	0.0318	16.0730	0.0000
QUAL_AVG	0.0611	0.0202	3.0205	0.0025	Q40	0.4801	0.0293	16.3870	0.0000
QUAL_GOOD	0.1216	0.0209	5.8232	0.0000	Q41	0.5171	0.0303	17.0575	0.0000
QUAL_GREAT	0.2261	0.0210	10.7407	0.0000	Q42	0.5167	0.0327	15.7784	0.0000
BUILD_AVG	0.1153	0.0176	6.5550	0.0000	Q43	0.5299	0.0310	17.0841	0.0000
BUILD_GOOD	0.1684	0.0183	9.1880	0.0000	Q44	0.6154	0.0331	18.5723	0.0000
BUILD_GREAT	0.2193	0.0207	10.5723	0.0000	Q45	0.5962	0.0323	18.4465	0.0000
FIRST	-0.0064	0.0417	-0.1546	0.8771	Q46	0.6554	0.0339	19.3438	0.0000
Q2	-0.0089	0.0355	-0.2506	0.8021	Q47	0.5668	0.0334	16.9807	0.0000
Q3	0.0771	0.0328	2.3494	0.0188	Q48	0.6533	0.0354	18.4475	0.0000
Q4	0.0539	0.0318	1.6970	0.0897	Q49	0.6647	0.0313	21.2262	0.0000
Q5	0.0031	0.0324	0.0962	0.9234	Q50	0.6534	0.0293	22.2783	0.0000
Q6	-0.0112	0.0374	-0.3007	0.7636	Q51	0.6976	0.0312	22.3426	0.0000
Q7	0.0053	0.0337	0.1587	0.8739	Q52	0.6971	0.0343	20.2977	0.0000
Q8	-0.0245	0.0320	-0.7676	0.4427	Q53	0.6933	0.0282	24.5668	0.0000
Q9	0.0345	0.0288	1.1983	0.2308	Q54	0.7170	0.0330	21.7251	0.0000
Q10	0.0183	0.0345	0.5314	0.5952	Q55	0.7488	0.0324	23.1118	0.0000
Q11	0.0346	0.0286	1.2115	0.2257	Q56	0.7124	0.0310	22.9809	0.0000
Q12	0.0562	0.0298	1.8818	0.0599	Q57	0.7244	0.0300	24.1146	0.0000
Q13	0.0543	0.0298	1.8245	0.0681	Q58	0.7341	0.0305	24.0783	0.0000
Q14	0.0633	0.0359	1.7613	0.0782	Q59	0.7710	0.0304	25.3621	0.0000
Q15	0.0608	0.0311	1.9542	0.0507	Rho	0.5500			

Table A.8: Regression results for condominiums in Zurich with SARLag method. This method didn't successfully adress the spatial autocorrelation in the data so the above regression results are not of much interest.

Geneva Houses - SARErr									
Variable	Estimate	Std. Error	z value	Pr(>|z|)	Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	8.0727	0.1511	53.4258	0.0000	Q15	0.1785	0.0314	5.6855	0.0000
log(KUBATUR_CHAR)	0.6426	0.0136	47.2800	0.0000	Q16	0.1610	0.0325	4.9497	0.0000
IS_DETACHED	0.0928	0.0084	11.0746	0.0000	Q17	0.2026	0.0313	6.4778	0.0000
BUILT_BEF1900	-0.0485	0.0185	-2.6238	0.0087	Q18	0.2459	0.0332	7.4163	0.0000
BUILT_71TO80	0.0390	0.0125	3.1311	0.0017	Q19	0.2417	0.0321	7.5416	0.0000
BUILT_81TO90	0.0576	0.0116	4.9583	0.0000	Q20	0.3159	0.0327	9.6716	0.0000
BUILT_91TO00	0.0520	0.0140	3.7210	0.0002	Q21	0.2931	0.0304	9.6291	0.0000
BUILT_AFT2000	0.0683	0.0149	4.5856	0.0000	Q22	0.3226	0.0334	9.6649	0.0000
AREA_SUB	-0.1073	0.0669	-1.6032	0.1089	Q23	0.3691	0.0324	11.3814	0.0000
AREA_RE	0.0400	0.0671	0.5966	0.5508	Q24	0.3558	0.0314	11.3224	0.0000
AREA_PERI	-0.1593	0.0741	-2.1508	0.0315	Q25	0.3346	0.0345	9.7029	0.0000
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	Q26	0.4318	0.0415	10.3996	0.0000
AREA_IND	#N/A	#N/A	#N/A	#N/A	Q27	0.4686	0.0345	13.5833	0.0000
AREA_PEND	-0.2016	0.1640	-1.2295	0.2189	Q28	0.4854	0.0356	13.6461	0.0000
AREA_MIX	-0.3254	0.2227	-1.4611	0.1440	Q29	0.4875	0.0355	13.7280	0.0000
AREA_AGR	#N/A	#N/A	#N/A	#N/A	Q30	0.4944	0.0401	12.3163	0.0000
BATHROOM2	0.1280	0.0184	6.9716	0.0000	Q31	0.5268	0.0371	14.1875	0.0000
BATHROOM3	0.1773	0.0198	8.9708	0.0000	Q32	0.5978	0.0378	15.8167	0.0000
BATHROOM4	0.2070	0.0249	8.2988	0.0000	Q33	0.6191	0.0412	15.0379	0.0000
GARAGE1	0.0223	0.0104	2.1538	0.0313	Q34	0.6016	0.0403	14.9412	0.0000
GARAGE2	0.0670	0.0100	6.7229	0.0000	Q35	0.6197	0.0406	15.2761	0.0000
GARAGE3	0.0670	0.0163	4.1111	0.0000	Q36	0.5888	0.0399	14.7649	0.0000
LOC_AVG	0.4775	0.0778	6.1369	0.0000	Q37	0.5761	0.0404	14.2735	0.0000
LOC_GOOD	0.5931	0.0776	7.6389	0.0000	Q38	0.6031	0.0429	14.0599	0.0000
LOC_GREAT	0.7149	0.0783	9.1252	0.0000	Q39	0.6446	0.0394	16.3575	0.0000
QUAL_AVG	0.0613	0.0387	1.5845	0.1131	Q40	0.5914	0.0365	16.2228	0.0000
QUAL_GOOD	0.0934	0.0395	2.3630	0.0181	Q41	0.6002	0.0385	15.5737	0.0000
QUAL_GREAT	0.1790	0.0393	4.5607	0.0000	Q42	0.6742	0.0415	16.2352	0.0000
BUILD_AVG	0.0543	0.0188	2.8963	0.0038	Q43	0.6675	0.0432	15.4668	0.0000
BUILD_GOOD	0.1231	0.0190	6.4707	0.0000	Q44	0.6981	0.0376	18.5657	0.0000
BUILD_GREAT	0.1020	0.0220	4.6398	0.0000	Q45	0.6986	0.0468	14.9429	0.0000
FIRST	0.3082	0.0648	4.7595	0.0000	Q46	0.6798	0.0427	15.9084	0.0000
Q2	-0.0102	0.0302	-0.3392	0.7344	Q47	0.7529	0.0379	19.8690	0.0000
Q3	0.0398	0.0308	1.2926	0.1962	Q48	0.7694	0.0455	16.9261	0.0000
Q4	0.0123	0.0296	0.4155	0.6778	Q49	0.7539	0.0406	18.5712	0.0000
Q5	0.0708	0.0307	2.3064	0.0211	Q50	0.7749	0.0445	17.3975	0.0000
Q6	0.1073	0.0362	2.9663	0.0030	Q51	0.7451	0.0420	17.7371	0.0000
Q7	0.0519	0.0347	1.4955	0.1348	Q52	0.7301	0.0425	17.1600	0.0000
Q8	0.0596	0.0338	1.7635	0.0778	Q53	0.6627	0.0447	14.8247	0.0000
Q9	0.1182	0.0343	3.4423	0.0006	Q54	0.7481	0.0463	16.1533	0.0000
Q10	0.0694	0.0352	1.9724	0.0486	Q55	0.7138	0.0444	16.0599	0.0000
Q11	0.1229	0.0327	3.7531	0.0002	Q56	0.6916	0.0415	16.6537	0.0000
Q12	0.1121	0.0329	3.4053	0.0007	Q57	0.7468	0.0443	16.8718	0.0000
Q13	0.1469	0.0342	4.2953	0.0000	Q58	0.6980	0.0433	16.1102	0.0000
Q14	0.1557	0.0337	4.6253	0.0000	Q59	0.7356	0.0442	16.6539	0.0000

Table A.9: Regression results for houses in Geneva with SARErr method. This is the method eventually applied to all districts so the above coefficients were the ones used to generate the price time-series for houses in Geneva.

Geneva Condominiums - SARErr

Variable	Estimate	Std. Error	z value	Pr(>|z|)	Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	8.4444	0.1044	80.9191	0.0000	Q16	0.2452	0.0253	9.6791	0.0000
log(NETTOWOHNFLAECHE_CHAR)	0.8945	0.0087	103.4050	0.0000	Q17	0.2613	0.0253	10.3204	0.0000
BUILT_BEF1900	0.0942	0.0165	5.7174	0.0000	Q18	0.3167	0.0251	12.6317	0.0000
BUILT_71TO80	0.0482	0.0093	5.1862	0.0000	Q19	0.3095	0.0233	13.2924	0.0000
BUILT_81TO90	0.0518	0.0091	5.6826	0.0000	Q20	0.3232	0.0241	13.3968	0.0000
BUILT_91TO00	0.0575	0.0107	5.3668	0.0000	Q21	0.3541	0.0230	15.4160	0.0000
BUILT_AFT2000	-0.0108	0.0119	-0.9086	0.3635	Q22	0.3700	0.0269	13.7332	0.0000
AREA_SUB	-0.1914	0.0218	-8.7793	0.0000	Q23	0.4556	0.0242	18.8394	0.0000
AREA_RE	0.0207	0.0296	0.6996	0.4842	Q24	0.4398	0.0255	17.2401	0.0000
AREA_PERI	-0.1690	0.0525	-3.2176	0.0013	Q25	0.4811	0.0273	17.6301	0.0000
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	Q26	0.5124	0.0274	18.7198	0.0000
AREA_IND	#N/A	#N/A	#N/A	#N/A	Q27	0.5837	0.0278	20.9892	0.0000
AREA_PEND	-0.3269	0.1147	-2.8496	0.0044	Q28	0.5476	0.0269	20.3246	0.0000
AREA_MIX	-0.2675	0.3008	-0.8893	0.3738	Q29	0.6186	0.0260	23.8060	0.0000
AREA_AGR	#N/A	#N/A	#N/A	#N/A	Q30	0.6174	0.0291	21.2010	0.0000
BATHROOM2	0.1102	0.0079	13.9708	0.0000	Q31	0.6576	0.0285	23.0678	0.0000
BATHROOM3	0.1295	0.0121	10.7414	0.0000	Q32	0.7044	0.0281	25.0584	0.0000
BATHROOM4	0.1432	0.0264	5.4291	0.0000	Q33	0.6702	0.0282	23.7321	0.0000
GARAGE1	0.0628	0.0066	9.5468	0.0000	Q34	0.6553	0.0281	23.3314	0.0000
GARAGE2	0.0967	0.0086	11.2212	0.0000	Q35	0.6941	0.0294	23.5908	0.0000
GARAGE3	0.1722	0.0242	7.1308	0.0000	Q36	0.6942	0.0282	24.6433	0.0000
LOC_AVG	0.1384	0.0736	1.8798	0.0601	Q37	0.7033	0.0273	25.7331	0.0000
LOC_GOOD	0.2339	0.0735	3.1809	0.0015	Q38	0.7569	0.0284	26.6308	0.0000
LOC_GREAT	0.3597	0.0739	4.8698	0.0000	Q39	0.7168	0.0260	27.5829	0.0000
QUAL_AVG	0.0237	0.0399	0.5941	0.5524	Q40	0.7993	0.0278	28.7287	0.0000
QUAL_GOOD	0.0187	0.0401	0.4667	0.6407	Q41	0.8112	0.0269	30.1113	0.0000
QUAL_GREAT	0.1703	0.0402	4.2350	0.0000	Q42	0.8650	0.0294	29.4629	0.0000
BUILD_AVG	-0.0120	0.0141	-0.8524	0.3940	Q43	0.8928	0.0270	33.0916	0.0000
BUILD_GOOD	0.0520	0.0144	3.6029	0.0003	Q44	0.8679	0.0306	28.3749	0.0000
BUILD_GREAT	0.0670	0.0168	3.9767	0.0001	Q45	0.9444	0.0290	32.5596	0.0000
FIRST	-0.0039	0.0441	-0.0888	0.9292	Q46	0.8956	0.0284	31.5458	0.0000
Q2	0.0578	0.0271	2.1352	0.0327	Q47	0.9309	0.0291	31.9758	0.0000
Q3	0.0344	0.0260	1.3241	0.1855	Q48	0.9062	0.0298	30.4598	0.0000
Q4	0.0601	0.0254	2.3606	0.0182	Q49	0.8527	0.0283	30.1695	0.0000
Q5	0.0745	0.0249	2.9857	0.0028	Q50	0.9985	0.0300	33.2991	0.0000
Q6	0.1231	0.0283	4.3500	0.0000	Q51	0.9901	0.0293	33.8494	0.0000
Q7	0.0768	0.0267	2.8767	0.0040	Q52	0.9969	0.0303	32.9277	0.0000
Q8	0.0883	0.0263	3.3613	0.0008	Q53	0.9785	0.0277	35.3178	0.0000
Q9	0.1150	0.0250	4.5961	0.0000	Q54	0.8994	0.0302	29.8109	0.0000
Q10	0.0963	0.0259	3.7250	0.0002	Q55	0.9510	0.0307	30.9722	0.0000
Q11	0.1844	0.0256	7.1913	0.0000	Q56	0.9770	0.0296	32.9566	0.0000
Q12	0.1568	0.0246	6.3712	0.0000	Q57	0.9302	0.0282	33.0000	0.0000
Q13	0.1594	0.0242	6.5902	0.0000	Q58	0.9435	0.0283	33.3583	0.0000
Q14	0.2282	0.0247	9.2229	0.0000	Q59	0.9139	0.0278	32.8656	0.0000
Q15	0.2094	0.0236	8.8572	0.0000					

Table A.10: Regression results for condominiums in Geneva with SARErr method. This is the method eventually applied to all districts so the above coefficients were the ones used to generate the price time-series for condominiums in Geneva.

Zurich Houses - SARErr									
Variable	Estimate	Std. Error	z value	Pr(>|z|)	Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	9.1401	0.1720	53.1255	0.0000	Q15	0.1395	0.0594	2.3502	0.0188
log(KUBATUR_CHAR)	0.6082	0.0260	23.4240	0.0000	Q16	0.0627	0.0644	0.9750	0.3295
IS_DETACHED	0.0939	0.0149	6.2876	0.0000	Q17	0.1377	0.0651	2.1146	0.0345
BUILT_BEF1900	-0.1702	0.0296	-5.7466	0.0000	Q18	0.1273	0.0625	2.0361	0.0417
BUILT_71TO80	-0.1348	0.0492	-2.7407	0.0061	Q19	0.2080	0.0582	3.5751	0.0004
BUILT_81TO90	0.0382	0.0420	0.9090	0.3634	Q20	0.2067	0.0586	3.5240	0.0004
BUILT_91TO00	0.0183	0.0374	0.4912	0.6233	Q21	0.1712	0.0608	2.8153	0.0049
BUILT_AFT2000	0.0524	0.0447	1.1725	0.2410	Q22	0.2268	0.0666	3.4056	0.0007
AREA_SUB	#N/A	#N/A	#N/A	#N/A	Q23	0.2182	0.0589	3.7035	0.0002
AREA_RE	#N/A	#N/A	#N/A	#N/A	Q24	0.2588	0.0616	4.2001	0.0000
AREA_PERI	#N/A	#N/A	#N/A	#N/A	Q25	0.4450	0.0733	6.0723	0.0000
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	Q26	0.3656	0.0702	5.2104	0.0000
AREA_IND	#N/A	#N/A	#N/A	#N/A	Q27	0.2133	0.0700	3.0449	0.0023
AREA_PEND	#N/A	#N/A	#N/A	#N/A	Q28	0.2936	0.0659	4.4557	0.0000
AREA_MIX	#N/A	#N/A	#N/A	#N/A	Q29	0.4040	0.0694	5.8215	0.0000
AREA_AGR	#N/A	#N/A	#N/A	#N/A	Q30	0.4886	0.0666	7.3352	0.0000
BATHROOM2	0.0744	0.0207	3.6014	0.0003	Q31	0.2471	0.0725	3.4090	0.0007
BATHROOM3	0.1112	0.0255	4.3622	0.0000	Q32	0.4655	0.0639	7.2798	0.0000
BATHROOM4	0.1768	0.0448	3.9450	0.0001	Q33	0.4661	0.0717	6.5044	0.0000
GARAGE1	0.0350	0.0158	2.2076	0.0273	Q34	0.4391	0.0818	5.3656	0.0000
GARAGE2	0.0800	0.0236	3.3874	0.0007	Q35	0.4665	0.0792	5.8897	0.0000
GARAGE3	0.0969	0.0525	1.8444	0.0651	Q36	0.4839	0.0648	7.4643	0.0000
LOC_AVG	0.0258	0.0358	0.7198	0.4716	Q37	0.5709	0.0648	8.8039	0.0000
LOC_GOOD	0.1546	0.0353	4.3828	0.0000	Q38	0.4888	0.0759	6.4364	0.0000
LOC_GREAT	0.2912	0.0393	7.4163	0.0000	Q39	0.4191	0.0703	5.9651	0.0000
QUAL_AVG	0.0172	0.0261	0.6578	0.5107	Q40	0.4489	0.0728	6.1616	0.0000
QUAL_GOOD	0.0688	0.0307	2.2385	0.0252	Q41	0.5205	0.0621	8.3792	0.0000
QUAL_GREAT	0.2201	0.0335	6.5642	0.0000	Q42	0.5803	0.0841	6.9011	0.0000
BUILD_AVG	0.0889	0.0215	4.1401	0.0000	Q43	0.6056	0.0712	8.5045	0.0000
BUILD_GOOD	0.1342	0.0236	5.6911	0.0000	Q44	0.5548	0.0873	6.3543	0.0000
BUILD_GREAT	0.0890	0.0394	2.2574	0.0240	Q45	0.5758	0.0685	8.4070	0.0000
FIRST	#N/A	#N/A	#N/A	#N/A	Q46	0.6872	0.0702	9.7912	0.0000
Q2	-0.0498	0.0697	-0.7151	0.4745	Q47	0.6106	0.0615	9.9331	0.0000
Q3	0.0945	0.0688	1.3733	0.1696	Q48	0.7476	0.0718	10.4090	0.0000
Q4	0.1426	0.0586	2.4323	0.0150	Q49	0.7146	0.0717	9.9660	0.0000
Q5	0.0702	0.0626	1.1223	0.2617	Q50	0.7232	0.0813	8.8988	0.0000
Q6	0.1176	0.0795	1.4802	0.1388	Q51	0.7331	0.0640	11.4550	0.0000
Q7	0.0197	0.0678	0.2906	0.7713	Q52	0.6716	0.0738	9.1054	0.0000
Q8	0.0569	0.0596	0.9547	0.3397	Q53	0.7425	0.0638	11.6399	0.0000
Q9	0.0370	0.0631	0.5862	0.5577	Q54	0.6550	0.0911	7.1889	0.0000
Q10	0.0038	0.0701	0.0547	0.9563	Q55	0.7633	0.0709	10.7644	0.0000
Q11	0.0496	0.0602	0.8232	0.4104	Q56	0.6294	0.0693	9.0837	0.0000
Q12	0.0651	0.0660	0.9868	0.3237	Q57	0.7202	0.0704	10.2285	0.0000
Q13	0.1043	0.0608	1.7146	0.0864	Q58	0.6399	0.0702	9.1166	0.0000
Q14	0.1015	0.0629	1.6147	0.1064	Q59	0.7515	0.0677	11.1042	0.0000

Table A.11: Regression results for houses in Zurich with SARErr method. This is the method eventually applied to all districts so the above coefficients were the ones used to generate the price time-series for houses in Zurich.

Zurich Condominiums - SARErr									
Variable	Estimate	Std. Error	z value	Pr(>|z|)	Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	8.5262	0.0741	115.1159	0.0000	Q16	0.1557	0.0295	5.2829	0.0000
log(NETTOWOHNFLAECHE_CHAR)	0.9011	0.0108	83.7872	0.0000	Q17	0.1270	0.0301	4.2227	0.0000
BUILT_BEF1900	0.0463	0.0145	3.2021	0.0014	Q18	0.1516	0.0279	5.4310	0.0000
BUILT_71TO80	0.0080	0.0118	0.6816	0.4955	Q19	0.1737	0.0267	6.5164	0.0000
BUILT_81TO90	0.0209	0.0127	1.6386	0.1013	Q20	0.2178	0.0278	7.8290	0.0000
BUILT_91TO00	0.0490	0.0116	4.2317	0.0000	Q21	0.2422	0.0269	9.0023	0.0000
BUILT_AFT2000	0.0765	0.0124	6.1484	0.0000	Q22	0.1490	0.0287	5.1927	0.0000
AREA_SUB	#N/A	#N/A	#N/A	#N/A	Q23	0.2405	0.0274	8.7725	0.0000
AREA_RE	#N/A	#N/A	#N/A	#N/A	Q24	0.2630	0.0290	9.0708	0.0000
AREA_PERI	#N/A	#N/A	#N/A	#N/A	Q25	0.3072	0.0281	10.9443	0.0000
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	Q26	0.3012	0.0285	10.5648	0.0000
AREA_IND	#N/A	#N/A	#N/A	#N/A	Q27	0.3366	0.0301	11.1908	0.0000
AREA_PEND	#N/A	#N/A	#N/A	#N/A	Q28	0.3447	0.0305	11.2874	0.0000
AREA_MIX	#N/A	#N/A	#N/A	#N/A	Q29	0.3214	0.0299	10.7670	0.0000
AREA_AGR	#N/A	#N/A	#N/A	#N/A	Q30	0.3606	0.0294	12.2590	0.0000
BATHROOM2	0.0572	0.0080	7.1197	0.0000	Q31	0.3110	0.0289	10.7683	0.0000
BATHROOM3	0.0789	0.0153	5.1591	0.0000	Q32	0.3339	0.0275	12.1405	0.0000
BATHROOM4	0.0611	0.0469	1.3024	0.1928	Q33	0.3861	0.0283	13.6586	0.0000
GARAGE1	0.0125	0.0070	1.7772	0.0755	Q34	0.3769	0.0280	13.4633	0.0000
GARAGE2	0.0817	0.0102	8.0376	0.0000	Q35	0.4211	0.0271	15.5468	0.0000
GARAGE3	0.1607	0.0335	4.7965	0.0000	Q36	0.4048	0.0264	15.3322	0.0000
LOC_AVG	0.0272	0.0136	1.9964	0.0459	Q37	0.4460	0.0289	15.4522	0.0000
LOC_GOOD	0.1280	0.0137	9.3141	0.0000	Q38	0.4742	0.0290	16.3591	0.0000
LOC_GREAT	0.2301	0.0152	15.1251	0.0000	Q39	0.5323	0.0300	17.7312	0.0000
QUAL_AVG	0.0598	0.0191	3.1286	0.0018	Q40	0.4934	0.0278	17.7618	0.0000
QUAL_GOOD	0.1205	0.0197	6.1121	0.0000	Q41	0.5227	0.0287	18.2151	0.0000
QUAL_GREAT	0.2113	0.0200	10.5887	0.0000	Q42	0.5392	0.0309	17.4279	0.0000
BUILD_AVG	0.1135	0.0166	6.8279	0.0000	Q43	0.5539	0.0293	18.8869	0.0000
BUILD_GOOD	0.1665	0.0173	9.6121	0.0000	Q44	0.6266	0.0313	20.0318	0.0000
BUILD_GREAT	0.2192	0.0196	11.1637	0.0000	Q45	0.6234	0.0306	20.3723	0.0000
FIRST	0.0070	0.0394	0.1766	0.8598	Q46	0.6664	0.0320	20.8072	0.0000
Q2	0.0219	0.0335	0.6545	0.5128	Q47	0.5976	0.0316	18.9395	0.0000
Q3	0.0916	0.0309	2.9597	0.0031	Q48	0.6704	0.0335	20.0347	0.0000
Q4	0.0596	0.0300	1.9824	0.0474	Q49	0.6810	0.0296	22.9838	0.0000
Q5	-0.0050	0.0307	-0.1634	0.8702	Q50	0.6839	0.0278	24.6417	0.0000
Q6	-0.0184	0.0353	-0.5223	0.6015	Q51	0.7234	0.0295	24.5045	0.0000
Q7	0.0230	0.0319	0.7190	0.4721	Q52	0.7206	0.0325	22.2061	0.0000
Q8	-0.0048	0.0303	-0.1591	0.8736	Q53	0.7225	0.0267	27.0689	0.0000
Q9	0.0586	0.0272	2.1530	0.0313	Q54	0.7503	0.0312	24.0726	0.0000
Q10	0.0332	0.0326	1.0185	0.3084	Q55	0.7680	0.0306	25.1101	0.0000
Q11	0.0442	0.0270	1.6369	0.1017	Q56	0.7506	0.0293	25.6010	0.0000
Q12	0.0779	0.0283	2.7572	0.0058	Q57	0.7506	0.0284	26.4187	0.0000
Q13	0.0695	0.0282	2.4688	0.0136	Q58	0.7552	0.0288	26.2495	0.0000
Q14	0.0672	0.0339	1.9841	0.0472	Q59	0.7655	0.0287	26.6722	0.0000
Q15	0.0759	0.0293	2.5878	0.0097					

Table A.12: Regression results for condominiums in Zurich with SARErr method. This is the method eventually applied to all districts so the above coefficients were the ones used to generate the price time-series for condominiums in Zurich.

Geneva Houses - SARMix									
Variable	Estimate	Std. Error	z value	Pr(>|z|)	Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	17.7191	4.0763	4.3469	0.0000	Rho	-0.9607			
log(KUBATUR_CHAR)	0.6473	0.0141	45.8610	0.0000	lag.log(KUBATUR_CHAR)	1.2823	0.4001	3.2053	0.0013
IS_DETACHED	0.0933	0.0089	10.4927	0.0000	lag.IS_DETACHED	0.2555	0.2559	0.9982	0.3182
BUILT_BEF1900	-0.0867	0.0202	-4.2941	0.0000	lag.BUILT_BEF1900	-1.6553	0.3914	-4.2295	0.0000
BUILT_71TO80	0.0382	0.0130	2.9278	0.0034	lag.BUILT_71TO80	-0.0878	0.4390	-0.2000	0.8415
BUILT_81TO90	0.0491	0.0122	4.0202	0.0001	lag.BUILT_81TO90	-0.6633	0.4023	-1.6487	0.0992
BUILT_91TO00	0.0397	0.0142	2.8035	0.0051	lag.BUILT_91TO00	-1.0616	0.3836	-2.7672	0.0057
BUILT_AFT2000	0.0646	0.0158	4.0746	0.0000	lag.BUILT_AFT2000	-0.4350	0.5523	-0.7877	0.4309
AREA_SUB	0.1117	0.2200	0.5077	0.6117	lag.AREA_SUB	-0.2937	0.2878	-1.0202	0.3076
AREA_RE	0.2481	0.2281	1.0879	0.2767	lag.AREA_RE	-0.2219	0.2984	-0.7438	0.4570
AREA_PERI	0.5184	0.3138	1.6520	0.0985	lag.AREA_PERI	-0.5972	0.3888	-1.5360	0.1245
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	lag.AREA_TOUR	#N/A	#N/A	#N/A	#N/A
AREA_IND	#N/A	#N/A	#N/A	#N/A	lag.AREA_IND	#N/A	#N/A	#N/A	#N/A
AREA_PEND	-77.4911	52.4246	-1.4781	0.1394	lag.AREA_PEND	77.1797	52.4309	1.4720	0.1410
AREA_MIX	-0.0256	0.4600	-0.0557	0.9556	lag.AREA_MIX	#N/A	#N/A	#N/A	#N/A
AREA_AGR	#N/A	#N/A	#N/A	#N/A	lag.AREA_AGR	#N/A	#N/A	#N/A	#N/A
BATHROOM2	0.1148	0.0201	5.7056	0.0000	lag.BATHROOM2	-0.7439	0.7614	-0.9770	0.3286
BATHROOM3	0.1596	0.0216	7.3935	0.0000	lag.BATHROOM3	-1.0467	0.8482	-1.2340	0.2172
BATHROOM4	0.1798	0.0263	6.8505	0.0000	lag.BATHROOM4	-1.8022	0.8525	-2.1140	0.0345
GARAGE1	0.0151	0.0108	1.4011	0.1612	lag.GARAGE1	-0.5932	0.2976	-1.9935	0.0462
GARAGE2	0.0697	0.0110	6.3346	0.0000	lag.GARAGE2	0.4067	0.4070	0.9992	0.3177
GARAGE3	0.0732	0.0186	3.9464	0.0001	lag.GARAGE3	0.7244	0.6768	1.0705	0.2844
LOC_AVG	0.4873	0.0877	5.5560	0.0000	lag.LOC_AVG	-0.2817	3.1590	-0.0892	0.9290
LOC_GOOD	0.5979	0.0873	6.8493	0.0000	lag.LOC_GOOD	-0.4669	3.1018	-0.1505	0.8804
LOC_GREAT	0.7303	0.0879	8.3035	0.0000	lag.LOC_GREAT	0.4179	3.1024	0.1347	0.8928
QUAL_AVG	0.0560	0.0450	1.2443	0.2134	lag.QUAL_AVG	-0.1461	2.1626	-0.0675	0.9461
QUAL_GOOD	0.0793	0.0453	1.7524	0.0797	lag.QUAL_GOOD	-0.5685	2.0719	-0.2744	0.7838
QUAL_GREAT	0.1713	0.0453	3.7818	0.0002	lag.QUAL_GREAT	0.0046	2.1279	0.0022	0.9983
BUILD_AVG	0.0582	0.0206	2.8206	0.0048	lag.BUILD_AVG	-0.0140	0.8133	-0.0173	0.9862
BUILD_GOOD	0.1269	0.0207	6.1282	0.0000	lag.BUILD_GOOD	0.2944	0.8208	0.3587	0.7198
BUILD_GREAT	0.1049	0.0233	4.4925	0.0000	lag.BUILD_GREAT	0.3621	0.8008	0.4521	0.6512
FIRST	0.2425	0.0718	3.3747	0.0007	lag.FIRST	-4.4104	2.2825	-1.9323	0.0533
Q2	0.0170	0.0327	0.5192	0.6036	lag.Q2	1.4481	1.0164	1.4248	0.1542
Q3	0.0578	0.0332	1.7405	0.0818	lag.Q3	0.7760	1.1193	0.6933	0.4881
Q4	0.0371	0.0317	1.1711	0.2415	lag.Q4	1.4039	0.8642	1.6245	0.1043
Q5	0.0799	0.0327	2.4474	0.0144	lag.Q5	0.2279	1.0686	0.2133	0.8311
Q6	0.1119	0.0383	2.9219	0.0035	lag.Q6	-0.4692	1.1442	-0.4100	0.6818
Q7	0.0463	0.0372	1.2436	0.2136	lag.Q7	-0.6485	0.9536	-0.6801	0.4964
Q8	0.0899	0.0371	2.4246	0.0153	lag.Q8	1.6669	1.2536	1.3297	0.1836
Q9	0.1295	0.0357	3.6311	0.0003	lag.Q9	0.1562	1.2739	0.1226	0.9024
Q10	0.1010	0.0376	2.6848	0.0073	lag.Q10	1.4951	0.9551	1.5654	0.1175
Q11	0.1205	0.0359	3.3532	0.0008	lag.Q11	-0.2927	1.0241	-0.2858	0.7751
Q12	0.1249	0.0359	3.4743	0.0005	lag.Q12	0.3342	1.1398	0.2932	0.7694
Q13	0.1891	0.0373	5.0658	0.0000	lag.Q13	2.8577	1.2219	2.3388	0.0193
Q14	0.1656	0.0349	4.7521	0.0000	lag.Q14	-0.1170	0.7891	-0.1482	0.8821
Q15	0.2265	0.0334	6.7723	0.0000	lag.Q15	3.3693	1.0192	3.3059	0.0009
Q16	0.1862	0.0351	5.2991	0.0000	lag.Q16	1.5163	1.2265	1.2363	0.2163
Q17	0.2272	0.0348	6.5298	0.0000	lag.Q17	1.5557	1.1467	1.3567	0.1749
Q18	0.2409	0.0359	6.7103	0.0000	lag.Q18	-0.4795	0.9586	-0.5003	0.6169
Q19	0.2742	0.0342	8.0107	0.0000	lag.Q19	1.7528	0.9010	1.9455	0.0517
Q20	0.3597	0.0349	10.3002	0.0000	lag.Q20	2.8104	0.9669	2.9065	0.0037
Q21	0.3109	0.0328	9.4876	0.0000	lag.Q21	1.0749	0.9396	1.1440	0.2526
Q22	0.3518	0.0362	9.7142	0.0000	lag.Q22	2.3589	1.4776	1.5964	0.1104
Q23	0.3836	0.0353	10.8542	0.0000	lag.Q23	0.7810	1.4025	0.5568	0.5777
Q24	0.3623	0.0327	11.0785	0.0000	lag.Q24	0.2365	0.8159	0.2899	0.7719
Q25	0.3113	0.0364	8.5543	0.0000	lag.Q25	-2.6759	1.1017	-2.4288	0.0151
Q26	0.4708	0.0444	10.6043	0.0000	lag.Q26	2.4280	1.3550	1.7919	0.0732
Q27	0.4862	0.0371	13.0880	0.0000	lag.Q27	1.1277	1.1395	0.9897	0.3223
Q28	0.5052	0.0395	12.7768	0.0000	lag.Q28	1.3987	1.4082	0.9933	0.3206
Q29	0.4884	0.0381	12.8329	0.0000	lag.Q29	-0.1660	1.1759	-0.1412	0.8877
Q30	0.4939	0.0426	11.5820	0.0000	lag.Q30	-0.4255	1.4019	-0.3035	0.7615
Q31	0.5347	0.0384	13.9243	0.0000	lag.Q31	1.3819	0.7281	1.8980	0.0577
Q32	0.6081	0.0408	14.9045	0.0000	lag.Q32	0.6984	1.7292	0.4039	0.6863
Q33	0.6520	0.0441	14.7771	0.0000	lag.Q33	2.9379	1.6789	1.7498	0.0801
Q34	0.6141	0.0424	14.4784	0.0000	lag.Q34	1.4455	1.1727	1.2326	0.2177
Q35	0.6113	0.0436	14.0301	0.0000	lag.Q35	0.0035	1.1313	0.0031	0.9975
Q36	0.6290	0.0428	14.7093	0.0000	lag.Q36	2.8328	1.2571	2.2534	0.0242
Q37	0.6142	0.0462	13.2820	0.0000	lag.Q37	3.4111	2.7534	1.2389	0.2154
Q38	0.6248	0.0470	13.3004	0.0000	lag.Q38	1.6657	2.0265	0.8220	0.4111
Q39	0.6828	0.0429	15.9308	0.0000	lag.Q39	3.1039	1.5968	1.9438	0.0519
Q40	0.6038	0.0398	15.1617	0.0000	lag.Q40	0.5527	1.2486	0.4426	0.6580
Q41	0.6200	0.0422	14.6778	0.0000	lag.Q41	1.0100	1.5901	0.6352	0.5253
Q42	0.6955	0.0447	15.5715	0.0000	lag.Q42	2.0920	1.8817	1.1118	0.2662
Q43	0.6763	0.0466	14.5232	0.0000	lag.Q43	0.1530	2.1282	0.0719	0.9427
Q44	0.7143	0.0397	18.0081	0.0000	lag.Q44	1.4731	1.0291	1.4315	0.1523
Q45	0.6935	0.0534	12.9965	0.0000	lag.Q45	-0.3045	2.2060	-0.1381	0.8902
Q46	0.7147	0.0450	15.8874	0.0000	lag.Q46	3.3692	1.7310	1.9464	0.0516
Q47	0.7872	0.0413	19.0387	0.0000	lag.Q47	2.6127	1.3666	1.9119	0.0559
Q48	0.7955	0.0502	15.8350	0.0000	lag.Q48	1.8745	1.8850	0.9944	0.3200
Q49	0.7519	0.0454	16.5592	0.0000	lag.Q49	-0.1074	1.8498	-0.0580	0.9537
Q50	0.8152	0.0500	16.3105	0.0000	lag.Q50	3.1667	2.5077	1.2628	0.2067
Q51	0.7578	0.0490	15.4700	0.0000	lag.Q51	0.8996	2.3066	0.3900	0.6965
Q52	0.7543	0.0475	15.8721	0.0000	lag.Q52	2.1152	2.7027	0.7826	0.4339
Q53	0.6950	0.0507	13.7203	0.0000	lag.Q53	2.7984	2.5190	1.1109	0.2666
Q54	0.7387	0.0525	14.0585	0.0000	lag.Q54	-0.7432	1.8160	-0.4093	0.6823
Q55	0.7180	0.0483	14.8750	0.0000	lag.Q55	0.3420	1.7372	0.1969	0.8439
Q56	0.7166	0.0462	15.5171	0.0000	lag.Q56	2.0143	1.4555	1.3839	0.1664
Q57	0.7516	0.0485	15.4908	0.0000	lag.Q57	0.4497	1.7477	0.2573	0.7970
Q58	0.7167	0.0462	15.5100	0.0000	lag.Q58	1.6569	2.0078	0.8253	0.4092
Q59	0.7201	0.0478	15.0618	0.0000	lag.Q59	-1.0075	1.6508	-0.6103	0.5417

Table A.13: Regression results for houses in Geneva with SARMix method. One can notice the larger number of coefficients that are not statistically significant as well as the few lagged coefficients with very high standard errors.

Geneva Condominiums - SARMix

Variable	Estimate	Std. Error	z value	$\Pr(>\lvert z\rvert)$	Variable	Estimate	Std. Error	z value	$\Pr(>\lvert z\rvert)$
(Intercept)	12.3461	6.0992	2.0242	0.0429	Rho	-0.9317			
log(NETTOWOHNFLAECHE_CHAR)	0.9000	0.0091	98.6189	0.0000	lag.log(NETTOWOHNFLAECHE_CHAR)	1.7602	0.4844	3.6335	0.0003
BUILT_BEF1900	0.0951	0.0166	5.7459	0.0000	lag.BUILT_BEF1900	0.0849	0.4278	0.1984	0.8427
BUILT_71TO80	0.0476	0.0092	5.1551	0.0000	lag.BUILT_71TO80	-0.1777	0.2543	-0.6986	0.4848
BUILT_81TO90	0.0534	0.0092	5.7954	0.0000	lag.BUILT_81TO90	-0.0359	0.3303	-0.1088	0.9134
BUILT_91TO00	0.0561	0.0108	5.2123	0.0000	lag.BUILT_91TO00	-0.4386	0.3027	-1.4489	0.1474
BUILT_AFT2000	-0.0080	0.0123	-0.6491	0.5163	lag.BUILT_AFT2000	-0.2033	0.5330	-0.3814	0.7029
AREA_SUB	-0.0719	0.0408	-1.7617	0.0781	lag.AREA_SUB	-0.1045	0.1125	-0.9283	0.3533
AREA_RE	0.2552	0.0531	4.8107	0.0000	lag.AREA_RE	-0.4977	0.1279	-3.8904	0.0001
AREA_PERI	0.0710	0.0971	0.7316	0.4644	lag.AREA_PERI	-0.2882	0.2091	-1.3780	0.1682
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	lag.AREA_TOUR	#N/A	#N/A	#N/A	#N/A
AREA_IND	#N/A	#N/A	#N/A	#N/A	lag.AREA_IND	#N/A	#N/A	#N/A	#N/A
AREA_PEND	-0.1602	0.2385	-0.6716	0.5018	lag.AREA_PEND	-0.4365	0.3685	-1.1847	0.2361
AREA_MIX	173.8219	151.1260	1.1502	0.2501	lag.AREA_MIX	-174.0985	151.1311	-1.1520	0.2493
AREA_AGR	#N/A	#N/A	#N/A	#N/A	lag.AREA_AGR	#N/A	#N/A	#N/A	#N/A
BATHROOM2	0.1120	0.0086	13.0275	0.0000	lag.BATHROOM2	0.2884	0.5990	0.4814	0.6302
BATHROOM3	0.1233	0.0130	9.4658	0.0000	lag.BATHROOM3	-0.4800	0.7834	-0.6128	0.5400
BATHROOM4	0.1494	0.0280	5.3310	0.0000	lag.BATHROOM4	0.2478	1.2888	0.1923	0.8475
GARAGE1	0.0629	0.0068	9.3191	0.0000	lag.GARAGE1	0.2133	0.2695	0.7915	0.4287
GARAGE2	0.0943	0.0090	10.5262	0.0000	lag.GARAGE2	-0.1925	0.3495	-0.5507	0.5818
GARAGE3	0.1798	0.0259	6.9487	0.0000	lag.GARAGE3	0.8808	1.1720	0.7515	0.4523
LOC_AVG	0.1812	0.0837	2.1640	0.0305	lag.LOC_AVG	4.2069	4.3643	0.9639	0.3351
LOC_GOOD	0.2756	0.0834	3.3034	0.0010	lag.LOC_GOOD	4.0485	4.2951	0.9426	0.3459
LOC_GREAT	0.4066	0.0833	4.8821	0.0000	lag.LOC_GREAT	5.5326	4.1645	1.3285	0.1840
QUAL_AVG	-0.0294	0.0418	-0.7042	0.4813	lag.QUAL_AVG	-7.8750	2.2580	-3.4876	0.0005
QUAL_GOOD	-0.0299	0.0422	-0.7068	0.4797	lag.QUAL_GOOD	-7.3182	2.3804	-3.0744	0.0021
QUAL_GREAT	0.1242	0.0422	2.9434	0.0032	lag.QUAL_GREAT	-6.5186	2.3089	-2.8233	0.0048
BUILD_AVG	-0.0073	0.0150	-0.4897	0.6244	lag.BUILD_AVG	0.6520	1.2294	0.5304	0.5959
BUILD_GOOD	0.0586	0.0152	3.8519	0.0001	lag.BUILD_GOOD	1.2765	1.1649	1.0957	0.2732
BUILD_GREAT	0.0656	0.0177	3.7001	0.0002	lag.BUILD_GREAT	0.4653	1.2927	0.3599	0.7189
FIRST	0.0046	0.0471	0.0976	0.9222	lag.FIRST	0.3538	2.6756	0.1322	0.8948
Q2	0.0758	0.0292	2.5962	0.0094	lag.Q2	2.4546	1.6250	1.5105	0.1309
Q3	0.0388	0.0270	1.4371	0.1507	lag.Q3	1.1311	1.0905	1.0372	0.2996
Q4	0.0617	0.0267	2.3094	0.0209	lag.Q4	0.5633	1.2953	0.4349	0.6636
Q5	0.0870	0.0268	3.2413	0.0012	lag.Q5	1.9810	1.3334	1.4857	0.1374
Q6	0.1288	0.0300	4.2902	0.0000	lag.Q6	1.1007	1.4256	0.7721	0.4401
Q7	0.0928	0.0279	3.3310	0.0009	lag.Q7	2.2141	1.2867	1.7208	0.0853
Q8	0.1092	0.0283	3.8530	0.0001	lag.Q8	2.6691	1.6682	1.6000	0.1096
Q9	0.1214	0.0265	4.5850	0.0000	lag.Q9	0.8049	1.5091	0.5333	0.5938
Q10	0.1074	0.0266	4.0346	0.0001	lag.Q10	1.3574	1.0804	1.2564	0.2090
Q11	0.2047	0.0262	7.8155	0.0000	lag.Q11	2.5330	0.9309	2.7211	0.0065
Q12	0.1649	0.0259	6.3740	0.0000	lag.Q12	1.2983	1.2109	1.0721	0.2837
Q13	0.1690	0.0256	6.6109	0.0000	lag.Q13	1.3209	1.5302	0.8632	0.3880
Q14	0.2429	0.0261	9.3056	0.0000	lag.Q14	1.7406	1.3321	1.3066	0.1913
Q15	0.2188	0.0248	8.8116	0.0000	lag.Q15	1.1476	1.2677	0.9053	0.3653
Q16	0.2526	0.0268	9.4396	0.0000	lag.Q16	1.2710	1.5298	0.8308	0.4061
Q17	0.2691	0.0266	10.1308	0.0000	lag.Q17	1.1813	1.3255	0.8912	0.3728
Q18	0.3333	0.0272	12.2442	0.0000	lag.Q18	2.1923	1.5983	1.3716	0.1702
Q19	0.3234	0.0247	13.1015	0.0000	lag.Q19	2.1864	1.2757	1.7139	0.0865
Q20	0.3375	0.0263	12.8233	0.0000	lag.Q20	2.4603	1.9523	1.2602	0.2076
Q21	0.3753	0.0243	15.4521	0.0000	lag.Q21	3.4354	1.4067	2.4422	0.0146
Q22	0.3922	0.0297	13.2079	0.0000	lag.Q22	3.2427	2.1327	1.5205	0.1284
Q23	0.4638	0.0256	18.0810	0.0000	lag.Q23	1.4747	1.3349	1.1047	0.2693
Q24	0.4594	0.0269	17.1025	0.0000	lag.Q24	2.8308	1.3422	2.1090	0.0349
Q25	0.4959	0.0288	17.2198	0.0000	lag.Q25	2.6023	2.0108	1.2942	0.1956
Q26	0.5338	0.0289	18.4823	0.0000	lag.Q26	2.8248	1.6949	1.6666	0.0956
Q27	0.5944	0.0297	20.0053	0.0000	lag.Q27	1.3530	2.4285	0.5571	0.5774
Q28	0.5638	0.0283	19.9002	0.0000	lag.Q28	2.2234	1.7590	1.2640	0.2062
Q29	0.6338	0.0273	23.2031	0.0000	lag.Q29	2.6496	1.4698	1.8027	0.0714
Q30	0.6237	0.0303	20.5788	0.0000	lag.Q30	1.7474	1.2398	1.4094	0.1587
Q31	0.6655	0.0293	22.6775	0.0000	lag.Q31	1.5500	1.2337	1.2563	0.2090
Q32	0.7032	0.0308	22.8017	0.0000	lag.Q32	0.1858	2.0999	0.0885	0.9295
Q33	0.6946	0.0297	23.3780	0.0000	lag.Q33	3.7947	1.3825	2.7447	0.0061
Q34	0.6549	0.0296	22.1064	0.0000	lag.Q34	1.1745	1.2103	0.9704	0.3318
Q35	0.7127	0.0312	22.8626	0.0000	lag.Q35	3.3222	1.3188	2.5191	0.0118
Q36	0.7235	0.0305	23.7427	0.0000	lag.Q36	4.4193	1.6367	2.7000	0.0069
Q37	0.7051	0.0283	24.9590	0.0000	lag.Q37	0.3246	1.2764	0.2543	0.7993
Q38	0.7824	0.0300	26.0468	0.0000	lag.Q38	4.5053	1.7532	2.5697	0.0102
Q39	0.7149	0.0266	26.8650	0.0000	lag.Q39	0.2445	1.0129	0.2413	0.8093
Q40	0.8222	0.0289	28.4545	0.0000	lag.Q40	3.7578	1.2102	3.1052	0.0019
Q41	0.8293	0.0283	29.3393	0.0000	lag.Q41	3.2466	1.2791	2.5383	0.0111
Q42	0.9090	0.0324	28.0655	0.0000	lag.Q42	7.6527	2.3654	3.2353	0.0012
Q43	0.9131	0.0290	31.5230	0.0000	lag.Q43	3.3373	1.6899	1.9748	0.0483
Q44	0.8586	0.0334	25.6877	0.0000	lag.Q44	-1.5639	2.5178	-0.6211	0.5345
Q45	0.9639	0.0305	31.6167	0.0000	lag.Q45	3.7944	1.6430	2.3094	0.0209
Q46	0.9163	0.0296	30.9732	0.0000	lag.Q46	4.1770	1.4015	2.9804	0.0029
Q47	0.9453	0.0309	30.5651	0.0000	lag.Q47	2.6883	2.1937	1.2255	0.2204
Q48	0.8995	0.0310	29.0279	0.0000	lag.Q48	-0.1421	1.5324	-0.0928	0.9261
Q49	0.8709	0.0302	28.8379	0.0000	lag.Q49	3.0299	1.7715	1.7103	0.0872
Q50	1.0176	0.0339	30.0561	0.0000	lag.Q50	3.6295	2.6349	1.3775	0.1684
Q51	1.0012	0.0303	33.0131	0.0000	lag.Q51	2.6046	1.4961	1.7409	0.0817
Q52	1.0239	0.0328	31.2252	0.0000	lag.Q52	3.7040	1.6665	2.2226	0.0262
Q53	0.9907	0.0294	33.7432	0.0000	lag.Q53	2.4927	1.6564	1.5049	0.1323
Q54	0.9337	0.0325	28.7236	0.0000	lag.Q54	6.5054	2.4129	2.6961	0.0070
Q55	0.9844	0.0335	29.4112	0.0000	lag.Q55	5.5576	1.9863	2.7980	0.0051
Q56	1.0122	0.0319	31.7662	0.0000	lag.Q56	6.0501	1.9017	3.1813	0.0015
Q57	0.9280	0.0298	31.1376	0.0000	lag.Q57	1.1716	1.4308	0.8189	0.4128
Q58	0.9760	0.0298	32.7186	0.0000	lag.Q58	3.2144	1.3019	2.4690	0.0135
Q59	0.9168	0.0285	32.1912	0.0000	lag.Q59	1.4891	1.0674	1.3951	0.1630

Table A.14: Regression results for condominiums in Geneva with SARMix method. One can notice the larger number of coefficients that are not statistically significant as well as the few lagged coefficients with very high standard errors.

Zurich Houses - SARMix

Variable	Estimate	Std. Error	z value	Pr(>|z|)	Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	15.7170	8.9590	1.7543	0.0794	Rho	-0.8029			
log(KUBATUR_CHAR)	0.5888	0.0325	18.1344	0.0000	lag.log(KUBATUR_CHAR)	0.3386	1.2551	0.2697	0.7874
IS_DETACHED	0.1050	0.0222	4.7233	0.0000	lag.IS_DETACHED	0.5886	1.1517	0.5111	0.6093
BUILT_BEF1900	-0.2520	0.0458	-5.4966	0.0000	lag.BUILT_BEF1900	-4.4163	2.0640	-2.1397	0.0324
BUILT_71TO80	-0.1571	0.0903	-1.7404	0.0818	lag.BUILT_71TO80	-1.0790	4.8016	-0.2247	0.8222
BUILT_81TO90	0.0944	0.0780	1.2102	0.2262	lag.BUILT_81TO90	1.4589	3.7546	0.3886	0.6976
BUILT_91TO00	-0.0942	0.0684	-1.3778	0.1683	lag.BUILT_91TO00	-8.5042	4.4162	-1.9257	0.0541
BUILT_AFT2000	-0.0234	0.0794	-0.2944	0.7685	lag.BUILT_AFT2000	-6.1955	5.2784	-1.1737	0.2405
AREA_SUB	#N/A	#N/A	#N/A	#N/A	lag.AREA_SUB	#N/A	#N/A	#N/A	#N/A
AREA_RE	#N/A	#N/A	#N/A	#N/A	lag.AREA_RE	#N/A	#N/A	#N/A	#N/A
AREA_PERI	#N/A	#N/A	#N/A	#N/A	lag.AREA_PERI	#N/A	#N/A	#N/A	#N/A
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	lag.AREA_TOUR	#N/A	#N/A	#N/A	#N/A
AREA_IND	#N/A	#N/A	#N/A	#N/A	lag.AREA_IND	#N/A	#N/A	#N/A	#N/A
AREA_PEND	#N/A	#N/A	#N/A	#N/A	lag.AREA_PEND	#N/A	#N/A	#N/A	#N/A
AREA_MIX	#N/A	#N/A	#N/A	#N/A	lag.AREA_MIX	#N/A	#N/A	#N/A	#N/A
AREA_AGR	#N/A	#N/A	#N/A	#N/A	lag.AREA_AGR	#N/A	#N/A	#N/A	#N/A
BATHROOM2	0.0586	0.0299	1.9580	0.0502	lag.BATHROOM2	-0.1832	1.4116	-0.1298	0.8967
BATHROOM3	0.0964	0.0349	2.7646	0.0057	lag.BATHROOM3	-0.5216	1.6409	-0.3179	0.7506
BATHROOM4	0.0568	0.0812	0.6992	0.4844	lag.BATHROOM4	-8.1194	4.8555	-1.6722	0.0945
GARAGE1	0.0296	0.0283	1.0451	0.2960	lag.GARAGE1	-0.7559	1.5963	-0.4736	0.6358
GARAGE2	0.1042	0.0383	2.7224	0.0065	lag.GARAGE2	1.1943	2.0706	0.5768	0.5641
GARAGE3	0.3906	0.1230	3.1746	0.0015	lag.GARAGE3	19.4595	7.4273	2.6200	0.0088
LOC_AVG	0.0792	0.0709	1.1162	0.2644	lag.LOC_AVG	3.0714	3.6733	0.8362	0.4031
LOC_GOOD	0.2032	0.0671	3.0269	0.0025	lag.LOC_GOOD	3.2269	3.3793	0.9549	0.3396
LOC_GREAT	0.3623	0.0740	4.8949	0.0000	lag.LOC_GREAT	5.0501	3.9066	1.2927	0.1961
QUAL_AVG	-0.0243	0.0517	-0.4707	0.6378	lag.QUAL_AVG	-2.3898	2.9484	-0.8106	0.4176
QUAL_GOOD	0.0247	0.0609	0.4052	0.6853	lag.QUAL_GOOD	-2.0368	3.4572	-0.5892	0.5557
QUAL_GREAT	0.1511	0.0681	2.2192	0.0265	lag.QUAL_GREAT	-3.2350	4.1016	-0.7887	0.4303
BUILD_AVG	0.0894	0.0409	2.1884	0.0286	lag.BUILD_AVG	-0.1238	2.3222	-0.0533	0.9575
BUILD_GOOD	0.1518	0.0468	3.2443	0.0012	lag.BUILD_GOOD	1.0737	2.7468	0.3909	0.6959
BUILD_GREAT	0.1016	0.0725	1.4013	0.1611	lag.BUILD_GREAT	0.3663	4.2262	0.0867	0.9309
FIRST	#N/A	#N/A	#N/A	#N/A	lag.FIRST	#N/A	#N/A	#N/A	#N/A
Q2	-0.1599	0.1406	-1.1375	0.2553	lag.Q2	-8.1444	7.7240	-1.0544	0.2917
Q3	0.1323	0.0983	1.3461	0.1783	lag.Q3	0.2957	3.8975	0.0759	0.9395
Q4	0.1659	0.0841	1.9734	0.0484	lag.Q4	1.1020	3.6258	0.3039	0.7612
Q5	0.2450	0.1161	2.1109	0.0348	lag.Q5	9.5799	5.8794	1.6294	0.1032
Q6	0.2714	0.1502	1.8076	0.0707	lag.Q6	8.9937	8.5013	1.0579	0.2901
Q7	0.0316	0.0969	0.3260	0.7444	lag.Q7	-0.5520	3.9967	-0.1381	0.8901
Q8	0.0898	0.1147	0.7831	0.4336	lag.Q8	1.3092	6.5926	0.1986	0.8426
Q9	-0.0382	0.1531	-0.2494	0.8031	lag.Q9	-8.3576	11.0749	-0.7546	0.4505
Q10	0.1075	0.1045	1.0281	0.3039	lag.Q10	4.4895	4.4081	1.0185	0.3085
Q11	0.0747	0.0939	0.7955	0.4263	lag.Q11	0.3005	4.3808	0.0686	0.9453
Q12	0.1806	0.1467	1.2309	0.2184	lag.Q12	7.0949	9.2334	0.7684	0.4422
Q13	0.1749	0.1009	1.7340	0.0829	lag.Q13	2.2939	4.7044	0.4876	0.6258
Q14	0.1207	0.1191	1.0134	0.3109	lag.Q14	-0.2391	7.2369	-0.0330	0.9736
Q15	0.2217	0.1052	2.1070	0.0351	lag.Q15	3.5734	5.1440	0.6947	0.4873
Q16	0.1567	0.1128	1.3885	0.1650	lag.Q16	4.4748	6.0150	0.7439	0.4569
Q17	0.2577	0.1172	2.1985	0.0279	lag.Q17	7.2034	7.0923	1.0157	0.3098
Q18	0.0361	0.1236	0.2917	0.7706	lag.Q18	-7.3193	6.7362	-1.0866	0.2772
Q19	0.2134	0.1000	2.1346	0.0328	lag.Q19	-0.9591	5.1847	-0.1850	0.8532
Q20	0.2883	0.0896	3.2177	0.0013	lag.Q20	3.4290	3.9199	0.8748	0.3817
Q21	0.2419	0.0902	2.6828	0.0073	lag.Q21	3.0638	4.1483	0.7386	0.4602
Q22	0.2328	0.1515	1.5367	0.1244	lag.Q22	-0.7243	9.7542	-0.0743	0.9408
Q23	0.2193	0.1013	2.1659	0.0303	lag.Q23	-0.9963	5.5134	-0.1807	0.8566
Q24	0.2806	0.1015	2.7657	0.0057	lag.Q24	0.8817	4.7330	0.1863	0.8522
Q25	0.6115	0.1564	3.9095	0.0001	lag.Q25	12.4546	10.8792	1.1448	0.2523
Q26	0.1766	0.1523	1.1592	0.2464	lag.Q26	-14.2075	9.0760	-1.5654	0.1175
Q27	0.2604	0.1358	1.9172	0.0552	lag.Q27	1.9337	7.8775	0.2455	0.8061
Q28	0.5468	0.1321	4.1407	0.0000	lag.Q28	17.1487	7.9832	2.1481	0.0317
Q29	0.5666	0.1377	4.1134	0.0000	lag.Q29	9.5607	7.7545	1.2329	0.2176
Q30	0.6848	0.1204	5.6865	0.0000	lag.Q30	11.6353	6.4017	1.8175	0.0691
Q31	0.3693	0.1253	2.9481	0.0032	lag.Q31	6.9374	6.6582	1.0419	0.2974
Q32	0.4488	0.1200	3.7413	0.0002	lag.Q32	-2.5040	7.0439	-0.3555	0.7222
Q33	0.5156	0.1323	3.8981	0.0001	lag.Q33	3.2122	7.1226	0.4510	0.6520
Q34	0.1967	0.1960	1.0039	0.3154	lag.Q34	-17.1430	11.7620	-1.4575	0.1450
Q35	0.7084	0.1479	4.7906	0.0000	lag.Q35	14.1758	7.5408	1.8799	0.0601
Q36	0.5320	0.1189	4.4737	0.0000	lag.Q36	2.5241	6.3633	0.3967	0.6916
Q37	0.7003	0.1204	5.8188	0.0000	lag.Q37	7.3040	6.4719	1.1286	0.2591
Q38	0.4260	0.1763	2.4160	0.0157	lag.Q38	-5.5339	10.9267	-0.5065	0.6125
Q39	0.4310	0.1275	3.3816	0.0007	lag.Q39	0.3332	6.2642	0.0532	0.9576
Q40	0.3468	0.1322	2.6234	0.0087	lag.Q40	-6.7205	6.6571	-1.0095	0.3127
Q41	0.5880	0.1114	5.2798	0.0000	lag.Q41	3.5114	5.8158	0.6038	0.5460
Q42	0.8570	0.1903	4.5026	0.0000	lag.Q42	19.0233	12.6461	1.5043	0.1325
Q43	0.6225	0.1507	4.1304	0.0000	lag.Q43	-0.3489	7.9709	-0.0438	0.9651
Q44	0.5011	0.2023	2.4773	0.0132	lag.Q44	-3.9422	9.6382	-0.4090	0.6825
Q45	0.3503	0.1600	2.1890	0.0286	lag.Q45	-20.0475	11.2280	-1.7855	0.0742
Q46	0.6395	0.1086	5.8862	0.0000	lag.Q46	-3.4894	5.2382	-0.6661	0.5053
Q47	0.5723	0.1005	5.6929	0.0000	lag.Q47	-2.4111	4.6516	-0.5183	0.6042
Q48	0.8406	0.1198	7.0142	0.0000	lag.Q48	5.4751	6.5072	0.8414	0.4001
Q49	0.8439	0.1421	5.9396	0.0000	lag.Q49	9.2695	8.9684	1.0336	0.3013
Q50	0.6968	0.2003	3.4792	0.0005	lag.Q50	-1.6581	11.4614	-0.1447	0.8850
Q51	0.8641	0.1155	7.4807	0.0000	lag.Q51	7.8412	6.1209	1.2811	0.2002
Q52	0.7670	0.1133	6.7715	0.0000	lag.Q52	5.4651	5.0228	1.0881	0.2766
Q53	0.7783	0.1268	6.1393	0.0000	lag.Q53	2.0350	7.1398	0.2850	0.7756
Q54	0.8820	0.1788	4.9318	0.0000	lag.Q54	13.8929	9.5084	1.4611	0.1440
Q55	0.7343	0.1268	5.7897	0.0000	lag.Q55	-1.8449	5.6153	-0.3285	0.7425
Q56	0.6439	0.1061	6.0687	0.0000	lag.Q56	0.1949	4.6124	0.0422	0.9663
Q57	0.7422	0.1005	7.3838	0.0000	lag.Q57	0.5221	4.5069	0.1158	0.9078
Q58	0.6839	0.1018	6.7207	0.0000	lag.Q58	1.7489	4.3860	0.3987	0.6901
Q59	0.8645	0.1367	6.3240	0.0000	lag.Q59	6.5454	7.5734	0.8643	0.3874

Table A.15: Regression results for houses in Zurich with SARMix method. One can notice the larger number of coefficients that are not statistically significant as well as the few lagged coefficients with very high standard errors.

Zurich Condominiums - SARMix									
Variable	Estimate	Std. Error	z value	Pr(>|z|)	Variable	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	97.9632	23.3978	4.1868	0.0000	Rho	-7.1824			
log(NETTOWOHNFLAECHE_CHAR)	0.8868	0.0160	55.5916	0.0000	lag.log(NETTOWOHNFLAECHE_CHAR)	3.7157	2.7523	1.3500	0.1770
BUILT_BEF1900	0.0336	0.0226	1.4879	0.1368	lag.BUILT_BEF1900	-1.5811	3.6191	-0.4369	0.6622
BUILT_71TO80	-0.0016	0.0168	-0.0957	0.9238	lag.BUILT_71TO80	-2.6225	2.9213	-0.8977	0.3693
BUILT_81TO90	0.0078	0.0169	0.4630	0.6434	lag.BUILT_81TO90	-1.9365	2.3659	-0.8185	0.4131
BUILT_91TO00	0.0682	0.0170	4.0192	0.0001	lag.BUILT_91TO00	4.6716	2.7977	1.6698	0.0950
BUILT_AFT2000	0.0872	0.0193	4.5086	0.0000	lag.BUILT_AFT2000	2.5617	3.5504	0.7215	0.4706
AREA_SUB	#N/A	#N/A	#N/A	#N/A	lag.AREA_SUB	#N/A	#N/A	#N/A	#N/A
AREA_RE	#N/A	#N/A	#N/A	#N/A	lag.AREA_RE	#N/A	#N/A	#N/A	#N/A
AREA_PERI	#N/A	#N/A	#N/A	#N/A	lag.AREA_PERI	#N/A	#N/A	#N/A	#N/A
AREA_TOUR	#N/A	#N/A	#N/A	#N/A	lag.AREA_TOUR	#N/A	#N/A	#N/A	#N/A
AREA_IND	#N/A	#N/A	#N/A	#N/A	lag.AREA_IND	#N/A	#N/A	#N/A	#N/A
AREA_PEND	#N/A	#N/A	#N/A	#N/A	lag.AREA_PEND	#N/A	#N/A	#N/A	#N/A
AREA_MIX	#N/A	#N/A	#N/A	#N/A	lag.AREA_MIX	#N/A	#N/A	#N/A	#N/A
AREA_AGR	#N/A	#N/A	#N/A	#N/A	lag.AREA_AGR	#N/A	#N/A	#N/A	#N/A
BATHROOM2	0.0743	0.0126	5.8958	0.0000	lag.BATHROOM2	3.6881	2.2108	1.6682	0.0953
BATHROOM3	0.1350	0.0256	5.2793	0.0000	lag.BATHROOM3	12.4477	4.8305	2.5769	0.0100
BATHROOM4	0.0290	0.1018	0.2849	0.7757	lag.BATHROOM4	-7.7252	20.8152	-0.3711	0.7105
GARAGE1	0.0070	0.0101	0.6969	0.4859	lag.GARAGE1	-1.2056	1.7539	-0.6874	0.4918
GARAGE2	0.0662	0.0145	4.5702	0.0000	lag.GARAGE2	-3.2889	2.5463	-1.2916	0.1965
GARAGE3	0.0031	0.0732	0.0417	0.9668	lag.GARAGE3	-39.7215	17.9484	-2.2131	0.0269
LOC_AVG	0.0173	0.0208	0.8287	0.4073	lag.LOC_AVG	-1.2162	3.6820	-0.3303	0.7412
LOC_GOOD	0.1235	0.0208	5.9525	0.0000	lag.LOC_GOOD	0.5940	3.6194	0.1641	0.8696
LOC_GREAT	0.2341	0.0236	9.9022	0.0000	lag.LOC_GREAT	3.8925	4.2111	0.9243	0.3553
QUAL_AVG	0.0408	0.0316	1.2886	0.1976	lag.QUAL_AVG	-2.1936	5.5691	-0.3939	0.6937
QUAL_GOOD	0.1069	0.0333	3.2103	0.0013	lag.QUAL_GOOD	-1.0329	6.0106	-0.1718	0.8636
QUAL_GREAT	0.2179	0.0324	6.7280	0.0000	lag.QUAL_GREAT	4.2993	5.6984	0.7545	0.4506
BUILD_AVG	0.1118	0.0248	4.5064	0.0000	lag.BUILD_AVG	0.0674	3.9908	0.0169	0.9865
BUILD_GOOD	0.1509	0.0262	5.7651	0.0000	lag.BUILD_GOOD	-2.3143	4.2896	-0.5395	0.5895
BUILD_GREAT	0.1876	0.0318	5.9009	0.0000	lag.BUILD_GREAT	-5.4232	5.7699	-0.9399	0.3473
FIRST	-0.0494	0.0826	-0.5976	0.5501	lag.FIRST	-11.8867	15.8583	-0.7496	0.4535
Q2	-0.0412	0.0649	-0.6356	0.5250	lag.Q2	-13.8903	13.3279	-1.0422	0.2973
Q3	0.1111	0.0414	2.6814	0.0073	lag.Q3	4.0556	5.4193	0.7484	0.4542
Q4	0.0155	0.0456	0.3400	0.7338	lag.Q4	-8.9175	7.3775	-1.2087	0.2268
Q5	0.0023	0.0405	0.0578	0.9539	lag.Q5	1.0161	4.9686	0.2045	0.8380
Q6	-0.0450	0.0474	-0.9504	0.3419	lag.Q6	-3.8279	5.8074	-0.6591	0.5098
Q7	0.0339	0.0497	0.6825	0.4949	lag.Q7	3.3137	8.3355	0.3975	0.6910
Q8	-0.0112	0.0439	-0.2540	0.7995	lag.Q8	-0.8030	6.7503	-0.1190	0.9053
Q9	0.0521	0.0378	1.3782	0.1681	lag.Q9	-0.6092	5.6192	-0.1084	0.9137
Q10	0.0018	0.0460	0.0385	0.9693	lag.Q10	-5.4595	6.5857	-0.8290	0.4071
Q11	0.0291	0.0409	0.7112	0.4770	lag.Q11	-2.0408	6.4619	-0.3158	0.7521
Q12	0.0797	0.0385	2.0682	0.0386	lag.Q12	2.0111	5.7239	0.3513	0.7253
Q13	0.1039	0.0393	2.6442	0.0082	lag.Q13	8.5778	5.9134	1.4506	0.1469
Q14	0.1224	0.0686	1.7839	0.0744	lag.Q14	14.2771	13.6846	1.0433	0.2968
Q15	0.0514	0.0542	0.9481	0.3431	lag.Q15	-4.7879	10.7842	-0.4440	0.6571
Q16	0.1343	0.0438	3.0683	0.0022	lag.Q16	-2.7736	7.1331	-0.3888	0.6974
Q17	0.1666	0.0528	3.1546	0.0016	lag.Q17	11.4461	10.8560	1.0544	0.2917
Q18	0.1321	0.0494	2.6726	0.0075	lag.Q18	-3.1756	9.7326	-0.3263	0.7442
Q19	0.1500	0.0410	3.6569	0.0003	lag.Q19	-3.7887	7.1600	-0.5291	0.5967
Q20	0.2308	0.0446	5.1799	0.0000	lag.Q20	5.4127	8.6224	0.6278	0.5302
Q21	0.2531	0.0463	5.4637	0.0000	lag.Q21	5.2211	9.0102	0.5795	0.5623
Q22	0.1307	0.0500	2.6154	0.0089	lag.Q22	-2.3718	9.1983	-0.2579	0.7965
Q23	0.2328	0.0389	5.9865	0.0000	lag.Q23	0.1538	5.8647	0.0262	0.9791
Q24	0.2680	0.0451	5.9445	0.0000	lag.Q24	3.6344	7.3585	0.4939	0.6214
Q25	0.3150	0.0387	8.1489	0.0000	lag.Q25	4.2477	5.3325	0.7966	0.4257
Q26	0.2654	0.0407	6.5190	0.0000	lag.Q26	-3.8755	5.9307	-0.6535	0.5135
Q27	0.3171	0.0424	7.4838	0.0000	lag.Q27	-0.8036	5.7228	-0.1404	0.8883
Q28	0.3830	0.0546	7.0106	0.0000	lag.Q28	11.3104	10.1115	1.1186	0.2633
Q29	0.2906	0.0417	6.9608	0.0000	lag.Q29	-2.9580	6.0567	-0.4884	0.6253
Q30	0.3079	0.0439	7.0153	0.0000	lag.Q30	-7.3549	6.7253	-1.0936	0.2741
Q31	0.3461	0.0406	8.5243	0.0000	lag.Q31	11.0867	6.1755	1.7953	0.0726
Q32	0.3775	0.0406	9.3026	0.0000	lag.Q32	13.2765	6.7206	1.9755	0.0482
Q33	0.3789	0.0426	8.8933	0.0000	lag.Q33	2.0997	6.9464	0.3023	0.7624
Q34	0.2700	0.0436	6.1980	0.0000	lag.Q34	-22.4789	7.7185	-2.9123	0.0036
Q35	0.4471	0.0426	10.4856	0.0000	lag.Q35	10.8463	8.3966	1.2917	0.1964
Q36	0.3890	0.0358	10.8621	0.0000	lag.Q36	0.6856	5.2432	0.1308	0.8960
Q37	0.3995	0.0505	7.9135	0.0000	lag.Q37	-6.9875	9.8798	-0.7072	0.4794
Q38	0.5223	0.0440	11.8801	0.0000	lag.Q38	15.2480	7.4708	2.0410	0.0413
Q39	0.5312	0.0447	11.8958	0.0000	lag.Q39	4.9245	7.0986	0.6937	0.4879
Q40	0.4788	0.0414	11.5678	0.0000	lag.Q40	1.2236	6.5530	0.1867	0.8519
Q41	0.5212	0.0412	12.6607	0.0000	lag.Q41	4.7927	6.0542	0.7916	0.4286
Q42	0.4754	0.0522	9.1107	0.0000	lag.Q42	-10.0215	9.6784	-1.0355	0.3005
Q43	0.5363	0.0449	11.9355	0.0000	lag.Q43	0.4571	7.7492	0.0590	0.9530
Q44	0.5919	0.0476	12.4402	0.0000	lag.Q44	-1.0971	7.8548	-0.1397	0.8889
Q45	0.6344	0.0424	14.9514	0.0000	lag.Q45	6.4726	5.9378	1.0901	0.2757
Q46	0.6531	0.0609	10.7237	0.0000	lag.Q46	2.3630	10.6352	0.2222	0.8242
Q47	0.5714	0.0579	9.8643	0.0000	lag.Q47	-0.6177	11.0703	-0.0558	0.9555
Q48	0.7045	0.0655	10.7527	0.0000	lag.Q48	13.1844	12.9381	1.0190	0.3082
Q49	0.6961	0.0510	13.6551	0.0000	lag.Q49	8.5811	8.7446	0.9813	0.3264
Q50	0.6968	0.0469	14.8652	0.0000	lag.Q50	8.5427	8.6481	0.9878	0.3232
Q51	0.7337	0.0407	18.0349	0.0000	lag.Q51	8.5893	6.0254	1.4255	0.1540
Q52	0.7495	0.0488	15.3594	0.0000	lag.Q52	10.7868	8.3047	1.2989	0.1940
Q53	0.6988	0.0378	18.4959	0.0000	lag.Q53	0.3586	6.2488	0.0574	0.9542
Q54	0.7340	0.0596	12.3213	0.0000	lag.Q54	1.7997	12.5396	0.1435	0.8859
Q55	0.8045	0.0461	17.4380	0.0000	lag.Q55	13.9930	7.4894	1.8684	0.0617
Q56	0.7013	0.0524	13.3858	0.0000	lag.Q56	-5.4653	10.4474	-0.5231	0.6009
Q57	0.7549	0.0391	19.3189	0.0000	lag.Q57	7.5299	6.1244	1.2295	0.2189
Q58	0.7479	0.0396	18.8977	0.0000	lag.Q58	4.7201	5.4656	0.8636	0.3878
Q59	0.7575	0.0404	18.7595	0.0000	lag.Q59	3.9482	5.7589	0.6856	0.4930

Table A.16: Regression results for condominiums in Zurich with SARMix method. One can notice the larger number of coefficients that are not statistically significant as well as the few lagged coefficients with very high standard errors.

Bezrik	AIC_SARErr	AIC_OLS	Bezrik	AIC_SARErr	AIC_OLS
District de Nyon	-439.10	-56.55	Bezirk Aarau	-357.66	-333.70
Verwaltungskreis Bern-Mittelland	-1482.11	-1101.74	Verwaltungskreis Seeland	-198.36	-175.22
Canton de Geneve	-248.98	52.69	Bezirk See / District du Lac	-111.98	-89.19
Bezirk Uster	-1329.38	-1071.54	District de la Riviera-Pays-d'Enhaut	237.57	259.81
Bezirk Baden	-1308.13	-1068.74	District du Gros-de-Vaud	-80.78	-59.16
Bezirk Bülach	-874.20	-651.70	Bezirk Lenzburg	-420.88	-400.55
Bezirk Meilen	58.56	278.40	Bezirk Zurzach	-234.64	-217.67
Bezirk Zurich	109.57	312.40	Bezirk Frauenfeld	-296.64	-279.75
District de Morges	228.76	419.87	Bezirk Wasseramt	-198.90	-184.52
Bezirk Bremgarten	-987.77	-799.22	Bezirk Laufenburg	-64.07	-51.14
Bezirk Winterthur	-961.99	-804.37	Bezirk Liestal	-572.40	-562.79
Bezirk Dietikon	-324.15	-198.53	Bezirk Weinfelden	-108.77	-100.82
Bezirk Dielsdorf	-869.13	-751.22	District de Boudry	-40.37	-32.53
Bezirk Affoltern	-624.73	-523.30	Bezirk Sissach	-180.25	-172.72
Verwaltungskreis Biel/Bienne	-32.98	49.95	Bezirk Schaffhausen	-152.08	-145.10
Arrondissement administratif Jura bernois	123.83	205.93	Bezirk Hinwil	-651.53	-644.62
Verwaltungskreis Interlaken-Oberhasli	161.80	243.58	District de la Broye-Vully	85.45	91.06
District d'Aigle	476.14	556.97	Bezirk Brugg	-31.74	-26.71
Bezirk Horgen	-124.24	-44.41	Kanton Zug	-146.01	-142.34
Distretto di Locarno	449.74	524.27	Verwaltungskreis Oberaargau	125.05	128.36
Bezirk Arlesheim	-1446.90	-1377.24	Bezirk Andelfingen	-232.35	-229.35
Distretto di Lugano	342.61	405.60	District de Sion	40.52	42.50
Bezirk Rheinfelden	-429.22	-372.16	Bezirk Zofingen	-340.20	-340.88
Kanton Basel-Stadt	-37.35	18.91	Verwaltungskreis Emmental	-289.33	-290.08
District de Martigny	53.77	102.77	Wahlkreis Hochdorf	-176.28	-177.43
District de Sierre	199.94	248.23	Bezirk Lebern	-123.68	-124.86
District de Lavaux-Oron	147.90	195.97	District de Delémont	-26.90	-28.35
District de Monthey	36.44	83.12	Bezirk Gösgen	-35.96	-37.48
Wahlkreis Sursee	-5.98	37.57	Bezirk Mittelland	196.03	194.41
Verwaltungskreis Thun	-260.15	-217.67	District de Conthey	106.86	105.10
District du Jura-Nord vaudois	61.15	101.05	Wahlkreis St. Gallen	4.13	2.34
Bezirk Pfaeffikon	-572.69	-534.99	District de la Gruyère	31.87	30.02
Bezirk March	-31.22	3.80	Wahlkreis Toggenburg	64.40	62.47
Wahlkreis Luzern-Land	-316.81	-283.05	Bezirk Muri	-274.53	-276.46
District de l'Ouest lausannois	-56.76	-25.58	Bezirk Kulm	9.57	7.60
District de la Sarine	-232.78	-204.39	Bezirk Olten	-182.72	-184.72
Bezirk Dorneck	-167.36	-139.83	Wahlkreis See-Gaster	63.35	61.36
District de Lausanne	-35.80	-10.26			

Table A.17: Comparison of AIC scores of SARErr and OLS methods for houses. One can see that the SARErr method has a slightly better fir that the OLS methods in the majority of districts, as evidenced by the smaller value of the AIC score.

Bezrik	AIC_SARErr	AIC_OLS	Bezrik	AIC_SARErr	AIC_OLS
Bezirk Zurich	-2389.43	-414.88	Bezirk Bremgarten	-1031.36	-948.16
Canton de Geneve	-1386.03	-615.59	Wahlkreis Luzern-Land	-932.42	-854.41
District de Nyon	-2703.91	-1990.35	Bezirk Pfaeffikon	-1818.27	-1740.66
Bezirk Meilen	-2219.21	-1535.24	Wahlkreis See-Gaster	-623.88	-547.49
Bezirk Visp	12.44	694.78	Kanton Obwalden	-219.74	-148.93
Bezirk Albula	-324.28	350.62	Bezirk Prättigau-Davos	-613.47	-544.25
District d'Entremont	90.78	722.87	Verwaltungskreis Seeland	-964.77	-900.21
Bezirk Baden	-2852.55	-2234.63	Bezirk Arlesheim	-1587.01	-1528.91
Bezirk Uster	-4284.18	-3733.81	Wahlkreis St. Gallen	-619.40	-564.84
Verwaltungskreis Bern-Mittelland	-2456.07	-1937.17	Bezirk Hinwil	-2518.26	-2464.82
Bezirk Surselva	-440.98	37.91	Bezirk Lenzburg	-707.62	-659.57
Bezirk Horgen	-1941.65	-1468.23	Bezirk Rheinfelden	-449.33	-403.41
Bezirk Bülach	-4241.46	-3806.53	Verwaltungskreis Emmental	-571.39	-527.89
Verwaltungskreis Interlaken-Oberhasli	-160.89	197.23	District de l'Ouest lausannois	-590.02	-567.55
District d'Aigle	-248.84	107.32	Kanton Zug	-1387.78	-1368.48
Distretto di Locarno	-530.45	-182.53	District de Lausanne	-742.77	-724.78
Bezirk Dielsdorf	-2713.19	-2371.47	Bezirk Aarau	-709.06	-694.25
Distretto di Lugano	-330.84	8.49	Wahlkreis Rorschach	-331.55	-319.16
District de Monthey	-708.06	-379.37	Verwaltungskreis Oberaargau	-558.16	-548.88
Bezirk Winterthur	-2413.42	-2099.07	Bezirk Brugg	-527.88	-519.44
Wahlkreis Luzern-Stadt	-507.77	-225.91	District de Neuchâtel	-336.40	-328.10
District de Sierre	342.51	583.84	Bezirk Höfe	-280.96	-272.96
Bezirk Maloja / Distretto di Maloggia	149.46	351.20	Wahlkreis Hochdorf	-698.00	-692.62
Bezirk Dietikon	-1900.62	-1699.55	Bezirk Schaffhausen	-536.31	-533.24
Bezirk Plessur	-478.44	-279.51	Bezirk Brig	-303.41	-300.56
Kanton Basel-Stadt	-944.24	-747.44	Bezirk Imboden	-391.62	-389.65
District de Morges	-823.07	-637.66	Bezirk Liestal	-521.10	-519.27
Bezirk Affoltern	-1395.58	-1213.67	Bezirk Leuk	-88.87	-87.98
Bezirk March	-421.30	-267.23	District de la Chaux-de-Fonds	-447.89	-447.34
Verwaltungskreis Biel/Bienne	-1369.30	-1227.16	District de Boudry	-462.07	-461.59
District de la Sarine	-697.53	-576.87	Bezirk Zofingen	-734.56	-734.45
District de la Riviera-Pays-d'Enhaut	-536.64	-437.91	District de la Gruyère	-620.42	-620.47
District de Lavaux-Oron	-996.28	-900.13	Kanton Nidwalden	-288.50	-289.36
District de Martigny	-448.52	-361.68	Wahlkreis Wil	-407.84	-409.01
Wahlkreis Sursee	-491.48	-405.36	District de Sion	-513.75	-515.53
Verwaltungskreis Thun	-1015.04	-929.12	District de Conthey	-243.44	-245.43

Table A.18: Comparison of AIC scores of SARErr and OLS methods for condominiums. One can see that the SARErr method has a slightly better fir that the OLS methods in the majority of districts, as evidenced by the smaller value of the AIC score

(a) Condominiums

District	Moran's I	p-value
Bezirk Affoltern	$-3.32 \cdot 10^{-03}$	0.7095
Bezirk Bülach	$-1.74 \cdot 10^{-04}$	0.4838
Bezirk Dielsdorf	$5.43 \cdot 10^{-04}$	0.3706
Bezirk Hinwil	$-3.13 \cdot 10^{-04}$	0.4858
Bezirk Horgen	$-1.93 \cdot 10^{-03}$	0.8033
Bezirk Meilen	$1.45 \cdot 10^{-04}$	0.3822
Bezirk Pfaeffikon	$1.17 \cdot 10^{-03}$	0.3180
Bezirk Uster	$-3.96 \cdot 10^{-04}$	0.5370
Bezirk Winterthur	$1.40 \cdot 10^{-04}$	0.4282
Bezirk Dietikon	$2.25 \cdot 10^{-04}$	0.3793
Bezirk Zurich	$-1.64 \cdot 10^{-04}$	0.4897
Verwaltungskreis Biel/Bienne	$-2.82 \cdot 10^{-03}$	0.7004
Verwaltungskreis Seeland	$-1.35 \cdot 10^{-02}$	0.9479
Verwaltungskreis Oberaargau	$-9.24 \cdot 10^{-04}$	0.4778
Verwaltungskreis Emmental	$1.11 \cdot 10^{-04}$	0.4434
Verwaltungskreis Bern-Mittelland	$-4.48 \cdot 10^{-03}$	0.9087
Verwaltungskreis Thun	$-2.70 \cdot 10^{-03}$	0.6248
Verwaltungskreis Interlaken-Oberhasli	$-6.15 \cdot 10^{-05}$	0.4406
Wahlkreis Luzern-Stadt	$-3.84 \cdot 10^{-04}$	0.4147
Wahlkreis Luzern-Land	$-1.56 \cdot 10^{-02}$	0.9969
Wahlkreis Hochdorf	$-2.27 \cdot 10^{-04}$	0.4412
Wahlkreis Sursee	$-3.85 \cdot 10^{-04}$	0.4528
Bezirk Höfe	$6.19 \cdot 10^{-04}$	0.3431
Bezirk March	$4.08 \cdot 10^{-07}$	0.3961
Kanton Obwalden	$-2.51 \cdot 10^{-03}$	0.5007
Kanton Nidwalden	$-8.79 \cdot 10^{-05}$	0.4191
Kanton Zug	$1.47 \cdot 10^{-04}$	0.4032
District de la Gruyère	$-7.13 \cdot 10^{-03}$	0.6946
District de la Sarine	$7.03 \cdot 10^{-03}$	0.2099
Kanton Basel-Stadt	$-1.39 \cdot 10^{-03}$	0.6525
Bezirk Arlesheim	$2.81 \cdot 10^{-04}$	0.3840
Bezirk Liestal	$-1.41 \cdot 10^{-04}$	0.4346
Bezirk Schaffhausen	$6.45 \cdot 10^{-04}$	0.3362
Wahlkreis St. Gallen	$-1.11 \cdot 10^{-03}$	0.4970
Wahlkreis Rorschach	$1.01 \cdot 10^{-03}$	0.3778
Wahlkreis See-Gaster	$-3.74 \cdot 10^{-03}$	0.6090
Wahlkreis Wil	$1.06 \cdot 10^{-03}$	0.3999
Bezirk Albula	$-3.26 \cdot 10^{-02}$	0.9996
Bezirk Imboden	$4.83 \cdot 10^{-04}$	0.3869
Bezirk Maloja / Distretto di Maloggia	$2.74 \cdot 10^{-04}$	0.3981
Bezirk Plessur	$-2.69 \cdot 10^{-03}$	0.6138
Bezirk Prättigau-Davos	$-3.94 \cdot 10^{-03}$	0.7456
Bezirk Surselva	$-9.45 \cdot 10^{-03}$	0.8570
Bezirk Aarau	$-5.69 \cdot 10^{-05}$	0.4264
Bezirk Baden	$-1.40 \cdot 10^{-03}$	0.6482
Bezirk Bremgarten	$1.37 \cdot 10^{-05}$	0.4417
Bezirk Brugg	$1.22 \cdot 10^{-04}$	0.4394
Bezirk Lenzburg	$-4.63 \cdot 10^{-03}$	0.6356
Bezirk Rheinfelden	$1.31 \cdot 10^{-03}$	0.3489
Bezirk Zofingen	$-2.91 \cdot 10^{-03}$	0.5685
Distretto di Locarno	$-2.92 \cdot 10^{-03}$	0.7370
Distretto di Lugano	$-2.32 \cdot 10^{-04}$	0.4914
District d'Aigle	$-1.64 \cdot 10^{-03}$	0.5946
District de Lausanne	$1.58 \cdot 10^{-04}$	0.4030
District de Lavaux-Oron	$4.58 \cdot 10^{-04}$	0.4009
District de Morges	$-4.62 \cdot 10^{-04}$	0.4868
District de Nyon	$-9.91 \cdot 10^{-04}$	0.6170
District de l'Ouest lausannois	$3.72 \cdot 10^{-04}$	0.3660
District de la Riviera-Pays-d'Enhaut	$-9.11 \cdot 10^{-04}$	0.5660
Bezirk Brig	$-2.19 \cdot 10^{-04}$	0.4047
District de Conthey	$-9.69 \cdot 10^{-05}$	0.4262
District d'Entremont	$-2.59 \cdot 10^{-02}$	0.9998
Bezirk Leuk	$-4.95 \cdot 10^{-03}$	0.6027
District de Martigny	$-4.78 \cdot 10^{-03}$	0.7645
District de Monthey	$-1.00 \cdot 10^{-03}$	0.5368
District de Sierre	$-6.42 \cdot 10^{-04}$	0.5153
District de Sion	$-7.43 \cdot 10^{-04}$	0.4707
Bezirk Visp	$-7.12 \cdot 10^{-03}$	0.8505
District de Boudry	$-3.68 \cdot 10^{-03}$	0.5769
District de la Chaux-de-Fonds	$-2.88 \cdot 10^{-03}$	0.6102
District de Neuchâtel	$1.27 \cdot 10^{-03}$	0.3420
Canton de Geneve	$-5.03 \cdot 10^{-04}$	0.6137

(b) Houses

District	Moran's I	p-value
Bezirk Affoltern	$-9.40 \cdot 10^{-05}$	0.438
Bezirk Andelfingen	$-2.55 \cdot 10^{-03}$	0.562
Bezirk Bülach	$-1.80 \cdot 10^{-03}$	0.720
Bezirk Dielsdorf	$-2.63 \cdot 10^{-03}$	0.695
Bezirk Hinwil	$-8.00 \cdot 10^{-04}$	0.541
Bezirk Horgen	$-1.55 \cdot 10^{-03}$	0.620
Bezirk Meilen	$-3.75 \cdot 10^{-04}$	0.484
Bezirk Pfaeffikon	$3.99 \cdot 10^{-04}$	0.401
Bezirk Uster	$6.15 \cdot 10^{-04}$	0.349
Bezirk Winterthur	$3.03 \cdot 10^{-04}$	0.401
Bezirk Dietikon	$-5.60 \cdot 10^{-04}$	0.469
Bezirk Zurich	$5.90 \cdot 10^{-04}$	0.401
Arrondissement administratif Jura bernois	$-4.12 \cdot 10^{-03}$	0.576
Verwaltungskreis Biel/Bienne	$-4.67 \cdot 10^{-03}$	0.766
Verwaltungskreis Seeland	$-2.28 \cdot 10^{-03}$	0.598
Verwaltungskreis Oberaargau	$-1.03 \cdot 10^{-03}$	0.514
Verwaltungskreis Emmental	$-1.59 \cdot 10^{-03}$	0.534
Verwaltungskreis Bern-Mittelland	$-1.55 \cdot 10^{-02}$	1.000
Verwaltungskreis Thun	$-2.69 \cdot 10^{-03}$	0.591
Verwaltungskreis Interlaken-Oberhasli	$-2.11 \cdot 10^{-04}$	0.456
Wahlkreis Luzern-Land	$-3.99 \cdot 10^{-03}$	0.630
Wahlkreis Hochdorf	$3.20 \cdot 10^{-04}$	0.430
Wahlkreis Sursee	$3.04 \cdot 10^{-03}$	0.379
Bezirk March	$6.57 \cdot 10^{-04}$	0.392
Kanton Zug	$2.70 \cdot 10^{-04}$	0.412
District de la Gruyère	$6.58 \cdot 10^{-04}$	0.430
District de la Sarine	$4.64 \cdot 10^{-03}$	0.305
Bezirk See / District du Lac	$-3.68 \cdot 10^{-03}$	0.541
Bezirk Dorneck	$2.99 \cdot 10^{-03}$	0.330
Bezirk Gösgen	$2.49 \cdot 10^{-03}$	0.339
Bezirk Wasseramt	$3.38 \cdot 10^{-04}$	0.414
Bezirk Lebern	$-1.30 \cdot 10^{-03}$	0.486
Bezirk Olten	$-4.27 \cdot 10^{-05}$	0.426
Kanton Basel-Stadt	$-8.42 \cdot 10^{-04}$	0.511
Bezirk Arlesheim	$1.29 \cdot 10^{-05}$	0.423
Bezirk Liestal	$-1.37 \cdot 10^{-04}$	0.433
Bezirk Sissach	$4.00 \cdot 10^{-04}$	0.438
Bezirk Schaffhausen	$2.81 \cdot 10^{-04}$	0.396
Bezirk Mittelland	$4.41 \cdot 10^{-04}$	0.382
Wahlkreis St. Gallen	$3.09 \cdot 10^{-04}$	0.429
Wahlkreis See-Gaster	$8.87 \cdot 10^{-05}$	0.436
Wahlkreis Toggenburg	$3.05 \cdot 10^{-04}$	0.449
Bezirk Aarau	$-8.82 \cdot 10^{-03}$	0.948
Bezirk Baden	$2.81 \cdot 10^{-05}$	0.444
Bezirk Bremgarten	$-9.34 \cdot 10^{-05}$	0.449
Bezirk Brugg	$-1.16 \cdot 10^{-03}$	0.491
Bezirk Kulm	$-1.22 \cdot 10^{-04}$	0.436
Bezirk Laufenburg	$9.78 \cdot 10^{-04}$	0.418
Bezirk Lenzburg	$2.81 \cdot 10^{-05}$	0.435
Bezirk Muri	$-3.40 \cdot 10^{-04}$	0.449
Bezirk Rheinfelden	$-4.28 \cdot 10^{-03}$	0.694
Bezirk Zofingen	$-4.21 \cdot 10^{-04}$	0.461
Bezirk Zurzach	$-3.39 \cdot 10^{-03}$	0.551
Bezirk Frauenfeld	$-3.32 \cdot 10^{-03}$	0.589
Bezirk Weinfelden	$1.95 \cdot 10^{-03}$	0.414
Distretto di Locarno	$2.29 \cdot 10^{-03}$	0.379
Distretto di Lugano	$-9.08 \cdot 10^{-03}$	0.792
District d'Aigle	$9.62 \cdot 10^{-04}$	0.378
District de la Broye-Vully	$-3.47 \cdot 10^{-03}$	0.526
District du Gros-de-Vaud	$-7.00 \cdot 10^{-03}$	0.663
District du Jura-Nord vaudois	$-6.44 \cdot 10^{-03}$	0.648
District de Lausanne	$-3.38 \cdot 10^{-03}$	0.644
District de Lavaux-Oron	$6.60 \cdot 10^{-04}$	0.409
District de Morges	$-1.03 \cdot 10^{-02}$	0.847
District de Nyon	$-6.22 \cdot 10^{-04}$	0.542
District de l'Ouest lausannois	$-2.72 \cdot 10^{-03}$	0.526
District de la Riviera-Pays-d'Enhaut	$-5.38 \cdot 10^{-03}$	0.781
District de Conthey	$-1.57 \cdot 10^{-03}$	0.472
District de Martigny	$1.14 \cdot 10^{-03}$	0.397
District de Monthey	$-1.97 \cdot 10^{-04}$	0.431
District de Sierre	$2.83 \cdot 10^{-03}$	0.352
District de Sion	$-1.43 \cdot 10^{-02}$	0.786
District de Boudry	$-1.72 \cdot 10^{-02}$	0.891
Canton de Geneve	$-1.30 \cdot 10^{-03}$	0.666
District de Delémont	$9.70 \cdot 10^{-04}$	0.424

Table A.19: Moran's I and corresponding p-value (SARErr method). No evidence of spatial autocorrelation in any of the districts.

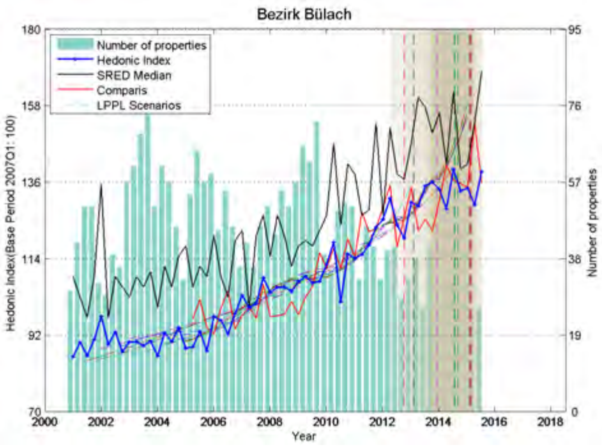
(a) Condominiums

District	Average Price Increase per Quarter
Canton de Geneve	1.59%
District d'Entremont	1.56%
District de la Riviera-Pays-d'Enhaut	1.55%
District de Lausanne	1.55%
District de Lavaux-Oron	1.48%
District d'Aigle	1.47%
Bezirk Visp	1.47%
District de Morges	1.43%
Distretto di Lugano	1.39%
District de Nyon	1.39%
Bezirk Maloja / Distretto di Maloggia	1.36%
Bezirk Höfe	1.34%
Bezirk Zurich	1.33%
Kanton Nidwalden	1.31%
District de Neuchâtel	1.27%
District de Sierre	1.26%
Kanton Obwalden	1.23%
Wahlkreis Sursee	1.19%
Bezirk Imboden	1.19%
District de l'Ouest lausannois	1.19%
Distretto di Locarno	1.18%
District de Sion	1.18%
Kanton Zug	1.13%
Bezirk Meilen	1.12%
Wahlkreis St. Gallen	1.11%
Bezirk Prättigau-Davos	1.10%
District de Boudry	1.09%
Wahlkreis Luzern-Stadt	1.08%
District de Martigny	1.08%
Kanton Basel-Stadt	1.06%
Bezirk Affoltern	1.03%
Bezirk Uster	1.01%
District de la Chaux-de-Fonds	1.00%
Wahlkreis See-Gaster	1.00%
Bezirk Pfaeffikon	0.99%
Bezirk Brig	0.97%
District de la Sarine	0.97%
Bezirk Bulach	0.96%
District de la Gruyère	0.93%
Bezirk Plessur	0.92%
Bezirk Dietikon	0.91%
Bezirk Horgen	0.91%
Bezirk Winterthur	0.91%
Wahlkreis Wil	0.90%
District de Monthey	0.90%
Verwaltungskreis Bern-Mittelland	0.88%
Bezirk Albula	0.86%
District de Conthey	0.85%
Wahlkreis Luzern-Land	0.85%
Verwaltungskreis Thun	0.84%
Wahlkreis Hochdorf	0.81%
Bezirk Baden	0.78%
Bezirk Schaffhausen	0.76%
Bezirk March	0.75%
Bezirk Surselva	0.72%
Bezirk Bremgarten	0.72%
Bezirk Arlesheim	0.71%
Verwaltungskreis Interlaken-Oberhasli	0.70%
Bezirk Leuk	0.63%
Bezirk Zofingen	0.62%
Wahlkreis Rorschach	0.59%
Bezirk Hinwil	0.59%
Verwaltungskreis Biel/Bienne	0.59%
Bezirk Dielsdorf	0.58%
Verwaltungskreis Seeland	0.55%
Bezirk Liestal	0.51%
Bezirk Rheinfelden	0.50%
Bezirk Lenzburg	0.43%
Verwaltungskreis Oberaargau	0.41%
Bezirk Aarau	0.39%
Verwaltungskreis Emmental	0.26%
Bezirk Brugg	0.26%
National Index	**0.93**%

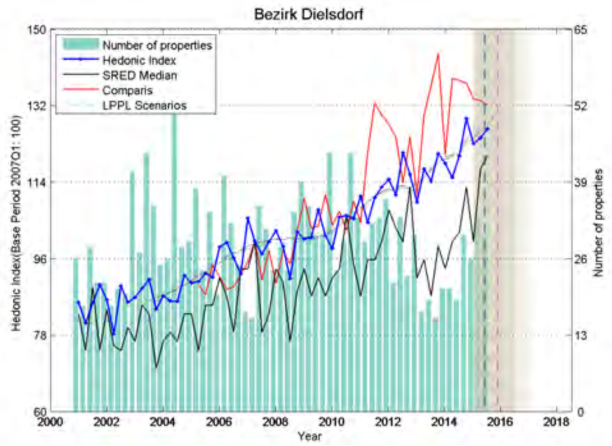
(b) Houses

District	Average Price Increase per Quarter
Bezirk Zurich	1.30%
Canton de Geneve	1.28%
Bezirk Horgen	1.26%
Kanton Zug	1.26%
District de la Riviera-Pays-d'Enhaut	1.25%
District de Sierre	1.14%
Bezirk March	1.08%
District de Lavaux-Oron	1.06%
Bezirk Meilen	1.05%
District de l'Ouest lausannois	1.03%
District de Nyon	1.02%
District de Lausanne	0.99%
District de Sion	0.92%
Wahlkreis Hochdorf	0.91%
District de Monthey	0.88%
Bezirk Dietikon	0.88%
Distretto di Lugano	0.87%
Kanton Basel-Stadt	0.86%
Bezirk Affoltern	0.85%
Wahlkreis Luzern-Land	0.84%
Bezirk Bülach	0.84%
Distretto di Locarno	0.83%
Bezirk Dorneck	0.82%
Wahlkreis See-Gaster	0.81%
Bezirk Uster	0.81%
District de la Gruyère	0.79%
District d'Aigle	0.78%
Bezirk Winterthur	0.78%
District du Jura-Nord vaudois	0.76%
District de Conthey	0.76%
District de Morges	0.76%
District de la Sarine	0.76%
Verwaltungskreis Emmental	0.72%
Verwaltungskreis Thun	0.72%
Bezirk Liestal	0.72%
Bezirk Hinwil	0.69%
Verwaltungskreis Interlaken-Oberhasli	0.69%
Bezirk Andelfingen	0.68%
Bezirk Arlesheim	0.68%
Bezirk Dielsdorf	0.67%
District du Gros-de-Vaud	0.67%
Verwaltungskreis Seeland	0.67%
Bezirk Pfaeffikon	0.64%
District de Boudry	0.64%
Bezirk Frauenfeld	0.60%
Bezirk Wasseramt	0.60%
Bezirk Zofingen	0.59%
District de la Broye-Vully	0.57%
Bezirk Lenzburg	0.55%
Bezirk Muri	0.55%
Wahlkreis Sursee	0.55%
Bezirk Zurzach	0.54%
Verwaltungskreis Bern-Mittelland	0.53%
Bezirk Sissach	0.52%
Bezirk Bremgarten	0.51%
Bezirk Rheinfelden	0.46%
Bezirk Baden	0.46%
Verwaltungskreis Biel/Bienne	0.45%
Bezirk Brugg	0.44%
Bezirk Aarau	0.42%
Bezirk Lebern	0.41%
Wahlkreis St. Gallen	0.40%
Bezirk Kulm	0.37%
District de Martigny	0.34%
Bezirk Gösgen	0.31%
Verwaltungskreis Oberaargau	0.26%
Bezirk See / District du Lac	0.23%
Bezirk Weinfelden	0.21%
Arrondissement administratif Jura bernois	0.21%
District de Delémont	0.18%
Wahlkreis Toggenburg	0.11%
Bezirk Schaffhausen	0.09%
Bezirk Olten	0.05%
Bezirk Laufenburg	−0.03%
Bezirk Mittelland	−0.10%
National Index	**0.70**%

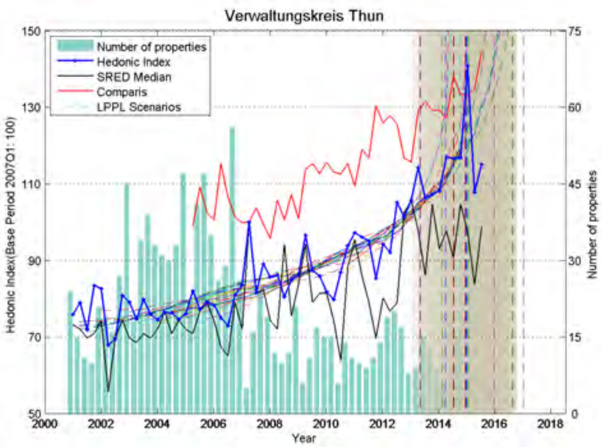
Table A.20: Average rates (per quarter) of price appreciation for each district. They differ a lot across districts. Overall, condominium prices have been rising faster than those of houses. Finally, increases in condominium prices are naturally correlated with increases in house prices in the same district.



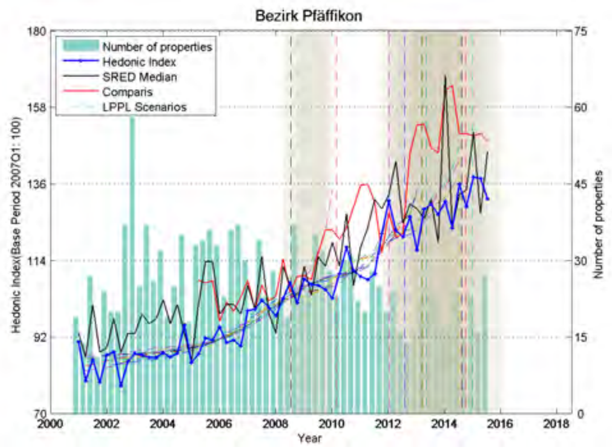
(a) Bezirk Bülach



(b) Bezirk Dielsdorf

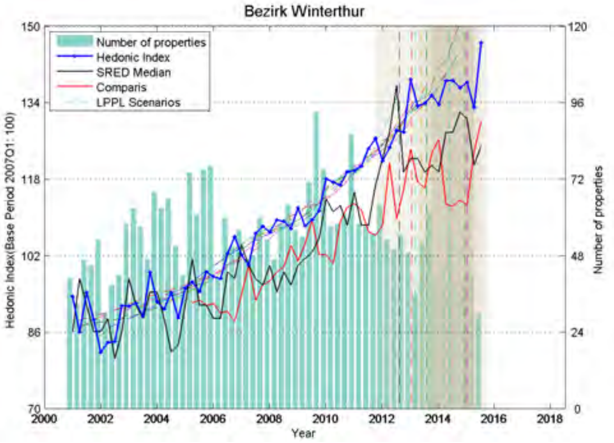


(c) Verwaltungskreis Thun

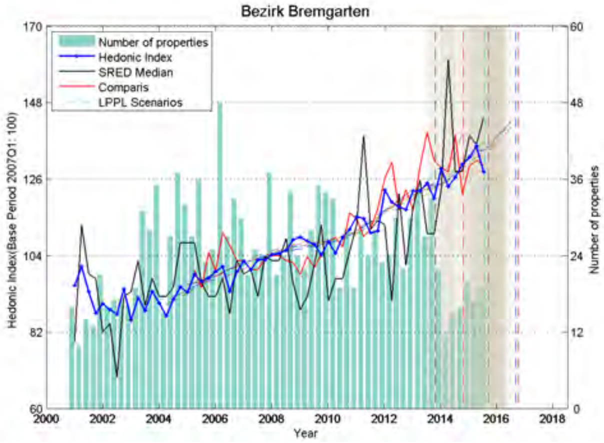


(d) Bezirk Pfaeffikon

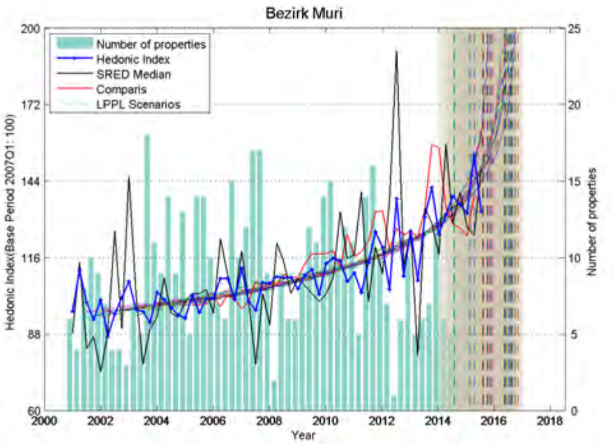
Figure A.1: Districts to watch for houses (1)



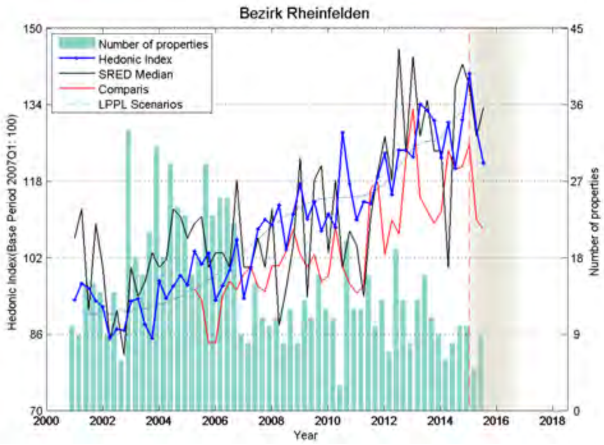
(a) Bezirk Winterthur



(b) Verwaltungskreis Bremgarten

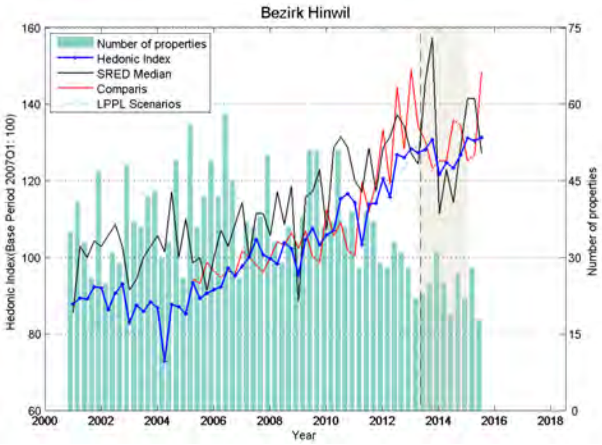


(c) Bezirk Muri

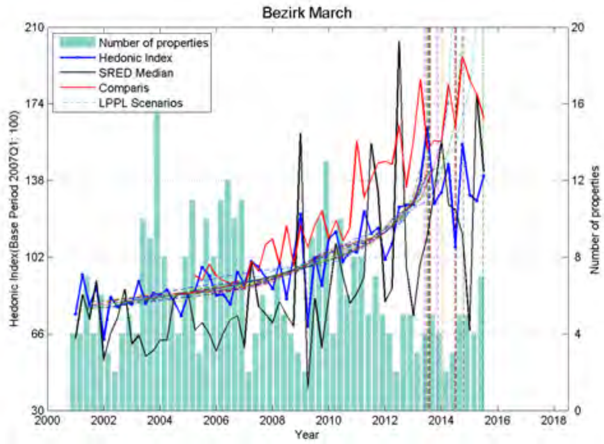


(d) Bezirk Rheinfelden

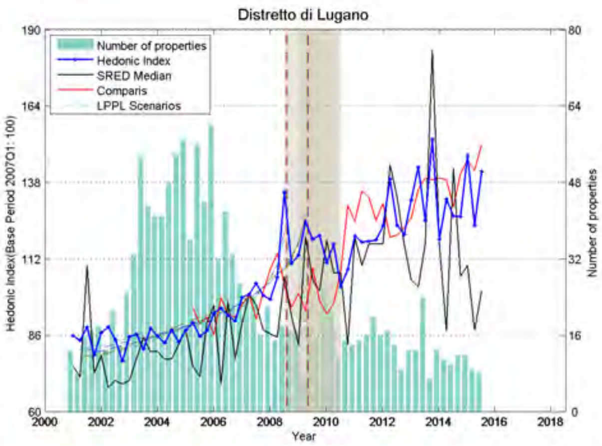
Figure A.2: Districts to watch for houses (2)



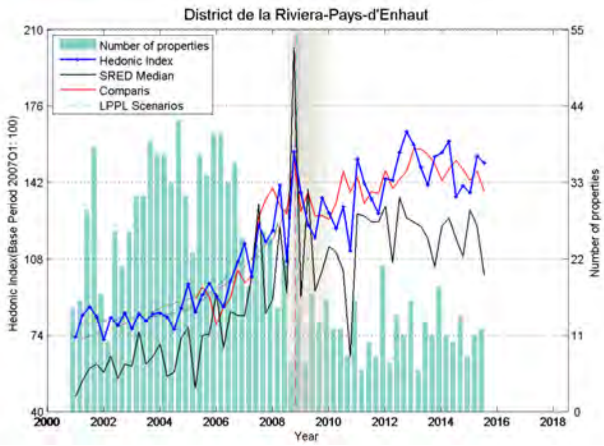
(a) Bezirk Hinwil



(b) Bezirk March

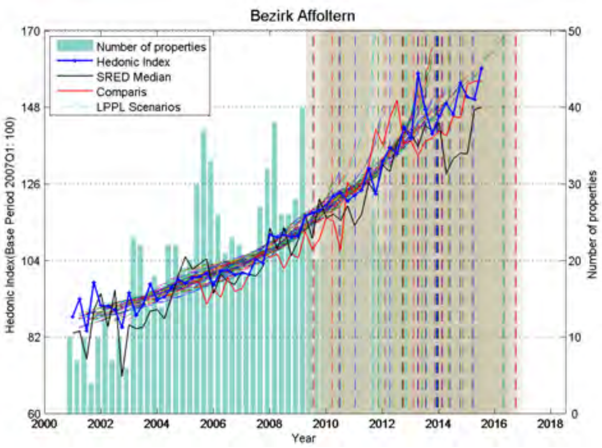


(c) Distretto di Lugano

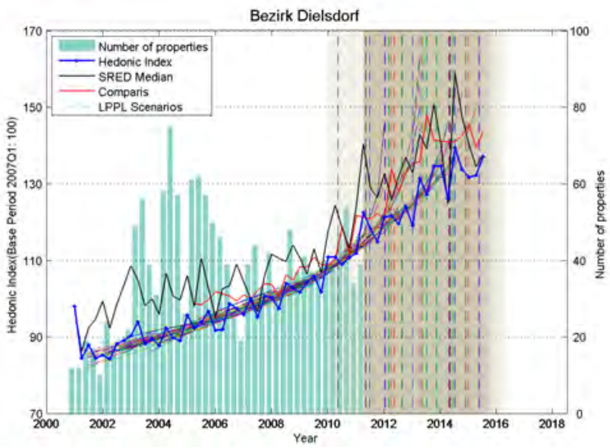


(d) District de la Riviera-Pays-d'Enhaut

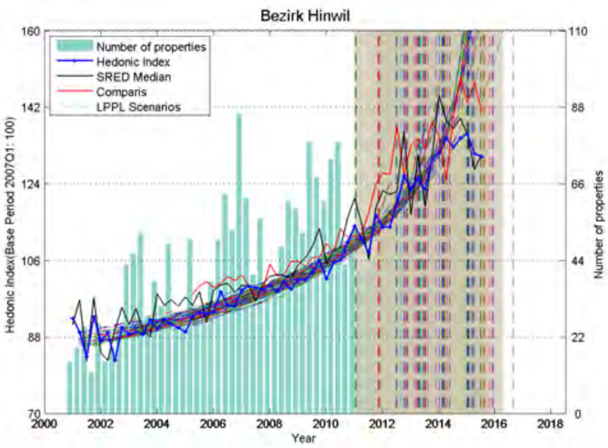
Figure A.3: Districts with past bubbles for houses



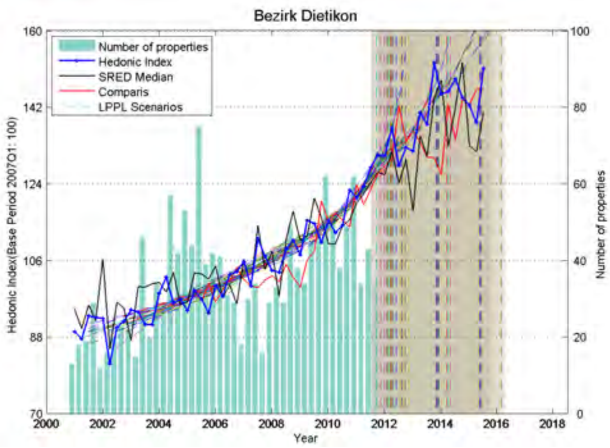
(a) Bezirk Affoltern



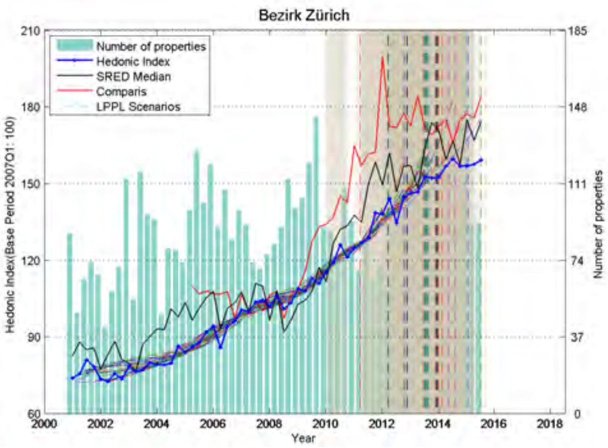
(b) Bezirk Dielsdorf



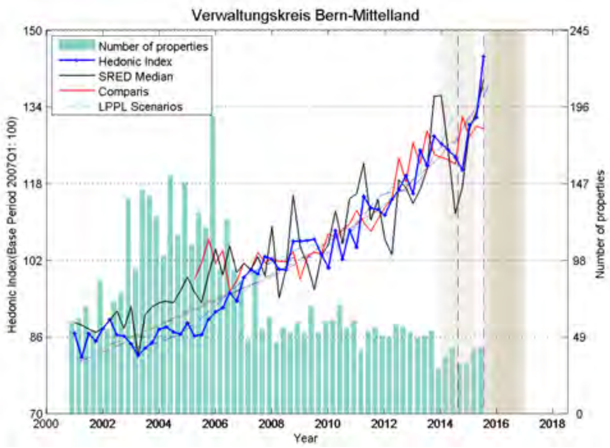
(c) Bezirk Hinwil



(d) Bezirk Dietikon

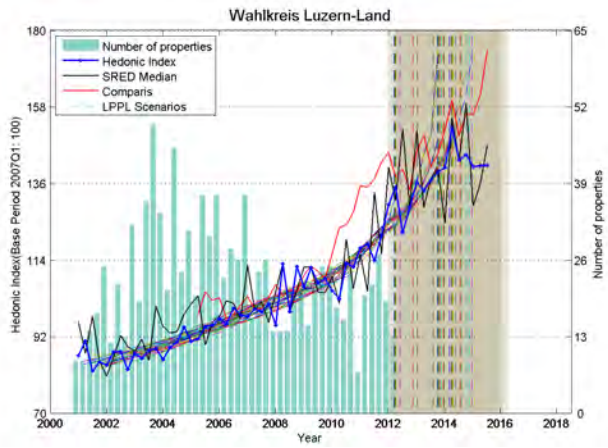


(e) Bezirk Zurich

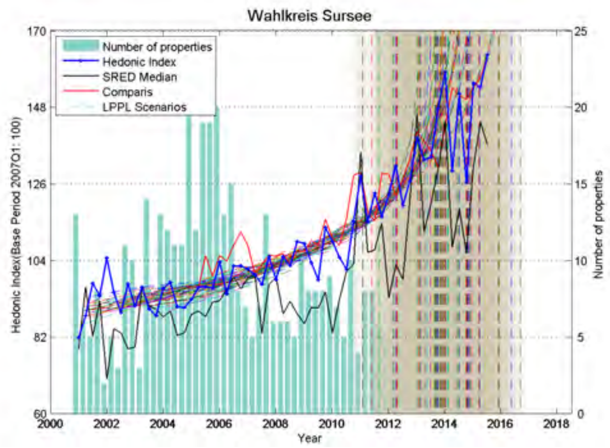


(f) Verwaltungskreis Bern-Mitteland

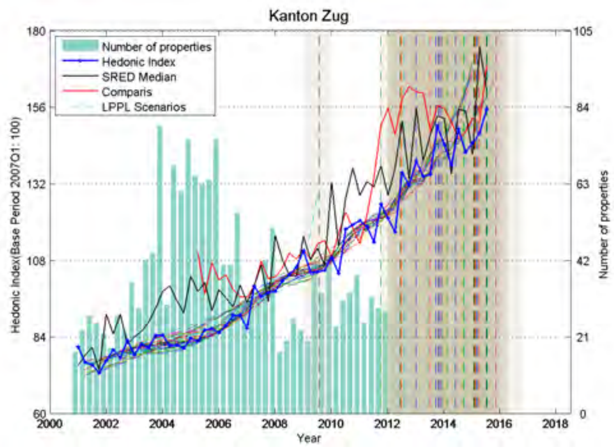
Figure A.4: Districts to watch for condominiums (1)



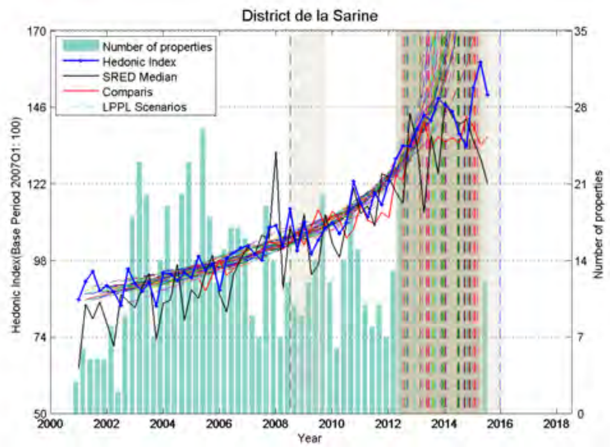
(a) Wahlkreis Luzern-Land



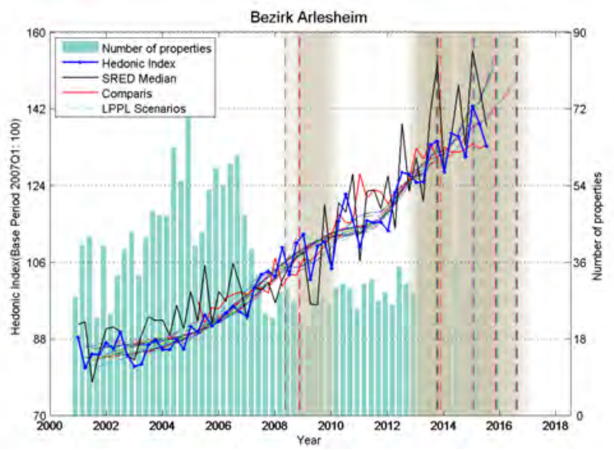
(b) Wahlkreis Sursee



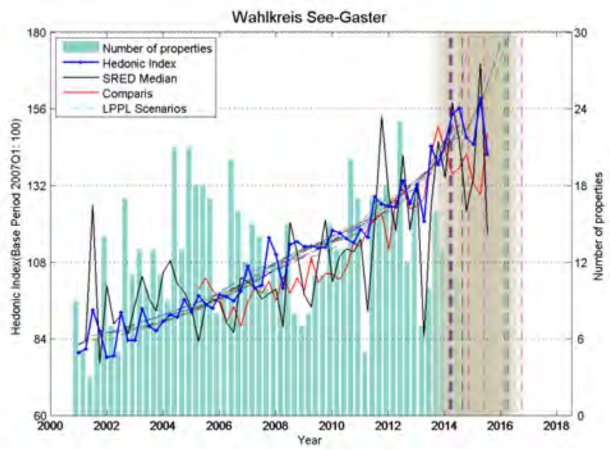
(c) Kanton Zug



(d) District de la Sarine

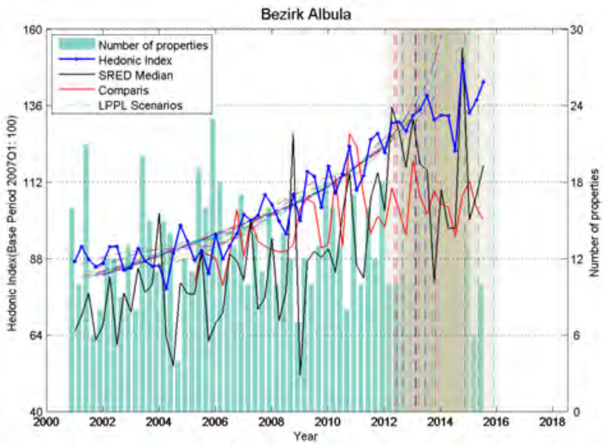


(e) Bezirk Alresheim

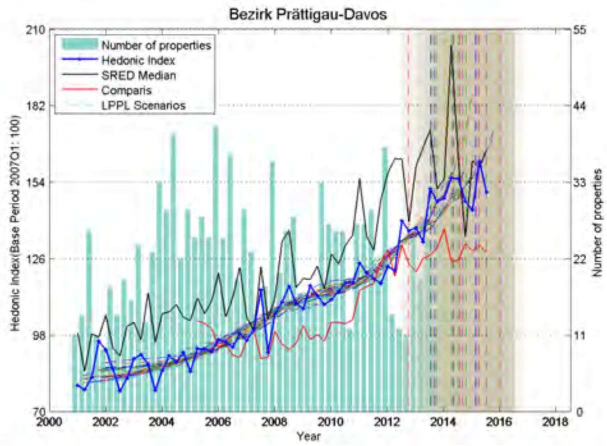


(f) Wahlkreis See-Gaster

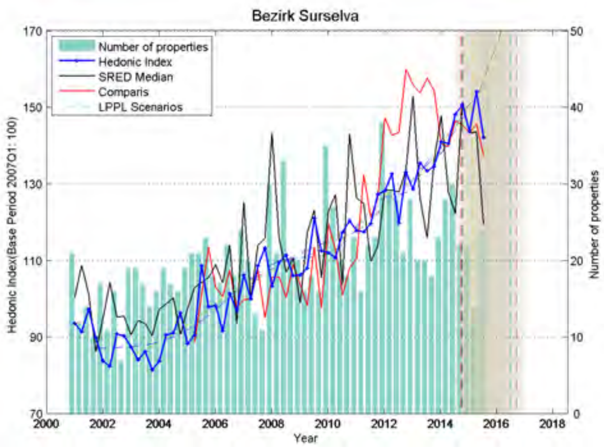
Figure A.5: Districts to watch for condominiums (2)



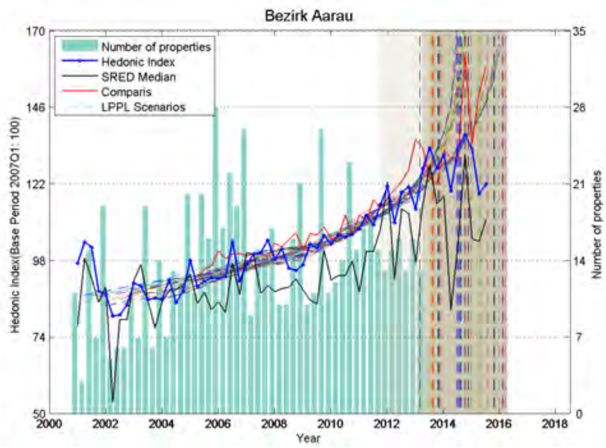
(a) Bezirk Albula



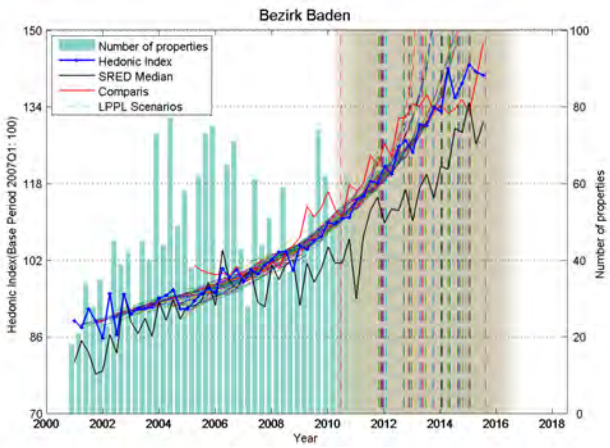
(b) Bezirk Prättigau-Davos



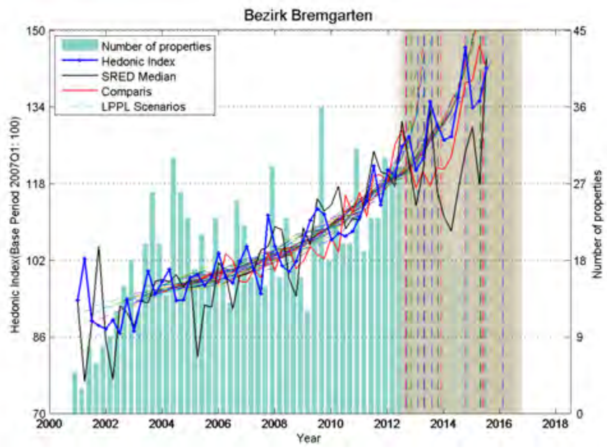
(c) Bezirk Surselva



(d) Bezirk Aarau

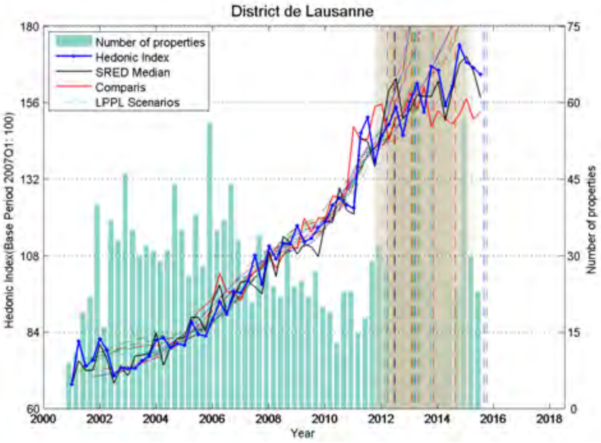


(e) Bezirk Baden

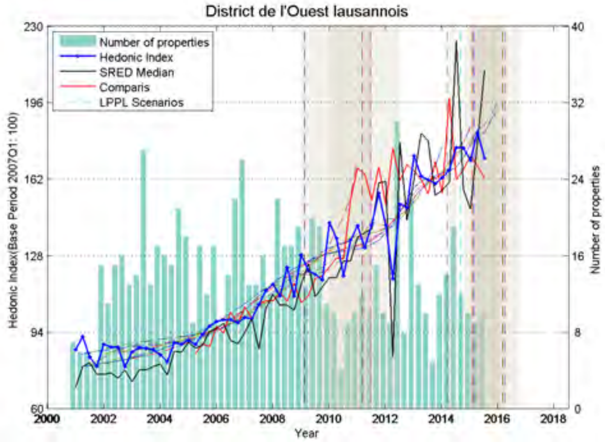


(f) Bezirk Bremgarten

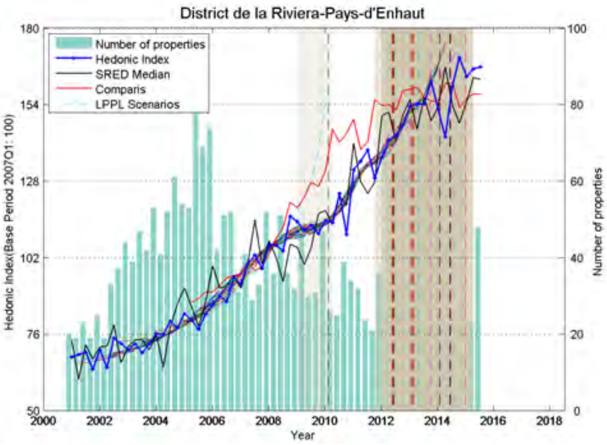
Figure A.6: Districts to watch for condominiums (3)



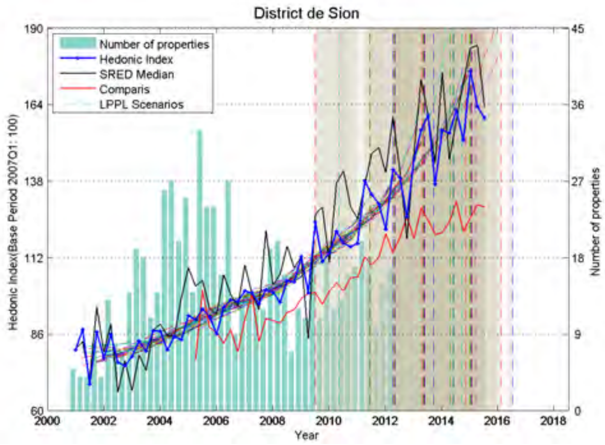
(a) District de Lausanne



(b) District de l'Ouest-Lausannois

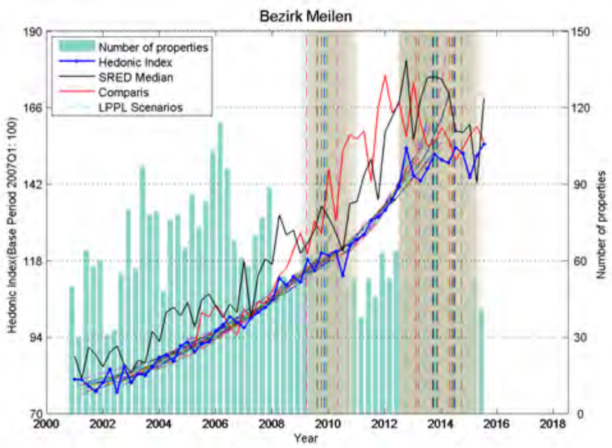


(c) District de la Riviera-Pays-d'Enhaut

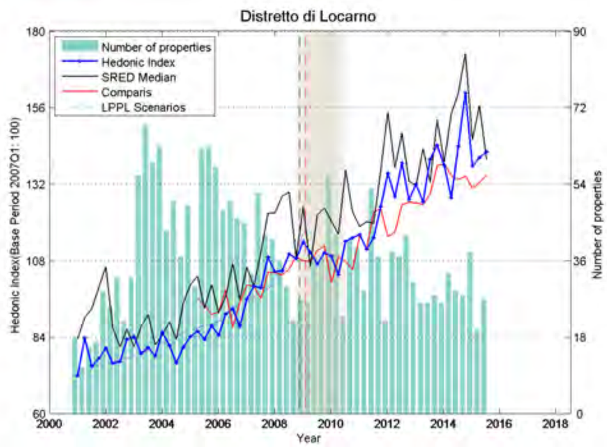


(d) District de Sion

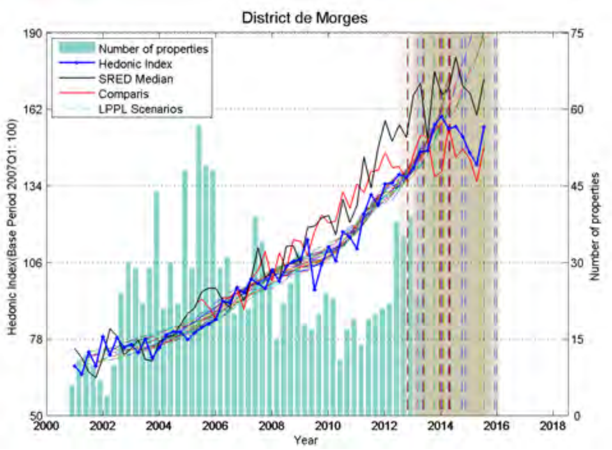
Figure A.7: Districts to watch for condominiums (4)



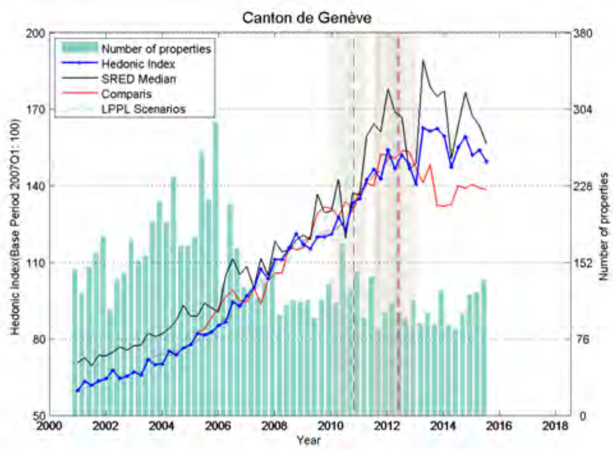
(a) Bezirk Meilen



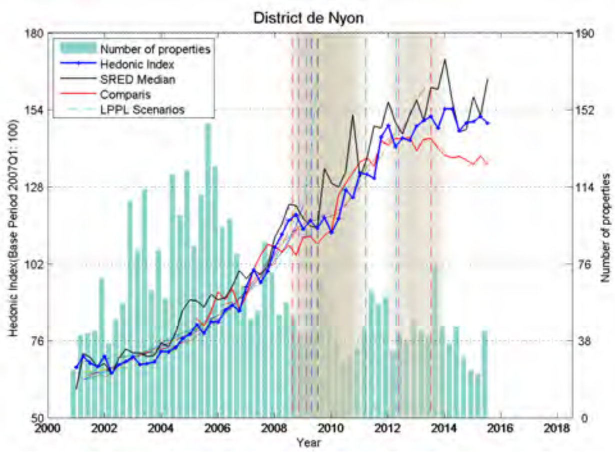
(b) Distretto di Locarno



(c) District de Morges



(d) Catone de Geneve



(e) District de Nyon

Figure A.8: Districts with past bubbles for condominiums