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Price Indices for Austrian municipalities - Hedonic models based on Microlevel Data

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Abstract:
Austrian municipalities must re-evaluate their real estate portfolios every year. The existing Austrian house price datasets (based on the Austrian land register) cannot fully fulfill these requirements due to a lack of descriptive variables. When constructing a hedonic model, it is vital to assemble a dataset as complete as possible to minimize the extent of the omitted variables problem. This paper shows how an existing micro-level dataset can be improved and extended to raise the data's explanatory power. Then these data are used to compile different temporal hedonic models for the nine regional capitals of Austria. The results show that the right choice of method is essential for smaller cities with fewer transactions. For bigger cities, with more transaction data, the choice of hedonic model is less important (with all suggested model formulations giving similar results). Thus, it is vital to consider the data structure and number of transactions when compiling indices for small regions (cities).
Keywords: Housing market; House price index; Hedonic regression; Rolling time dummy method; Average characteristics method; Repricing method; Stratified median

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1 Introduction

The impact of the housing market on the overall economy and financial stability has become widely visible since the global financial crisis in 2007, which originated in the US housing market. As a result, central banks, governments and international organisations (such as the IMF, OECD or Eurostat) are encouraging National Statistical Institutes (NSIs) to collect better quality housing data.

In Austria, adequate housing data are important for the Austrian National Bank for macroprudential regulation purposes. In addition, better housing data are also important for the taxation of capital gains from housing, the accurate calculation of property taxes, the valuation of mortgage loans by banks and new regulatory data requirements. In 2019, the Voranschlags- und Rechnungsabschlussverordnung (VRV), 2015, came into force in Austria. It obliges Austrian municipalities to report the value of their properties annually in a financial report. They must also revalue their real estate portfolio every year. This regulation poses an intensive challenge to municipalities and increases their need for high-quality property price indices for different sectors and regions of Austria. Since 2012, the National Statistical Institutes (NSIs) in all countries of the European Union have to calculate official house price indices on a quarterly basis. Eurostat recommends the use of a hedonic method for this purpose. Apart from a few countries that use stratified medians to calculate house price indices, most NSIs have followed Eurostat's advice and use different hedonic methods, although there are some differences in the method used (Hill et al., 2018).

Currently, there are three main house price indices in Austria. In the "Immobilienpreisspiegel", the Austrian Federal Economic Chamber publishes transaction and rental prices for different categories in all political districts of Austria on an annual basis. In addition to rental prices for flats and commercial properties, the index also includes prices for building land, single-family houses and flats. The resulting indices are mostly divided into different quality categories. The database of the "Immobilienpreisspiegel" is compiled by asking 7,500 real estate agents and brokers and 1,000 other real estate experts for their opinion on the prices for each of a series of quality characteristics. The average price levels (based on the arithmetic mean) are calculated for each district in each category (WKO, 2015).

Since 2014, Statistics Austria has published quarterly property price indices based on a hedonic method. The underlying dataset is based on transaction prices from the land register and includes all real estate transactions between private households and those where private households buy real estate from companies. The price index of Statistics Austria does not contain any regional differentiation, and the calculations of Statistics Austria are based on the Laspeyres formula (www.Statistik.gv.at). The Austrian National Bank calculates (together with the Vienna University of Technology) a real estate price index which is mainly based on supply data. There are sub-indices for used and new dwellings in Vienna and the rest of Austria. There are index series for other individual components such as rents and building land (Mundt and Wagner, 2017). However, as the HPI of the Oesterreichische Nationalbank only covers two separate regions (i.e., Vienna and the rest of Austria), it cannot fully meet the increased demand for more regional house price indices.

When constructing a hedonic model, it is first important to assemble as complete a dataset as possible (in terms of the number of observations and the list of characteristics) to minimize the extent of the omitted variables problem, and second, to use a hedonic method that is robust with respect to omitted variables (Rambaldi and Fletcher, 2014). Every house is different in terms of physical and locational characteristics. Real estate price indices can be highly sensitive to the method of construction. More accurate measurement of price trends over time (i.e., temporal price indices) and across locations (i.e., spatial price indices) requires better-quality data and advanced measurement methods.

Hedonic methods (which regress real estate prices on a vector of characteristics) are well suited for measuring trends in house prices. Methods that rely on median prices and/or means, by contrast, fail to adjust for quality differences in the samples that are compared and hence can generate erratic and unreliable price indices. This happens because the quality of the median dwelling tends to differ from one period to another. Nevertheless, some European countries like Bulgaria, Czech Republic, Estonia, and Poland base their calculation of HPIs on a stratified median or a mixed-adjusted median (Hill, 2013). Among those countries that use hedonic methods, the repricing method is the most popular (e.g., by Belgium, Finland, Norway, Slovenia).

The repeat sales method, the most popular method to compile house price indices in the USA, is hardly used in Europe. For the calculation of an HPI in Austrian cities, these methods are unsuitable because the rate of turnover in the Austrian housing market is much lower than in the US.

HPIs should reflect the changing market prices and be reported in a timely manner. In a temporal context, the most widely used hedonic indices are the rolling time dummy method, the hedonic imputation method, the repricing method, and the average characteristics method (see Hill 2013 and Eurostat 2016).

This paper explores the performance of various hedonic methods and model specifications for Austrian data and addresses the need for reliable local house price indices in Austria in the following way:

Apartment price indices for each of the 9 Austrian capital cities will be constructed. All indices are based on a specially augmented micro-level housing dataset. Various temporal hedonic pricing models are examined in this paper. As well as comparing price changes across cities, the paper also explores how price changes differ across market segments within the same city. Different hedonic temporal methods are compared to see how sensitive the house price indices are to the choice of method in the different cities. Applying different methods also provides a robustness check. I will perform a forward stepwise regression to see which mix of characteristics best fits each city's data. The goal is to see how different methods perform in different cities that differ strongly in size and structure and, as a result, to construct comparable house price indices for all the capital cities in Austria. In this way the quality of available house price indices in Austria can be improved.

2 Literature Review

In the literature, the hedonic approach is regarded as the preferred method for constructing reliable house price indices (Silver, 2011, Rambaldi and Rao 2013 and Hill, 2013). In 2006, when residential property price developments could be inferred only from a few indicators, Hofmann and Lorenz confirmed the need for hedonic indices (Hofmann and Lorenz, 2006). Diewert (2011) suggested constructing a sales price index with the hedonic imputation method. Rambaldi and Rao (2013) concluded that future studies of house price indices should use time-varying hedonic models because of their predictive power.

To resolve the problem of the need to revise historical series when new data become available constantly, Shimizu et al. (2010) pioneered the rolling window technique. The Rolling time dummy hedonic method proved very successful and is now one of the most widely used methods for house price indices, along with the repricing and the average characteristics method (Hill 2013). That real estate price indices can be highly sensitive to the method of construction was confirmed by Silver (2015). He used three different country studies to identify differences in measured national house price inflation between different indexes within a country. He identified similarities of the indices and also the challenges that occur for each method.

There exist several studies on the price influencing characteristics for dwelling units. Shimizu (2014) distinguishes between physical and locational characteristics. In his paper, he stated that incorporating neighborhood effect variables (represented by the environmental variables and the incomes of households) can reduce the omitted variables bias problem. Rambaldi and Fletcher (2014) also suggest a hedonic method that is robust with respect to omitted variables. Hill et al. (2018) evaluated the methods used by the European countries to compute their official house price indices and applied some of these methods to two different datasets. They found that overall hedonic house price indices are robust over the range of hedonic methods used by the national statistical institutes in Europe. However, the choice of the hedonic method becomes more important the smaller the country (i.e., the number of transactions per quarter).

3 Micro-Level Housing Data in Austria

This section discusses the availability of micro-level property transaction data in Austria.

3.1 Legal Provisions

According to the Austrian property-valuation law, for the valuation of a property, a valuation method has to be chosen that corresponds to the state of the art. The comparative value method, the income value method, and the asset value method are generally used in Austria. Using the comparative value method assumes comparing actual purchase prices of comparable properties to determine the value of a property (Liegenschaftsbewertungsgesetz,2019).

In Austria, all property transactions have to be entered into the Austrian land registry. Collecting data of actually transacted properties in Austria means that one has to collect these purchase contracts. The Austrian system of urban and spatial planning is formed by the cadastre and the land register. These two registers fall under the authority of the federal government. The system is accessible for the general public in PDF format at 1,2 € per contract. The cadastre documents the current and objective property state as it relates to boundaries, location, size, and use. The Austrian land registry is a public register of all real estate properties and is maintained by the district courts, each responsible for the area of its local jurisdiction. It records ownership and rights pertaining to real estate property. The land register and its electronic document archive can be consulted via the Austrian Justice homepage. (see BEV, 2018)

Contracts that regulate the sale of real estate have to comply with a textual and formal minimum. The transacted property must be defined, and the price must be determined or determinable. Contracts with properties subject to restrictions as an object of purchase have to provide information about the agreement that carries the burden (see Artner and Kohlmaier, 2017).

3.2 Improving the Property Transaction Data in Austria

To ensure that a house price index takes account of the quality differences of houses, a data collection that is as complete as possible is needed. However, even the best data collection process cannot capture all relevant physical and locational characteristics. Hence there will inevitably be an omitted variables bias problem. In order to minimize the extent of the omitted variables bias, the micro-level housing data base provided by the ZT Datenforum will be extended by locational and, if possible, also by physical characteristics. ZT Datenforum already has an extensive dataset featuring all real estate transactions in Austria. The first step is to clean the dataset. This means that transactions that do not represent market conditions will be excluded from the data base. After this cleaning process, the existing dataset is improved by correcting some gaps caused by mistakes (e.g., caused by changes in the data collection process). Then additional publicly available datasets can be integrated. The data's explanatory power will rise because these variables impact real estate values. Characteristics that measure the noise, commuting time to the district center, or distances to schools are examples of additional characteristics that will be added.

3.2.1 The share of usable data

The lack of uniform standards for transaction contracts in Austria negatively affects the available transaction data. Many contracts do not contain enough information to be usable in a hedonic model (e.g., only price, object ID, seller and buyer names recorded). Regarding calculating a price index for apartments, the contract needs to include at least the price and the floor space. I exclude all transactions which do not contain the size of the property. The percentage of data that is dropped because of such missing size estimates depends on the region of Austria. Table 1 provides an overview of the exclusion rate because of missing floor space:

city	count_total	count_use	percentage
Bregenz	1396	472	33.81%
Eisenstadt	825	189	22.91%
Graz	23422	18128	77.40%
Innsbruck	7266	4083	56.19%
Klagenfurt	5062	2677	52.88%
Linz	6737	2849	42.29%
Salzburg	8177	4951	60.55%
St.Pölten	1404	413	29.42%
Wien	88516	48947	55.30%

Table 1: Share of usable data

The percentage of usable data of transacted apartments varies from about 20 to 35 percent in smaller cities like Eisenstadt or Bregenz to over 50 percent in the biggest city of Austria, Vienna. With over 70 percent usable data Graz constitutes an exception. The loss of transactions due to missing size entries is particularly a problem for smaller cities, which already have low numbers of transactions.

3.2.2 Increasing the share of usable data

To increase the share of usable transaction data, the challenge is to fill the gaps of missing floor space entries. Here an extra data source can play an important role. Since 2006, the Austrian land registry has also provided value appraisals. A value appraisal is an appraisal prepared by an expert to determine the utility values of the individual condominium objects, which determine the size of the ownership shares of the individual condominium objects (apartments) in the land register (Stadt Wien, 2006). The data out of the available value appraisals build the value data base. Included in this dataset is a value-in-use calculation that determines the ratio of the ownership shares of the individual co-owners of a specific property.

As the ownership shares in the value dataset are exact, I can use them to determine missing floor space entries in the transaction data from the registry office (land register).

This is just one of the quality improvements I perform on the transaction data. Other information is also used to raise the information content of the transaction contract data (see discussion in section **??**).

3.2.3 The Raw Data

The raw data base used for this paper consists of all transactions entered into the Austrian land registry and describes each transaction with up to 34 characteristics. Each transaction is assigned to one of five main- and 49 sub-categories. The dataset is based on actually transacted properties. Since the year 2014, the dataset contains 100 percent of the Austrian real estate market transactions. Trained personnel add more than 100.000 contracts to the data base with a maximum time lag of one month after title registration. This rapid process allows updates of the resulting price indices with good timeliness. I will use the data between 2015-2021 to compile the prices for apartments in the regional capitals of Austria.

Characteristics	**Specifications of characteristics**
Purchase price	total price, taxes included
Basement/other storage area	Yes/no, if available area in m^2
Date of contract	Date of transaction as mentioned in registry
On-site parking	Yes/no, if available area in m^2
Living area	Interior living area of building or apartment in m^2
Terrace	Yes/no, if available area in m^2
Year of parification	Year (mostly for pre-WWII buildings)
Balcony	Yes/no, if available area in m^2
Postal code	Postal code of sold apartment
Garden	Yes/no, if available area in m^2
Contract partners	information about buyer and seller
Age of building	Age of the building
Building contractor	Apartment sold by a building contractor
Plotsize	Size of plot
Construction area	Size of construction area (building area)

Table 2: Characteristics of data base (information from land registry)

Table 2 gives all information about the transacted apartment that is available through the contract that is entered into the Austrian land registry. For the creation of a price index the value-influencing features of the properties (listed in Table 2) are included into the analysis.

3.2.4 Data Cleaning

As a first step, the whole dataset is cleaned. Especially very high and very low prices need to be checked. Gaps in the data base are filled up to get a dataset that is as complete as possible. First of all, gaps for some variables can be filled up by information provided in other fields of the same observation. For example, a missing entry concerning the name of the village/town can be filled up if the postal code is available (or vice versa). For the analysis, only transactions should be used that represent the existing market conditions. For this, transactions that took place under special conditions like bankruptcy or estate and those where the buyers and sellers have somehow a relationship that can influence the price are excluded from the data base.

3.2.5 Filling Up Gaps

Another challenge occurred because the process of data collection changed in 2015. Some variables collected together as one entry in the dataset before 2015 are now split into several collumns. Also, other additional variables were created at that point. To achieve more uniformity of the datasets, the old entries are adjusted, and where possible, variables for the newly created variables are established using the information from other fields. The text field "memo" contains additional information on the contract. The memo field records specific information on the transaction contract that does not fit into one of the existing variables but might influence the price. Especially before the data collection process change in 2015, when the number of collected variables was still smaller, this field was used to include additional information.

A good, quality-adjusted property price index needs high-quality information on the features of the price-determining characteristics of a property. As discussed before, some contracts do not contain any information on the property apart from its price and address.

To reduce the amount of missing information about apartment features, it is assumed that if there is information about the existence of any features of the transacted apartment, then the other features are not available. For example, if the contract provides information about an existing terrace but does not mention whether or not there is a balcony, it can be reasonably expected that there is no balcony. However, if there is no information about such features, the feature variables are classified as unknowns.

3.2.6 Merging of Variables

In order to use some data features more efficiently and reduce the problem of missing entries, some of the variables are combined. Age and parification year are two variables in the dataset that each specifies a particular age aspect. Age specifies when the building is built, while the year of parification states when the building is last measured and fully renovated. Both entries are available for some apartments in the dataset; for others, it is one or the other, or none. It is desirable to know how old an apartment is or when it was last fully renovated (when the last parification occurred). I introduce a new variable that classifies apartments as new when the last parification took place after 2010 or the building was constructed after 2010. Additionally, I classify all apartments that are sold by a building contractor as new, even when age or last parification is before 2010. To infer whether a seller is a contractor or not, I refer to the tax rate and the name (firm name) on the contract.

3.2.7 Extending The Transaction dataset

Next, I extend the dataset with new variables created from publicly available datasets. The Directive 2003/98 / EC (PSI Directive) of the European Parliament regulates the re-use of public sector information. It was implemented in Austria in 2015 through the Information Re-use Law (IWG) and facilitates access to public documents for commercial and non-commercial purposes.

It is essential to describe dwellings well to establish good hedonic price indices. In the hedonic context, a house is thought of as a composite property whose value is determined by the value of the sum of its physical and locational characteristics. It is impossible to find additional information from publicly available data that better describes the inside quality of sold properties. However, there exist many additional datasets describing locational aspects. To save these additional locational aspects concerning the transactions in my original dataset, I use a grid structure that covers the area of Austria with a 100m x 100m grid structure. Each grid cell contains locational aspects that could influence the price of nearby properties and is linked with the transacted dwelling via the longitude and latitude that is available for each transacted unit. The following characteristics are added in this way:

- zoning (classification of building land)
- adress-specific noise level (maximum noise level of different noise sources)
- education (count of schools in cell or distance to next school)
- childcare (count of kindergartens or distance to next kindergarten)
- local shops (count of local supply institutions or distance to next institution of local supply)
- medical care and pharmacies (count of medical care institutions and pharmacies or distance to next medical institution or pharmacy)
- stops of public transport (count of stops of public transport or distance to next stop of public transport)

The address-specific noise level informs on the maximum daily average noise level within the relevant 100m by 100m cell. I include information about how many schools and childcare facilities exist within each cell. If no such institution exists within the grid cell, I include the distance to the next cell where such an institution is available.The same steps are followed for other amenities such as doctors' offices, pharmacies, and public transport stops. The added data also informs about the distance from the middle of the applicable cell to the city center. The zoning information is divided into five categories: open land, commerce and industry zone, center zone, housing area, and mixed area.

4 Temporal Property Price Indices for the Nine Regional Capitals of Austria

In order to investigate the temporal development of house prices in Austria I apply three different hedonic methods to the dataset. The methods are compared to see how sensitive the results are to the choice of method and how the choice of method varies depending on the bundle of explanatory characteristics and the level of aggregation.

4.1 Rolling Time Dummy Method

Shimizu et al. (2010) proposed the Rolling Time Dummy method with a window length of k+1 periods. A semilog hedonic model is estimated as follows:

$$\ln(price) = X\beta + Dd + \epsilon, \tag{1}$$

The dependent variable is the natural logarithm of the price of a dwelling while X represents a matrix of characteristics for each of the dwellings. D is the time dummy variable and is a random error term. A fixed number of periods (here quarters) are included each time the model is estimated. Considering the case where five quarters are included, the estimated hedonic model in which t is the first period is then used to compute the change in the price index from the second last quarter (t+3) to the last quarter (t+4) as follows:

$$\frac{p_{(t+4)}}{p_{(t+3)}} = \frac{exp(d^*_{t+4})}{exp(d^*_{t+3})}, \tag{2}$$

where d^*_{t+4} is the estimated value of d_{t+4} obtained from the hedonic model To compute the price change from period t+4 to t+5, we will then re-estimate the hedonic model with t+1 as the first period. This is what is meant by a rolling window. To get an overall price index, the price changes of the successive quarters have to be chained together. (Shimizu et al, 2010)

4.2 Repricing Method

Nine European countries use the Repricing method to compute their House Price Indices. An advantage of this method is, that the hedonic model has to be estimated only for the base year using the data of the first year. It is computed without using any time dummies. The hedonic model has the following form:

$$\ln p_{1,q} = \sum_{c=1}^{C} \beta_{1,c} z_{1,c} + \epsilon_{1,q}, \tag{3}$$

C indexes the characteristics of the dwellings that are available in the dataset and ϵ stands for the random error term. Through estimating the hedonic model, the shadow prices $\beta_{(1,c)}$ for the first year are calculated using the whole year´s available data. The estimated shadow prices will then be used to compare the average difference in quality between the average dwelling sold in each period (quarters) and the average dwelling sold in the base period. The resulting price index consists of two components. First the quality unadjusted price index is the ratio of the geometric mean price of dwellings sold in the compared quarters:

$$QUPI_{(t,1),(t,q-1)} = \frac{\tilde{p}_{(t,q)}}{\tilde{p}_{(t,q-1)}}, \tag{4}$$

The denominator is the geometric mean of prices of sold dwellings in the base period while the nominator is calculated by building the geometric mean of the prices of sold dwellings in the following period. For the quality unadjusted price index the geometric mean is used because it is compatible with a semi-log regression model. Second a quality adjusted factor has to be computed with the following formula:

$$QAF_{(t,q-1),(t,q)} = \frac{exp(\sum_{c=1}^{C} \hat{\beta}_{1,c}\bar{z}_{(t,q),c})}{exp(\sum_{c=1}^{C} \hat{\beta}_{1,c}\bar{z}_{(t,q-1),c})}, \tag{5}$$

The $\bar{z}$ denote the average basket of characteristics of both periods and are constructed by using the arithmetic mean formula. The repricing method divides the quality unadjusted index by the quality adjustment factor and the overall price index between the first quarter and the concerned period looks like:

$$\frac{p_{(t,q)}}{p_{(t,q-1)}} = \frac{\tilde{p}_{(t,q)}}{\tilde{p}_{(t,q-1)}} / \frac{exp(\sum_{c=1}^{C} \hat{\beta}_{1,c}\bar{z}_{(t,q),c})}{exp(\sum_{c=1}^{C} \hat{\beta}_{1,c}\bar{z}_{(t,q-1),c})}, \tag{6}$$

4.3 Average Characteristics Method

A characteristics price index is defined in characteristics space. Characteristics methods typically construct an average dwelling for each period and the imputed price of this hypothetical dwelling is calculated as a function of its characteristics using the shadow prices derived from the hedonic model. The average dwelling can be computed as an arithmetic mean or median. The price index is constructed by taking the ratio of the imputed price of the same average dwelling in two different periods (Hill, 2013 and Hill et al., 2018). The hedonic model does not include any time dummies. For periods (t,q-1) and (t,q) the model looks like:

$$\ln p_{(t,q-1),h} = \sum_{c=1}^{C} \beta_{t,q-1} z_{(t,q-1),h,c} + \epsilon_{(t,q-1),h}, \tag{7}$$

$$\ln p_{(t,q),h} = \sum_{c=1}^{C} \beta_{t,q} z_{(t,q),h,c} + \epsilon_{(t,q),h}, \tag{8}$$

H indexes the dwelling transactions in period (t,q), p the price and z the level of characteristic c in dwelling h. The estimated shadow prices on the characteristics $\beta_{(t,q),c}$ are specific to period (t,q) and are updated every period. They will then be used to compare the average difference in quality between the dwelling sold in the next period and the average dwelling sold in the base period. To do this, an average basket of characteristics has to be constructed. The hedonic model will be estimated for every period and then the model shows how the imputed price of an average dwelling changes over time. The price index between two adjacent quarters in the same year is calculated as follows:

$$\frac{p_{(t,q)}}{p_{(t,q-1)}} = \frac{exp(\sum_{c=1}^{C} \hat{\beta}_{(t,q),c} \bar{z}_{t-1,c})}{exp(\sum_{c=1}^{C} \hat{\beta}_{(t,q-1)} \bar{z}_{t-1,c})} = \frac{exp(\sum_{c=1}^{C} \hat{\beta}_{(t,q),c} \bar{z}_{t-1,c})}{exp(\sum_{c=1}^{C} \hat{\beta}_{(t-1,c)} \bar{z}_{t-1,c})} / \frac{exp(\sum_{c=1}^{C} \hat{\beta}_{(t,q-1),c} \bar{z}_{t-1,c})}{exp(\sum_{c=1}^{C} \hat{\beta}_{(t-1,c)} \bar{z}_{t-1,c})} = \frac{P^L_{t-1,(t,q)}}{P^L_{t-1,(t,q-1)}}, \tag{9}$$

$P^L_{(t-1,(t,q))}$ stands for a Laspeyres price index between periods (t-1) and (t,q). The average characteristic basket has to be updated each year. The price index between the fourth quarter in one year and the first quarte of the following year has to be calculated in a different way:

$$\frac{p_{(t+1,1)}}{p_{(t,4)}} = \frac{exp(\sum_{c=1}^{C} \hat{\beta}_{(t+1,1),c} \bar{z}_{t,c})}{exp(\sum_{c=1}^{C} \hat{\beta}_{(t,4)} \bar{z}_{t,c})}, \tag{10}$$

The price index for the last quarter in the dataset relative to the first quarter in the dataset can be calculated by multiplying the price indices of the successive quarters.

4.4 Stratified Median

In addition stratified medians will be computed to provide a point of reference for the hedonic indices. The first step in constructing a stratified median index is to split the data into strata based on locational or physical characteristics. Once the strata have been constructed, the median price for each stratum is computed using the arithmetic mean formula.

5 Results

5.1 The Dataset

For all variables that represent the features of an apartment, dummy variables are created with Yes when the relevant feature exists, No when it does not exist, and NA (not available) when there is no information available in the contract. The previous section already discussed that the dataset contains outliers whose prices do not represent the existing market conditions. Where possible, these outliers are excluded. A prime example of price outliers is transactions between relatives which often occur at prices far below the market value. Luckily it is easy to spot transactions between close relatives as they incur a lower tax rate than other transactions. Transactions that occur due to bankruptcy procedures are another likely cause for abnormal prices and are thus excluded.In order to get rid of too high or too low prices, 1 percent of the highest and 1 percent of the lowest prices are cut out for each city in each quarter as extreme values can distort the results. Also, apartments with floor space below 20 or above 160 square meters are not included in the analysis as they are rare and often have square meter prices far from the existing market prices.

Based on these rules, the dataset contains the following numbers of observations for each city:

city	2016	2017	2018	2019	2020	2021
Wien	7753	7598	7856	7265	6828	3280
Graz	2072	2159	2289	2662	2145	817
Linz	330	371	409	554	443	214
Salzburg	789	696	797	810	607	260
Innsbruck	719	538	531	606	562	351
Klagenfurt	423	406	305	414	421	169
St. Pölten	39	59	84	67	52	23
Bregenz	92	85	36	43	46	28
Eisenstadt	19	3	13	19	23	34

Table 3: Number of obvervations in each city after cleaning process

While there is a stable amount of transactions each year in the bigger cities, the number of usable transactions varies strongly in the smalles cities.

5.2 Variable selection

When building a hedonic model, variable selection plays an important role. An essential step in constructing economic models is the removal of irrelevant predictors. Including predictors with little explanatory power makes the model difficult to interpret and decreases its predictive ability. The same applies to the inclusion of strongly correlated features.

In this paper, price indices are constructed for nine different cities. The cities differ in size and structure. Therefore the number of variables that can be included will vary between cities. To ensure that the best bundle of characteristics is used for each city, I employ the forward stepwise selection algorithm.

Forward stepwise selection is a commonly used method for variable selection in linear models and goes back to Efroymson (1966) and Draper and Smith (1966). The procedure of forward stepwise selection starts with an empty active set $A_0 = 0$ and for $k = 1, ..., min[n, p]$ selects the variable

$$j_k = argmin||Y - P_{A_{k-1 \cup [j_k]}} Y||_2^2 = argmax \tag{11}$$

that leads to the lowest squared error when added to the previous empty set and therefore achieves the maximum correlation with the dependent variable, in this case, the price of the dwellings (Tibshirani, 2017).

A forward stepwise selection procedure is performed for each city, resulting in different bundles of characteristics for the different cities.

	Bregenz	Eisenstadt	Graz	Innsbruck	Klagenfurt	Linz	Salzburg	Sankt Pölten	Wien
floor space (log)	✓	✓	✓	✓	✓	✓	✓	✓	✓
category	x	x	x	x	x	x	x	x	✓
cellar	x	x	x	x	x	x	x	x	x
balcony	x	x	✓	x	x	x	x	x	✓
terrace	x	x	x	x	x	x	x	x	✓
garden	x	x	x	x	x	x	x	x	✓
parking space	x	x	✓	✓	✓	✓	✓	x	✓
distance to pharmacy (log)	✓	✓	x	x	x	x	x	✓	x
distance to local supply (log)	✓	✓	✓	✓	x	x	x	✓	✓
distance to family doctor (log)	✓	✓	x	x	x	x	x	✓	✓
distance to doctor (log)	✓	✓	✓	x	x	x	x	✓	✓
distance to public transport (log)	✓	✓	x	x	x	x	x	✓	x
distance to next school (log)	✓	✓	x	x	x	x	x	✓	✓
maximum level of noise pollution	x	x	x	x	✓	✓	x	x	✓
age: new/old	x	x	✓	✓	✓	✓	✓	x	✓
postal code	x	x	x	x	x	x	x	x	✓
zone	x	x	x	x	x	x	x	x	x
plotsize (log)	x	x	x	x	x	x	x	x	x
construction area (log)	x	x	✓	x	✓	✓	✓	x	x
outarea	x	x	x	x	x	x	x	x	x

Table 4: Chosen variables as result of stepwise forward selection in Austrian municipalities

To construct the price indices the selected methods are all used on the defined bundle of characteristics of the cleaned dataset from 2016 to 2021 for each city. A semilog hedonic model is used for all methods.

5.3 Comparison of results

To compare the behavior of the different methods, I use the root mean squared error (RMSE) on a quarter by quarter basis. These values provide a good indication of the indices' volatility. High volatility can indicate insufficient quality adjustment (see Hill et al., 2018). The RMSE is defined as follows:

$$RMSE = \sqrt{\frac{1}{4}\sum_{t=1}^{4}[\ln(\frac{p_{(t+1,q)}}{p_{(t,q)}}) - \frac{1}{T-1}\ln(\frac{p_{(T,q)}}{p_{(1,q)}})]^2}, \tag{12}$$

The level of volatility is only an approximate measure of index quality as markets can be volatile and a volatile index can reflect such a market behaviour. Therefore comparing the volatility of indices based on different methods should help to compare the performance of those methods in each city.

The mean absolute difference is calculated between all the hedonic methods used within one city. The sum over the absolute values of the difference of the quarter on quarter price changes calculated by two different methods is built and then averaged. Table 7 shows these results for all combinations of methods.

$$MAD = \frac{1}{T}\sum_{1}^{T}|pricechange_{method_1} - pricechange_{method_2}|, \tag{13}$$

5.4 Vienna

In the city with the most transactions in each year price indices based on all chosen methods are created on the whole dataset as well as for sub markets. To do so, Vienna is divided into five zones - each containing several districts of Vienna - to see how prices have changed in different regions of the capital city of Austria.

5.4.1 Price indices on whole dataset

For the whole city of Vienna indices based on different hedonic methods are calculated that include the chosen explainatory variables listed in Table 4. The results in Figure 1 show that the measured price rise for the hedonic methods ranges between 28 and 30 percent. The stratified median index rises by only 23 percent.

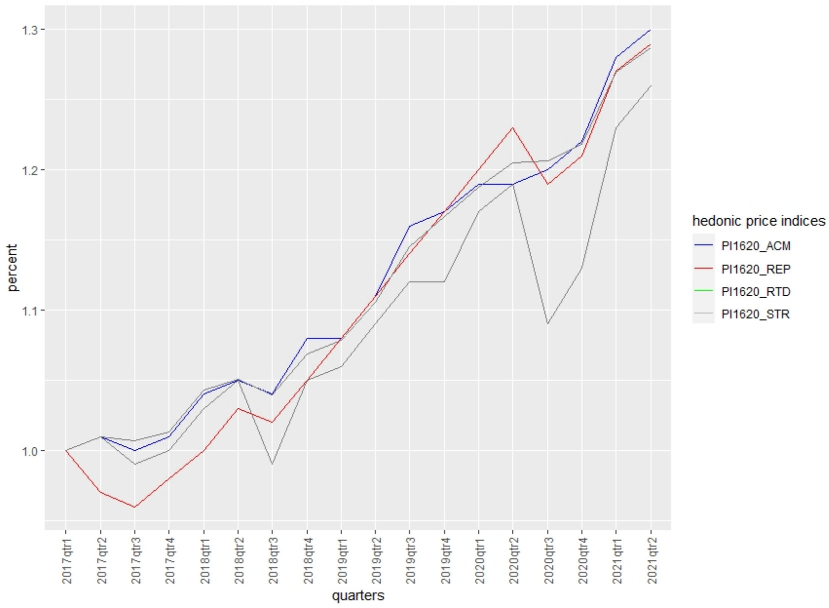


Figure 1: Estimates of price indices for apartments in Vienna (2017Q1 = 1)

Looking at the RMSE in Table 6 at the end of the results section shows that the index constructed by the Repricing method is the most volatile of the hedonic indices but less volatile than the stratified median index. The difference between the quarter on quarter price changes show that on average the hedonic indices create less mean differences between the results based on hedonic methods as compared with stratified medians (see Table 7).

5.4.2 Price indices distinguishing new and existing apartments

Beside the development of prices for the whole of Vienna it is also possible to look only at the price development of a specific submarket. The results of stepwise forward selection show, that age has a strong influence on the price of apartments in Vienna. For that reason price indices are calculated both for new and old apartments where new is defined as apartments with a minimum price of 2200 euros per squaremeter, a developer as seller, a parification year after 2010.

The process of stepwise forward selection gives two different outputs. Having both area and postcode as most price influencing variables, the selection process includes more variables for the dataset of new apartments.

Figure 2 compares the price developments on the submarket of new apartments with that of the submarket of existing apartments. The indices are more volatile for existing apartments (see Table 6). The index for existing apartments based on the Repricing method differs the most from all other indices.

The prices of existing apartments have risen stronger compared to those for new apartments from 2020 onwards. One possible explanation could be that preferences of buyers have changed as a result of the covid-19 crisis.

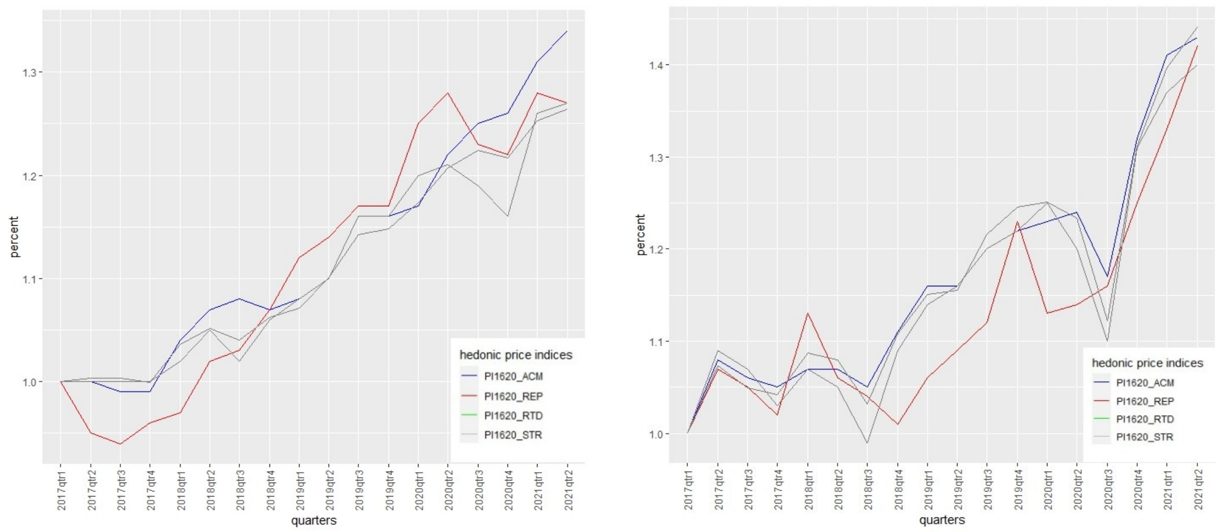


Figure 2: Price Indices for new apartments and existing apartments in Vienna

5.4.3 Price indices in subregions

Sales prices differ strongly in different regions of Vienna. Therefore zones are built grouping districts with a similar price structure. Comparing statistical indicators (like price range, standard deviation and median price per square meter) and also including expert opinion five zones are built as can be seen in Figure 3.

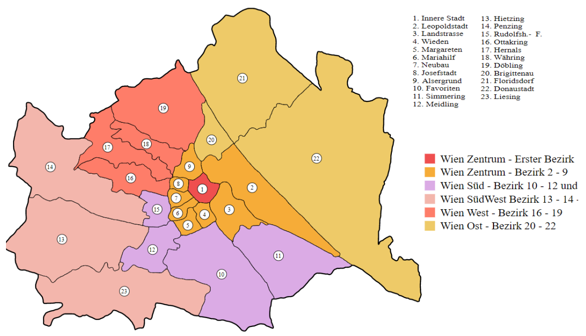


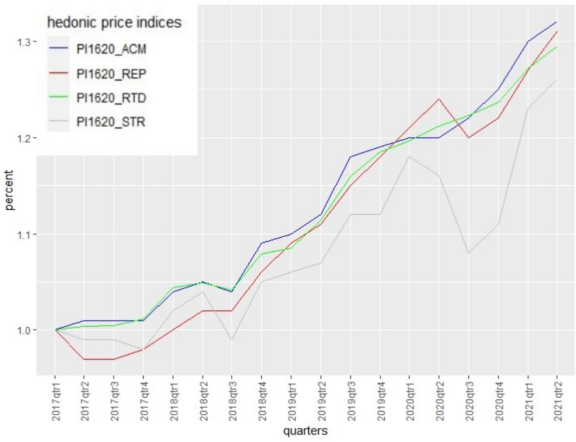
Figure 3: Zones of Vienna

Table 5 gives an overview of the price landscape in the Austrian capital. For each zone the table includes the number of observations, the minimum and maximum price per square meter and the arithmetic mean of the square meter price in the specific region.

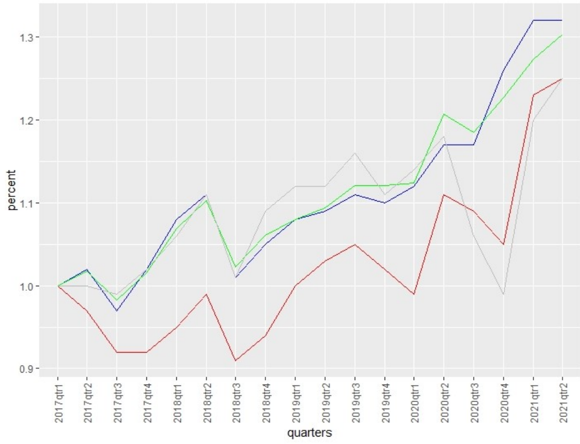
zone	count	minprice	maxprice	meanprice
Wien Ost - Bezirk 20 - 22	11264	1294.22	15718.24	4161.30
Wien Süd - Bezirk 10 - 12 und 15	11444	1293.46	13595.31	3897.91
Wien SüdWest Bezirk 13 - 14 - 23	7327	1296.90	26565.80	4277.05
Wien West - Bezirk 16 - 19	7597	1261.94	15966.28	4618.32
Wien Zentrum - Bezirk 2 - 9	12994	1263.54	26003.12	5129.22

Table 5: Price landscape in different defined zones in Vienna

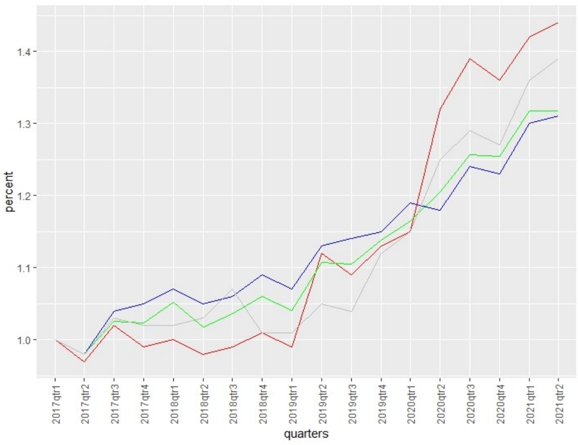
While the bottom of the price range is similar through all zones, the maximum prices differ strongly having the center and the southwest of Vienna at the top. Looking at the mean price of sold apartments identifies the center as the region with the highest prices.
The calculated indices with different methods show that in smaller subregions the indices get less stable according to the choice of method. The RMSE as visible in table 6 is higher for all methods than for indices on the whole Vienna dataset. Indices constructed by the ACM method and the RTD method show less volatile behaviour. That is the same for those constructed for the whole data base. The Repricing method shows more volatile outputs for zone indices compared to those on the whole dataset. Looking at the Stratified median shows that this method often underestimates the price change. In the Eastern part of Vienna, the overall price change in the considered period created by a Stratified median method lies clearly under that of a hedonic method. While the overall price change is almost the same as in Vienna for the Center, South and Southwest zone (except Repricing method), the prices have risen stronger in the zones of West and East Vienna. The following figures show the indices for all used methods in the different zones.



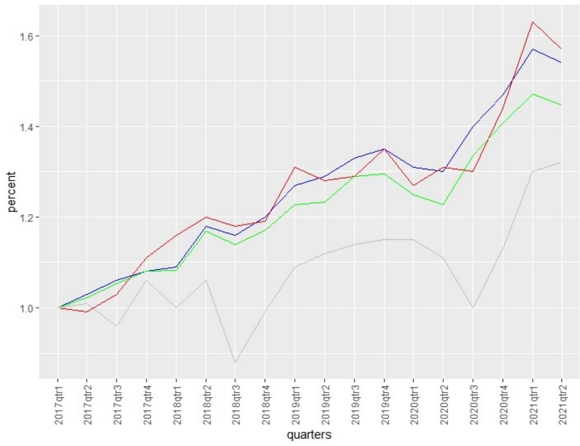
Center (districts 1-9)



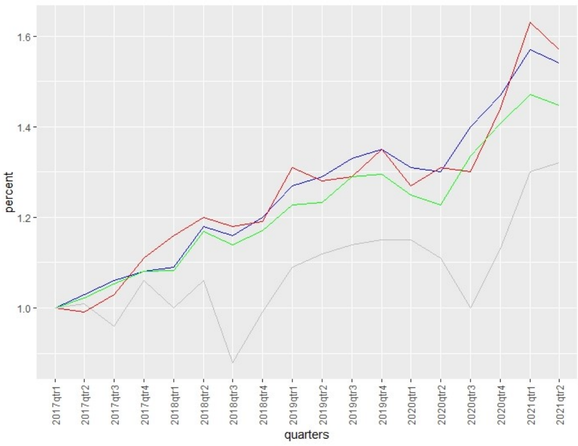
South (districts 10-12,15)



Southwest (districts 13-14,23)



West (districts 16-19)



East (districts 20-22)

Figure 4: Price indices in defined zones in Vienna

5.5 Graz

With almost 300,000 inhabitants Graz is the second biggest city in Austria. Compared to other cities the biggest proportion of transaction data can be used because almost 80 percent of the contracts fulfil the defined minimum standard of given price and given area as outlined in section 3. With Vienna, also Graz is divided here into zones containing several districts. Indices are created on the whole dataset as well as for new and existing apartments. To see how the different indices behave, the root mean squared error is again created on a quarter on quarter basis.

5.5.1 Price indices on whole dataset

Compared to Vienna the calculated indices for Graz are more volatile. The individual results differ more strongly. This means that the index is less stable to the choice of construction method. Also the number of chosen variables out of the stepwise forward selection process differ.

Between 2017 and mid of 2021 prices have risen about 40 percent with a stronger increase from 2020 onwards compared to the other time period. The overall price change as output created by the stratified median method lies under the hedonic outputs. Figure 5 shows that from 2020 onwards the indices start to drift apart, especially the indices created by the ACM and the Repricing method.

Figure 5: Estimates of price indices for apartments in Graz

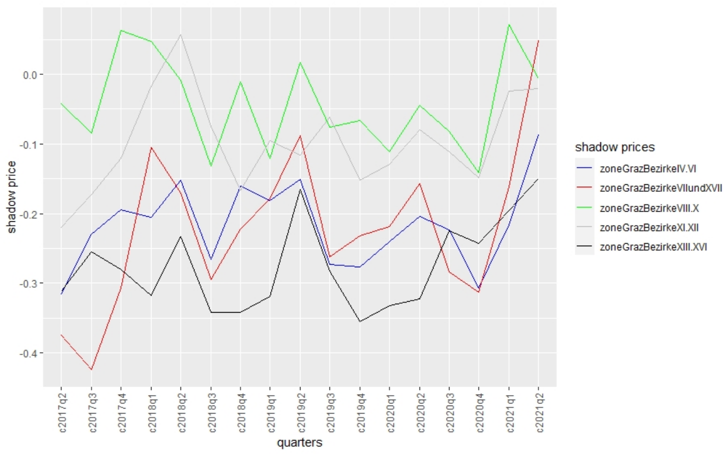


Figure 6: Shadowprices of zones in Graz

An advantage of the ACM method is that the shadow prices are calculated for each quarter, therefore the development of the shadow prices can be presented on a quarterly basis. Looking at the shadow prices for the different zones in Graz (see figure 6) indicates that the price discount for apartments in regions not in the center of Graz gets smaller in the last quarters.

5.5.2 Price indices distinguishing new and existing apartments

Comparing the resulting indices for new and existing apartments in Graz shows that indices created on a subset of the original data tend to be more volatile. Calculated RMSE (table 6) of all indices confirm this. As a contrast to the results in Vienna the MAD between the price changes created by the indices is much higher for the indices constructed on the database for new apartments compared to that of existing apartments.

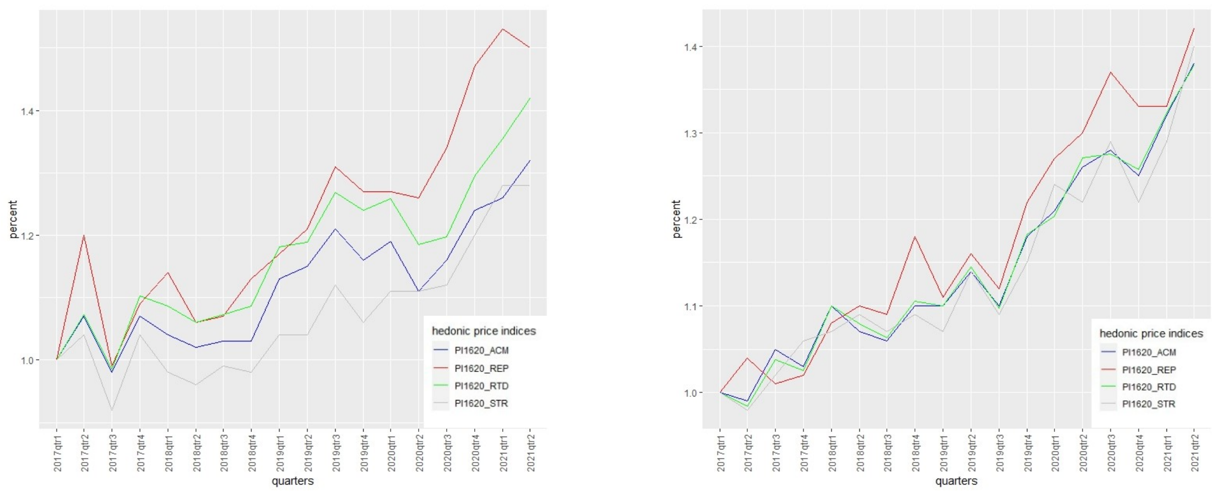


Figure 7: Price Indices for new apartments on the left and existing apartments on the right in Graz

5.6 Linz, Salzburg, Innsbruck and Klagenfurt

Linz, Salzburg,Innsbruck and Klagenfurt have between 100,000 and 200,000 inhabitants and therefore indices have to be constructed on a much smaller database compared to Vienna and Graz. With a smaller dataset some challenges occur. The number of variables that can be entered into the variable selection process gets smaller as not all characteristics of variables occur in every quarter. To keep some of those variables, they are combined. The existence of a balcony, a terrace or a garden is reduced to one variable that informs about the existence of one of those variables. As expected the indices in smaller cities tend to be more volatile than those indices created for the 2 big cities in Austria. Also the number of variables that are chosen from the variable selection process is smaller (see Table 4).

Figure 8: Price indices for Salzburg, Linz (top lef and right), Innsbruck (bottom left) and Klagenfurt

The Stratified median method tends to underestimate the price change except in Linz where upward spikes are visible. The distances between the price changes each quarter created by the hedonic methods are smaller for Salzburg and Innsbruck compared to Linz and Klagenfurt (see Table 7). Overall it can be seen that smaller datasets create less stable indices when comparing the chosen method. This means that the distance between the calculated price change of the different methods gets bigger the smaller the database is.

5.7 St. Pölten, Bregenz und Eisenstadt

Creating a price index for the three smallest municipalities in Austria is difficult because of such small datasets (compare table 3). Of course the number of transacted properties is less compared to other cities but also the number of usable observations is smaller than in others. Just between 23 and 34 percent of the contracts fulfil the minimum standard of given price and area (see Table 1). Therefore the variable selection process is excluded and the indices are created on a database with price as dependent variable and the distance variables as independent variables because those are available for every transaction in each quarter. The analysis just includes the Rolling time dummy method as hedonic method. As expected the indices for all 3 cities are much more volatile than those for bigger cities. This fact is confirmed by high values for the RMSE (see Table 6). With just a few sold apartments in each quarter, sales with prices much higher or lower than the mean price have a higher influence on the indices. With such a small database it gets more difficult to derive a price trend for apartments.

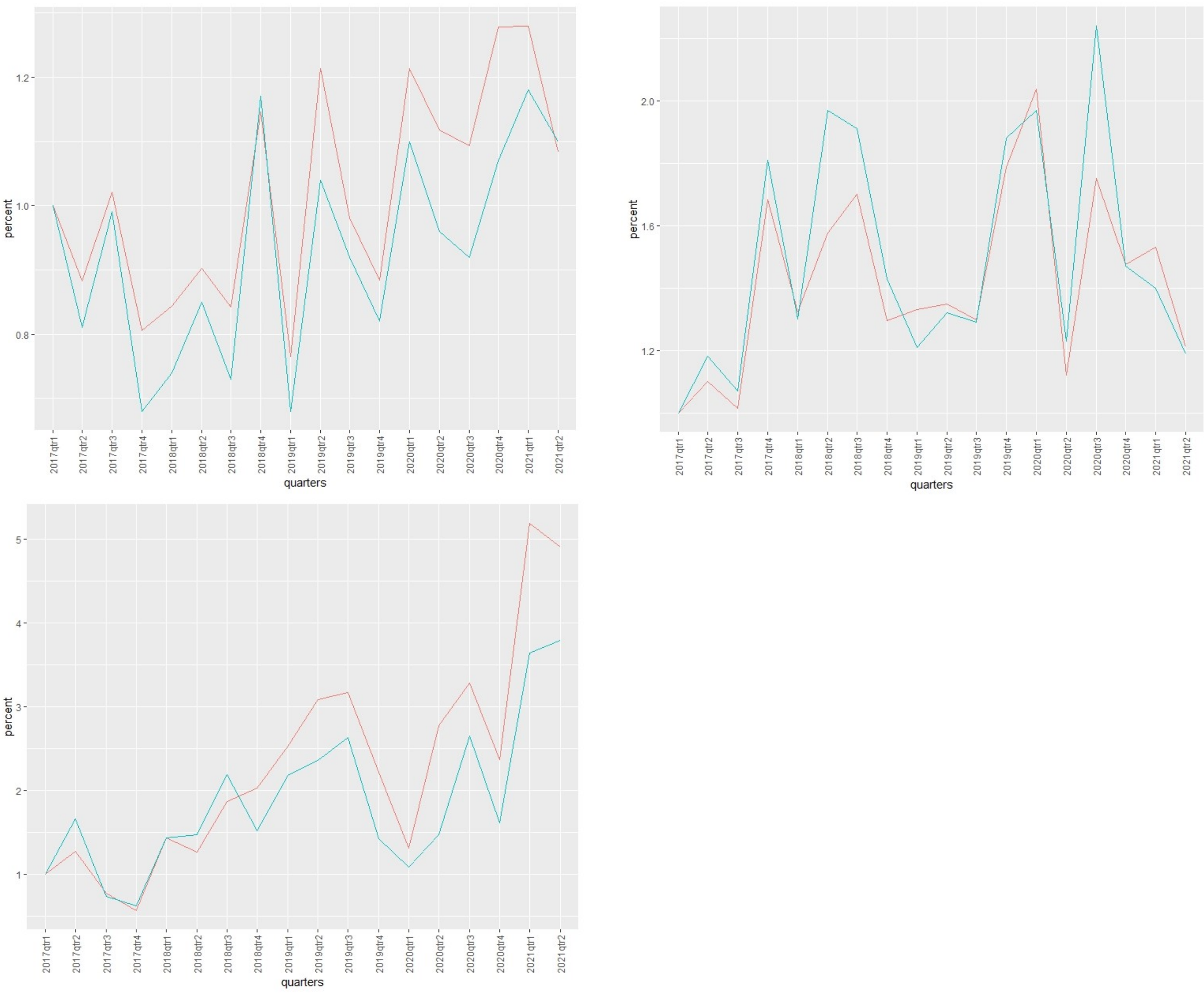


Figure 9: Price indices for Bregenz, St. Pölten (top left and right) and Eisenstadt.

To get a realistic picture of the development of prices in these small cities, it is even more important to exclude outliers and those contracts that do not represent market conditions. On the other hand this causes the problem that the database gets smaller.

quarter on quarter	acm	rep	rtd	str
Vienna	0.01723	0.02708	0.02068	0.0407
Vienna new	0.02085	0.03373	0.0189	0.03063
Vienna old	0.04611	0.0593	0.05965	0.07069
Center	0.01657	0.02708	0.0191	0.04117
Southwest	0.02662	0.05719	0.03086	0.0454
West	0.03373	0.06038	0.04056	0.08573
East	0.0387	0.05203	0.03129	0.04401
South	0.03963	0.06213	0.03606	0.07019
Mean zones	0.03105	0.05176	0.03158	0.0573
Graz	0.03907	0.05656	0.03173	0.06176
Graz new	0.05064	0.08512	0.05424	0.0622
Graz old	0.03577	0.04849	0.0388	0.04441
Linz	0.11579	0.10529	0.08171	0.14778
Salzburg	0.06816	0.08507	0.07416	0.1038
Innsbruck	0.07954	0.10502	0.07084	0.07468
Bregenz	-	-	0.21602	0.28785
Eisenstadt	-	-	0.43433	0.47622
St.pölten	-	-	0.26742	0.31023

Table 6: Root mean squared error for different hedonic methods in different cities in Austria

	dist rep str	dist rep acm	dist rep rtd	dist acm rtd	dist acm str	dist rtd str
Vienna	0.03277	0.01944	0.01728	0.00464	0.02888	0.02749
South	0.07944	0.08777	0.08817	0.01393	0.04611	0.04094
West	0.17666	0.03222	0.0496	0.0407	0.17555	0.13495
East	0.04055	0.065	0.04967	0.02556	0.05333	0.03566
Center	0.03944	0.02388	0.01866	0.00897	0.04888	0.04235
Southwest	0.04	0.06944	0.0509	0.01997	0.045	0.02961
Graz	0.04705	0.0547	0.03715	0.02339	0.0547	0.05146
Graz old	0.04222	0.03722	0.03491	0.00472	0.02055	0.02159
Graz new	0.15222	0.10222	0.05603	0.04924	0.05222	0.09924
Innsbruck	0.05888	0.04388	0.0484	0.03616	0.04944	0.03663
Klagenfurt	0.10444	0.07555	0.07192	0.03789	0.10222	0.10823
Salzburg	0.10055	0.055	0.06131	0.0258	0.08333	0.0789
Linz	0.10055	0.1	0.07237	0.07001	0.10277	0.11024

Table 7: Mean absolute difference for different hedonic methods in different cities in Austria

6 Conclusion

This paper described the processes involved in optimizing the available transaction data for apartment purchases in Austria for the last five years. There were several challenges involved in creating reliable price indices for apartments in Austrian cities. First, Austrian law requires very little detail on real estate transactions: the only mandatory information on a purchase contract is the price, the identity code of the property, and the identities of buyer and seller. As a result, many contracts do not contain any qualitative information. However, hedonic real estate models require qualitative information on properties for the hedonic method to work. The first part of this paper showed how to augment the transaction dataset with other government-based and open-source data. To increase the explanatory power of the transaction dataset (and to counteract the omitted variable bias that would otherwise prevail).

Austrian cities differ strongly in size and structure; therefore, each city needs a hedonic model that is optimized to its available data size (in terms of observations as well as available characteristics). I chose the stepwise forward selection method to perform this trade-off between model complexity and the number of available observations. It is true that the smaller the dataset, the smaller the set of variables that can be selected for the hedonic model. But chosen variables also differ because of other reasons, such as the relevant importance of variables for specific markets.

The next step in index compilation was to choose the appropriate hedonic method for index construction. For bigger datasets, with enough transactions in each quarter, the results are pretty robust to the construction method, and all typically discussed hedonic methods show pretty similar results. However, this paper shows that the choice of method becomes important when the number of observations is small. In the smaller cities, the Stratified Median index results differ more from those created by a hedonic index compared to those in cities with a bigger database. Indices for smaller cities (or indices for sub-markets) are more dependent on the hedonic method. For such datasets with a low number of transactions, it is essential to choose a hedonic method that can pool data across different quarters. The hedonic time-dummy, the RTD, and the repricing method satisfy this “pooling” condition and are thus preferable to other hedonic methods (e.g., the Average characteristics method).

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