

A New Residential Property Price Index for Austria

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As the availability and quality of residential property price statistics are very limited in Austria, the construction of a state-of-the-art residential property price index (RPPI) has become an urgent topic. In this paper, we therefore describe the setup of a new RPPI for Austria. So far, two separate indices – one for Vienna and one for the rest of Austria – have been calculated and weighted by population to get an aggregated time series for Austria. But besides the fact that the weighting is rather difficult to justify, both indices are calculated using a hedonic regression model with a fixed structure over time. This approach can lead to biased effects for current estimation results if changes in the variable effects occur over time. Thus, for the new RPPI, we use a different approach: On the one hand, we estimate a single model for Austria which makes arbitrary weighting by share of population unnecessary. We apply semi-parametric models that take into account nonlinearity and spatial heterogeneity and result in unbiased quality-adjusted time effects as omitted variable effects are modeled adequately. On the other hand, since we use imputation methods, structural changes in estimated effects no longer result in distorting effects. Given the sophisticated modeling of variable effects, spatial heterogeneity and variation over time, the new RPPI can be considered a further milestone in residential property price modeling and data quality enhancement in Austrian residential property price statistics.

It is widely known that housing wealth is one of the most important components of household wealth. Furthermore, it often serves as collateral for households when taking out loans. Therefore, on the one hand residential property price dynamics influence households' consumption and investment decisions via wealth effects. On the other hand, property transactions are often financed by loans, and fluctuations of residential property prices therefore directly affect households' liability and credibility. As the wish to own one's home is fundamentally human, it is important to monitor residential property price fluctuations from a social perspective as well. This is, in fact, all the more important under circumstances of economic uncertainty and when

an escape to real property investment is imminent.

The correct collection of data on price movements is the key prerequisite for analyzing property market developments; particularly against the background of global and strongly interlinked financial markets, a harmonized collection of property price data has become more and more important. An analysis of property market developments should then be twofold, covering both commercial and residential property prices to get a comprehensive picture. This paper discusses some possible methods how to calculate a residential property price index (RPPI) and introduces the newly available RPPI for Austria as a whole.

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Box 1

Macroeconomic Impacts of Residential Property Price Developments

Empirical evidence shows that residential property prices drive macroeconomic developments as a leading indicator and that there exists a causal relationship between developments in the housing market and the real economy.

Residential property prices and ownership rates: While residential property prices recorded all-time increases in the past years in Spain, the United Kingdom and Ireland, comparably low increases were recorded in Austria and in Germany. These differences reflect country-specific factors like demographic changes, institutional regulations and the specific economic and/or cyclical situations. Different ownership rates (43% in Germany versus 86% in Spain) can be explained by taxation incentives and a different access to real estate financing. The living situation (home owner or tenant) is determined by people's income and the ratio of the costs of owning a home versus those of renting a home (price-rent ratio) as well as by demographic variables.

Residential property price fluctuations as a reason for wealth effects: The life cycle model (Ando and Modigliani, 1963) states that consumers distribute the increases in their expected wealth over time and that their marginal propensity to consume (MPC) out of wealth – independent of the type of wealth – has always the same magnitude. The housing market influences consumption in various ways – wealth effects from the housing market have not the same intensity as wealth effects from the stock market (Case et al., 2005). Housing wealth most often serves as collateral. An increase in residential property prices can alleviate loan repayment and cause spillover effects, thereby driving up consumption. Some papers (e.g. Altissimo et al., 2005) show that housing wealth has a significantly positive effect on consumption. The authors calculate that the MPC comes to between 2 and 9 cents per U.S. dollar of nominal housing wealth. In the euro area this effect is far less significant.

Residential property prices and the business cycle: Some recessions were predicted by the housing or the construction sectors, although these sectors are too small to cause a recession on their own. Residential property price fluctuations not only generate substantial wealth effects on consumption but also – and this became obvious during the most recent financial crisis – significant spillover effects for the whole macroeconomy. For example, booms in housing investment often result in increased employment.

Residential property prices and financial markets: In principle, housing is a local good and dependent on national regulations. Institutional arrangements on the housing and mortgage markets play a role not only for macroeconomic development but also in the transmission of shocks. They influence the intensity and speed of monetary transmission, and they affect the characteristics of the mortgage market (the level of the loan-to-value ratio, banks' valuation methods in lending, etc.) and can strengthen or dampen the transmission of residential property price developments on the availability of loans for households and investors.

Regulation may soften fluctuations in the housing market – one of the main arguments for promoting regulation efforts. Additionally, there are quite clear differences across countries in the taxation and tax deductibility of mortgage interest rates and in the various types of loans and grants to households.

1 What Makes the Construction of Residential Property Price Indices so Difficult?

There are several factors that complicate the construction of an RPPI: The construction of price indices is typically based on a comparison of prices of

identical goods over time, which makes the measurement of price changes relatively easy. By contrast, each piece of property is located in a unique place and has a unique set of characteristics, which is why real estate is considered a *heterogeneous* good. Therefore, matching

property prices exactly is often very difficult or even impossible. Furthermore, one and the same piece of property may be subject to depreciation, renovation and changes in maintenance costs, which renders longitudinal comparisons *within* properties over time problematic. Moreover, residential property transactions occur on an irregular basis and are unequally distributed over space. Finally, as explained in box 1, residential property price data may serve for a wide range of purposes. It is therefore appropriate to apply different measurement and modeling methods in this context. Property price data are e.g. interesting

- for the owners of residential property in order to assess the profitability and earning power of their property investment,
- for housing market participants (funds, issuing agencies, banks) in order to be able to recommend residential property to their clients, etc.,
- for real estate agencies, for mortgage banks and insurance agencies in order to be able to assess the respective collateral,
- for municipalities in order to be able to assess the price effects of investments in infrastructure projects,
- for sworn appraisers, who may use this information as a basis for the detailed assessment of specific pieces of property,
- and for a number of other economic agents.

Another problem concerning residential property price analysis is the availability of appropriate data. Generally, two separate types of RPPIs can be distinguished: a constant-quality price index either for the *stock* of housing at a particular moment or for residential property *sales* that took place during a particular period of time. Naturally,

these two indices will be constructed in different ways. As housing stock data are not available, however, we have to rely on quotation or transaction price data. Basically, three different types of primary data on residential property prices are available in Austria, each with different (dis-)advantages:

1. (Mortgage) data provided by banks, insurance companies, etc.: These data are often very detailed, as they are also used for documentation purposes. However, in addition to the fact that these data are rarely disclosed, they are usually based on only a small number of observations and are often not representative of the entire market as the business activities of the data-providing banks and companies are usually concentrated within certain regions.
2. Data on quotation prices from real estate platforms: Usually these data comprise many observations with a detailed measurement of property characteristics. However, as real estate platforms usually also focus on certain regions, they cannot be considered representative of the whole market, either. Moreover, these data may be biased: Several studies (e.g. Knight, 2002) show that quotation prices may vary over time and differ from the actual transaction prices. However, if this bias does not vary significantly over time, this problem hardly affects price index construction.
3. Transaction price data from the land register: In Austria, transaction prices for real estate have to be entered in the land register. Therefore, this source is clearly representative of the entire market. However, there are again some serious drawbacks in using these data: First, they may also be biased, e.g. due to tax avoidance behavior, which may vary over

different types of residential property as well as over space and time. Second, these data contain only a small number of explanatory variables, which results in an omitted-variable bias if they are used for hedonic residential property price modeling.

For constructing the RPPI proposed in this paper, we decided to use quotation prices because of their relative advantages.² However, further research will be required to examine the spatial and temporal variation of offer markups, i.e. the quality-adjusted difference between quotation and transaction prices, in more detail. Especially if systematic links are found between index level and index development on the one hand and offer markups on the other, this circumstance has to be carefully taken into account in index construction.

2 Methods for the Calculation of Residential Property Prices

To measure pure price changes, residential property prices have to be adjusted for quality changes. Basically, there are three main issues in the construction of property price indices:

1. **Comparability:** The index must take into account different quality levels (e.g. location, size, age, technical equipment) and make the results comparable across time periods. Therefore, it is necessary to avoid misspecification and, particularly, omitted variables.
2. **Change of standards:** To construct a representative index, it is necessary

to consider changes in quality standards over time and to rely on comparable characteristics. If price indices are evaluated for nonrepresentative characteristics, this may result in biased results.

3. **Time-varying effects:** Even if the effects of price-determining characteristics change only gradually, in the long run they cannot be assumed to be fixed.

Four main methods to control for changes in property characteristics are discussed in the literature: *stratification* or *mix adjustment*, *repeat sales methods*, *hedonic regression methods* and *the use of property assessment information*³.

The *stratification* of transactions according to specific price-determining characteristics is the simplest way to adjust for changes in the quality mix that occurs in the samples at different points in time. Homogeneous strata or cells are defined within the data set and the average transaction price within each stratum or cell is used as a proxy for the prices of objects featuring the same quality mix. These prices are aggregated across cells into an overall index.

Given the positive skew of transaction prices, median indices render a more realistic picture than simple mean indices. But the problem with median indices is short-term noise and a systematic bias if quality improvements occur over time⁴. But such a bias also occurs when using hedonic and repeat sales methods.

A method often applied to reduce this bias is the *post-stratification* of sam-

² Quotation prices are provided by the internet platform Ametynet of the Austrian real estate software company EDI-Real.

³ For more details, see European Commission (2011, chapters 3 and 4).

⁴ If houses of a higher quality are sold more often than houses of minor quality and the price changes of the former are more pronounced than of the latter, a downward bias will occur as the number of sales per house type does not correctly represent the number of existing houses per house type (sample selection problem).

ples, which controls for changes in the quality mix of properties sold. This method is known as *mix adjustment*.

The *repeat sales method* compares properties that are sold more than once over the sample period. The standard repeat sales method is based on a regression model pooling the repeat sales data over all periods under observation. One drawback of this method is how to control for changes in the quality of a property over time (e.g. a quality increase caused by renovation). Furthermore, the sample sizes available for this method are usually very small and prone to measurement errors due to false matching.

Hedonic regression methods adjust for differences in the quality mix using information on the underlying characteristics of a property. In the literature, two subgroups are discussed. The *time dummy variable method*, which models the property's price as a function of its characteristics and a set of time dummy variables, is most popular. As data on all sample periods are pooled, the resulting indices may be subject to revisions. To deal with this problem, *hedonic imputation methods* were developed.

Countries charging a real estate tax often have an official property valuation office providing appraisals of properties. *Assessment-based methods* combine transaction prices with appraisals and calculate transaction price-to-appraisal ratios, thereby controlling for quality mix changes. Contrary to the repeat sales method, assessment-based methods rely on all available transaction data, and previously calculated indices are not revised.

3 The Austrian RPPI

3.1 The Old and the New Austrian RPPI

Both the old and the new Austrian RPPI rely on quotation prices, which include price observations combined with “structural” (property-specific) variables. Approximately 10,000 observations are available each year. “Locational” (location-specific) variables are used to adjust for spatial differences down to census tract level⁵. On the basis of the available data, indices are estimated for condominiums and family homes (single- and two-family homes, semidetached and terraced houses). The following section describes the old Austrian RPPI and the improvements leading to the new RPPI.

For the old Austrian RPPI, two separate indices (one for Vienna and one for the rest of Austria) are estimated and weighted by population, which is somewhat arbitrary as this approach does not take into account the underlying model and data structure leading to the respective indices. Another problematic issue in constructing the old RPPI is that it is based on time dummy evaluation in a model with fixed variable effects over time. Basically, hedonic price models are used in both the old and the new RPPI to model the effects of structural and locational characteristics (including the time trend) on prices. In an unconstrained version of such a model, the parameters for these characteristics are allowed to vary over time. However, this leads to very unstable results, which is why effects are usually held constant over certain time periods, with time dummies describing quality-adjusted changes in the price level over

⁵ In Austria, there are 8,748 census tracts in 2,379 municipalities, which form 121 districts across the 9 Austrian provinces.

time. As changes in preferences occur only gradually, this is a reasonable approach if applied only for a limited time period. However, if variable effects turn out to vary significantly over time, this results in model misspecification. The model can then either be modified using time-interaction effects, or must be completely re-estimated on the basis of a new subsample of observations. However, both approaches do not allow for applying the relatively simple time dummy variable method (i.e. evaluating time dummy effects) as in a model based on time-constant parameters, because the time-varying effects may interfere with the time dummies. As described above, this is why imputation methods are applied in constructing the new RPPI.

Another issue in hedonic price modeling is the occurrence of nonlinear functional relationships and unexplained spatial heterogeneity, i.e. spatially varying relationships that cannot be explained by location-related variables. The old Austrian RPPI is based on classical linear models, which allow for nonlinearity in covariate effects only in a very restricted fashion (by integrating polynomial terms in the equation), again possibly resulting in functional misspecification. Furthermore, unexplained spatial variation is modeled by dummy effects. This approach yields very unstable results in districts where only few observations are recorded. Also, the time index is modeled according to the dummy approach, which results in very volatile effects if, in a certain time period, there are relatively few or outlying observations. To sum up, linear models seem to exhibit some drawbacks that cause them to yield biased or insufficient results which

may seriously impair index construction.

Therefore, the new model uses a semiparametric approach, namely Generalized Additive Models (GAMs) as described in Wood (2006a). GAMs model continuous covariates using penalized regression splines, which allow for nonlinearity in a regularized statistical framework. Distributional and structural assumptions, given covariates and parameters are based on Generalized Linear Models (GLMs), $E(y_i | z_i, x_i) = h(\eta_i)$ ⁶. However, instead of a linear predictor, GAMs apply the additive predictor $\eta_i = f_i(z_{i1}) + \dots + f_q(z_{iq}) + x_i' \gamma$, where $x_i' \gamma$ is the usual parametric part of the predictor, z_j is a continuous covariate, time scale or district index and f_j are (not necessarily continuous) functions of these covariates. The trade-off between data fidelity and smoothness is governed by model selection criteria, in our case the generalized cross-validation criterion (Wood, 2006a). Unexplained spatial heterogeneity is modeled by random effects. Random effects penalize the lack of information in a district: The fewer observations there are in one unit, the more they tend toward the “baseline” effect of the model, i.e. the level predicted by location-specific levels of covariates. Again, penalization is achieved by model selection criteria.

The new RPPI takes these problems into account in the following way: In a first step, a reference model with time-invariant effects is estimated using all available data. The time period for condominiums covers 5 years (from 2007 to 2012), that for family homes 7 years (from 2005 to 2012). For the current version of the RPPI, the log of the property price is taken as the dependent variable. The effect of the

⁶ For the models applied here, we use the identity link, i.e. the linear predictor corresponds to the mean of the distribution function.

age of the respective object, the specific living area and, in the case of family homes, also the plot area as well as locational covariates⁷ are modeled as penalized regression splines, and unexplained spatial heterogeneity is modeled by district random effects⁸. The time trend is considered in five different ways:

1. In the *dummy approach*, quarterly time dummy effects are estimated like in the old model. However, as can be seen in charts 1 and 2, this leads to rather volatile estimation results, e.g. for condominiums in Q4 08 and for family homes in Q4 06.
2. The second version is a *smooth trend estimation*, where a nonlinear time trend is estimated using penalized regression splines. However, for both models, this approach seems to underestimate abrupt jumps.
3. The third version estimates a *random time effect*. As mentioned before, random effects models tend to weight the estimated parameters toward zero. Although this helps prevent large outliers, the effect is underestimated if the market truly tends up- or downward over time.
4. The fourth model combines a nonlinear time trend and random effects for modeling deviations from this trend, which is why it is called “*smooth-random*” model. This approach should account for abrupt deviations from a continuous baseline trend. Nevertheless, the results seem to be dominated by the nonlinear trend.
5. Finally, a model is estimated that integrates time effects in a hierarchical manner: The baseline time effect is estimated as a yearly effect, and deviations from that effect are

Chart 1

Pooled Index for Condominiums



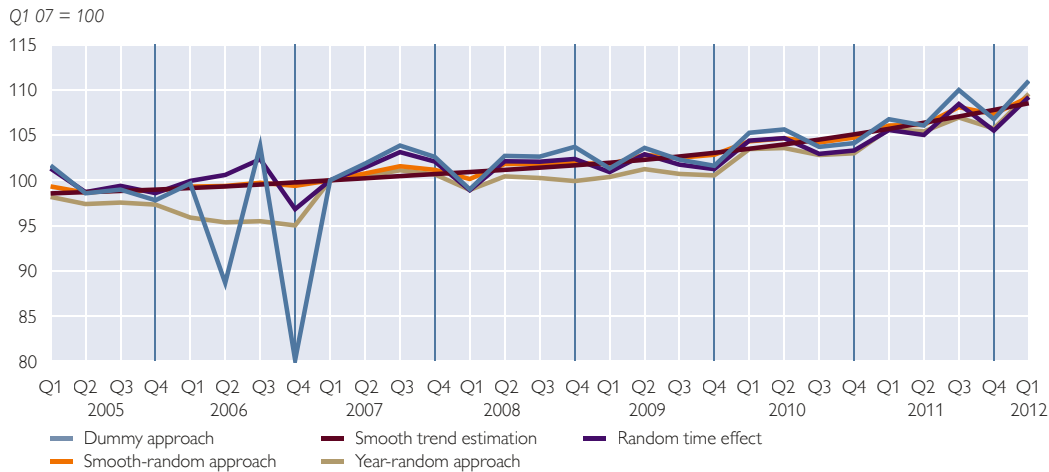
Source: Authors' calculations.

⁷ For the new RPPI, the log of the share of academics or high school graduates in the total population of a census tract is taken as a proxy for the social composition of the neighborhood. Furthermore, four variables enter the model at the municipality level: an index for the price of building land; the number of overnight stays (as a proxy for touristic activity in the municipality); a measure for accessibility (as a measure of centrality); and the growth of purchasing power from 2005 to 2009.

⁸ There are 121 census districts in Austria.

Chart 2

Pooled Index for Family Homes



Source: Authors' calculations.

Table 1

RPPI for Condominiums and Family Homes

Q1 07 = 100	Condominiums	Family homes
Q1 05	x	98.16
Q2 05	x	97.38
Q3 05	x	97.54
Q4 05	x	97.32
Q1 06	x	95.89
Q2 06	x	95.35
Q3 06	x	95.49
Q4 06	x	95.02
Q1 07	100.00	100.00
Q2 07	100.30	100.45
Q3 07	100.79	101.11
Q4 07	102.10	100.66
Q1 08	103.18	98.94
Q2 08	105.20	100.44
Q3 08	105.69	100.25
Q4 08	106.46	99.91
Q1 09	106.25	100.36
Q2 09	108.88	101.23
Q3 09	106.90	100.70
Q4 09	110.04	100.55
Q1 10	112.30	103.45
Q2 10	115.55	103.56
Q3 10	115.20	102.79
Q4 10	116.01	102.98
Q1 11	120.92	105.69
Q2 11	122.39	105.39
Q3 11	125.45	106.94
Q4 11	126.39	105.72
Q1 12	129.91	109.56

Source: Authors' calculations.

captured by random effects on a quarterly basis, which is why this model is called “*year-random*” model. It seems to provide a robust trade-off between data fidelity and penalization, as the baseline effect is defined by a relatively large sub-sample while abrupt changes are also captured to some extent.

Given the relative advantages described above, namely the penalization of abrupt changes without over-smoothing, the “*year-random*” model is preferable for both condominiums and family homes. In a next step, time effects are evaluated at the level of characteristics for the year 2012 and rebased for the year 2007, which yields the current index values as displayed in table 1.

3.2 Imputation for Index Update

As mentioned above, one undesirable feature of a time effect resulting from a pooled model is the index revision that goes with it. If the time series is extended, i.e. new observations enter the data base, the estimated effects, including the time effect, tend to change gradually. Therefore, an in-

dex constructed this way is of limited use.

In order to circumvent this problem, imputation methods are applied. This means that separate models are estimated for each time period, and the RPPI is constructed by evaluating these models on a period-average level of property characteristics, while locational covariates are evaluated at the local level of characteristics for each census tract. Hence, a set of synthetic properties is constructed, with prices varying over 8,748 census tracts. As, by construction, census tracts are comparable in terms of population data, this approach represents an implicit population weighting. Since the implicit price functions are thus allowed to vary over time and also incorporate spatial variation, this approach is very flexible.

The crucial point is how to choose the level of characteristics applied. Basically, there are two possibilities: The Laspeyres-type hedonic imputation index applies the level of characteristics of the base period 0 (indicated by the superscripts) and evaluates the estimated predictors $\hat{\eta}$ for the base period (subscript 0) and the current period (subscript t)⁹:

$$P_{HL}^{0t} = \frac{\exp\left(\hat{\eta}_t^0 + \frac{\hat{\sigma}_t^2}{2}\right)}{\exp\left(\hat{\eta}_0^0 + \frac{\hat{\sigma}_0^2}{2}\right)},$$

while the Paasche-type hedonic index evaluates the models at the mean level of the current period:

$$P_{HP}^{0t} = \frac{\exp\left(\hat{\eta}_t^t + \frac{\hat{\sigma}_t^2}{2}\right)}{\exp\left(\hat{\eta}_0^t + \frac{\hat{\sigma}_0^2}{2}\right)}.$$

The Fisher-type hedonic imputation index combines these types by taking the geometric mean of these indices:

$$P_{HF}^{0t} = [P_{HL}^{0t} \times P_{HP}^{0t}]^{\frac{1}{2}}.$$

Thus, the updates for the new index in period t are derived as follows:

1. Selection of a base period 0 (in this case Q1 12) and estimation of a pooled base model, obtaining $\hat{\eta}_0, \hat{\sigma}_0^2$. This base model is
 - a) evaluated for period 0 on the period-average level of attributes. However, instead of just taking the mean attributes from one quarter, we take the average level of attributes over one year (in this case from Q1 11 to Q1 12) in order to stabilize the results, so for any variable

$$\bar{x}_k, \bar{x}_k = \sum_{i=-4}^0 \sum_{j=1}^n x_{it},$$
 and
 - b) evaluated at the mean level of attributes for period t . Again, the mean of these attributes is taken over one year.
2. Estimation of a new model for the current index level in time period t , similar to the model for the base period. For this purpose, data over a period of two years are pooled, obtaining $\hat{\eta}_t, \hat{\sigma}_t^2$. Again, this model is evaluated at the period-average level of attributes a) in 0 and b) in t as described above.
3. Calculation of the Laspeyres-type hedonic imputation index, using the results from 1a) and 2a).
4. Calculation of the Paasche-type hedonic imputation index, using the results from 1b) and 2b).
5. Calculation of the Fisher-type hedonic imputation index, taking the geometric mean of 3) and 4).

⁹ As we take the log of the dependent variable in this model, half of the estimated variance has to be added to the estimated predictors for the base period before exponentiation in order to get unbiased results.

6. After five years, the indices will be rebased to a new base period (in this case Q1 17) to prevent too strong deviations between the Laspeyres- and the Paasche-type hedonic imputation indices.

3.3 Prospects for Future Development

The new RPPI seems to overcome most of the difficulties in hedonic index construction very well. However, there are still some issues that will have to be considered in the future. First, the base model currently captures spatial heterogeneity only on the intercept (i.e. the spatial variation in price levels) using a hierarchical fixed- and random-effects structure. Spatial *slope* heterogeneity (i.e. spatial variation in price changes) might be incorporated to improve the model's predictive quality. In a semiparametric framework similar to the one described in this paper, this has been done by Brunauer et al. (2010). Furthermore, a way to model continuous spatial heterogeneity in a GAMs framework would be the integration of tensor product splines (TP splines, Wood, 2006b), which extend the spline basis to two or even higher dimensions. As the observations used for index construction are geo-coded, TP splines could be estimated over the respective geo-coordinates.

Nevertheless, the most important topic seems to be the data base. As mentioned before, we use quotation price data for this study. Several other studies show that quotation price data differ systematically from transaction price data (e.g. Knight, 2002). As price data are usually hardly available – and if so, only in a form that makes them difficult to use (i.e. a very small number of characteristics, see section 1.1) –

they cannot easily be used in hedonic price index construction. Therefore, in order to derive the offer markup, one could either perform a kind of data matching to find the actual purchase prices that correspond to the quotation prices in question or derive some kind of *spatially varying markup*, again using imputation methods (in this case spatial imputation) that cope with the lack of explanatory covariates.

Finally, as mentioned in section 1.1, the RPPI should be constructed either for the stock of housing or for property sales, using spatially varying weighting schemes. The new RPPI described in this paper only accounts for such schemes implicitly, by evaluating the model for census tracts, which roughly corresponds to population weights. However, on a small scale, hardly any data are available to construct a spatially varying weighting scheme. Furthermore, it seems that the application of such a weighting scheme in some respects produces more model-related problems than it solves: It might assign very high weights to outliers in regions with small numbers of observations or induce specification problems like heteroskedasticity. This topic will have to be considered carefully in the future.

4 Alternative RPPIs in Austria

4.1 The OOH Project of the ECB, Eurostat and Statistics Austria

As housing market analysis is becoming increasingly important, there is an obvious need for harmonized statistical data. First efforts to survey owner-occupied housing (OOH) at the European level were made in 2000 as the Statistical Programme Committee proposed to implement an OOH price index. A pilot project was launched, which followed the net acquisitions

principle¹⁰; after the pilot, a possible inclusion of the OOH index in the Harmonized Indices of Consumer Prices (HICP) was to be considered. The project was to be conducted in five stages, during which the methodological and procedural framework for regularly calculating and transmitting residential property prices was to be developed. Finally, in December 2010, these efforts led to the first release of experimental harmonized RPPIs¹¹. Statistics Austria¹² transmitted the first experimental results to Eurostat in February 2010.

OOH Stage 5 started in January 2012 and is scheduled for 27 months. So far, a regulation on the OOH index has not been passed, but a draft regulation has been prepared, laying down detailed rules for the implementation of Council Regulation (EC) No. 2494/95 as regards establishing OOH price indices within the HICP. The respective regulation is to be passed in the fall of 2012.

The OOH index will be produced on a quarterly basis with T+75 and will be calculated backward to Q1 05. For this new index, Statistics Austria calculates a data series which includes new and used houses, prefabricated houses and data on maintenance and repairs. Self-construction, insurance and charges related to property purchases will not be captured in the series. The calculation by Statistics Austria will be based on data provided by the Austrian Federal Ministry of Finance from its property acquisition tax database. Should the OOH index be integrated in

the HICP, calculating it on a monthly basis will be another difficult challenge.

4.2 Further Data Published by Real Estate Agents and Companies

There are further indices provided e.g. by the Austrian Economic Chambers (Wirtschaftskammer Österreich). The so-called *Immobilienpreisspiegel* is a rather detailed database capturing data on the quotation prices of new and used condominiums, family houses, detached houses, building areas, rented flats, office space and business premises. As data are available on this disaggregated level for all political districts of Austria, the sample numbers of the respective districts are sometimes quite small. There is no underlying model; rather, the data are based on a survey among real estate trustees and estate agents. Moreover, some real estate agencies publish related data – e.g. RE/MAX in its RE/MAX *ImmoSpiegel*, using data from the land registry, or the platform *www.immobilien.net*, which publishes *immoDex*, using the median of quotation price data from their database.

5 Conclusions

Housing wealth is one of the key components of household wealth. As residential property price dynamics exert a crucial influence on consumption and investment but also on households' financial position, the correct collection of price data is one of the fundamental prerequisites for analyses of residential property price movements and their effects.

¹⁰ *The Handbook on Residential Property Prices Indices suggests four possible approaches (European Commission, 2011, chapter 3): The money outlays or payments approach (adding up the expenses of home ownership including expenditure on repairs, mortgage interest costs, etc.), the net acquisition approach (ignoring the service costs of OOH and applying only the purchase price), the rental equivalence approach and the user cost approach (calculating the financial opportunity cost of owning a house).*

¹¹ See European Commission (2010). For further releases, see: http://epp.eurostat.ec.europa.eu/portal/page/portal/hicp/methodology/owner_occupied_housing_hpi/experimental_house_price_indices.

¹² In Austria, Statistics Austria is the institution responsible for calculating the OOH index.

In this paper, we describe the setup of a new residential property price index (RPPI) for Austria. So far, a time series for Austria has been calculated by taking the two existing RPPIs – one for Vienna and one for the rest of Austria – and applying population weights. But in this old model, weighting is arbitrary and both indices are calculated using a hedonic regression model with a fixed structure over time. This approach can lead to biased effects for current estimation results if changes in the variable effects occur over time. For the new RPPI, we estimate a single model for Austria which makes arbitrary weighting unnecessary. However, in order to avoid biased results due to spatial heterogeneity and nonlinearity in variable effects, we propose the use of Generalized Additive Models (GAMs), i.e. a semiparametric regression method. Comparing five alternative model specifications, a model integrating time effects in a hierarchical manner is chosen for both condominiums and family houses: The baseline time effect is estimated as a yearly dummy effect, and

deviations are captured by random effects on a quarterly basis. In addition, in the old model the relevant time trend is derived by evaluating time effects, which can lead to unstable results regarding previous time effects on the one hand and does not account for the change in variable effects over time on the other. Thus, for updating the new RPPI, we suggest using an imputation method that avoids these problems. Our paper explains in detail the individual steps in the calculation of the new RPPI and its advantages over the old index.

To sum up, the new RPPI represents a further milestone in the field of residential property price modeling and data quality enhancement in Austrian residential property price statistics. However, there are still some open issues to be considered in the future, e.g. allowing for spatial slope heterogeneity or smooth spatial heterogeneity, taking offer price markups into account and applying weighting schemes to gain even higher representativeness and precision in the estimated RPPI.

References

- Altissimo, F., E. Georgiou, T. Sastre, M. T. Valderrama, G. Sterne, M. Stocker, M. Weth, K. Whelan and A. Willman. 2005.** Wealth and Asset Price Effects on Economic Activity. Occasional Paper Series 29. ECB. June.
- Ando, A. and F. Modigliani. 1963.** The Life-Cycle Hypothesis of Saving: Aggregate Implications and Tests. In: *American Economic Review* 103. 55–84.
- Brunauer, W., S. Lang, P. Wechselberger and S. Bienert. 2010.** Additive Hedonic Regression Models with Spatial Scaling Factors: An Application for Rents in Vienna. In: *Journal of Real Estate Finance and Economics* 41(4). 390–411.
- Case, K., J. Quigley and R. Shiller. 2005.** Comparing Wealth Effects: The Stock Market Versus the Housing Market. In: *Advances in Macroeconomics* 5(1).
- European Commission. 2010.** Experimental House Price Indices for the Euro Area and the European Union. Retrieved from http://epp.eurostat.ec.europa.eu/portal/page/portal/hicp/documents/Tab/Tab/METH-HPI_Research_paper_2010-12.pdf on July 19, 2012.
- European Commission. 2011.** Handbook on Residential Property Prices Indices. November. Retrieved from http://epp.eurostat.ec.europa.eu/portal/page/portal/hicp/methodology/owner_occupied_housing_hpi/rppi_handbook on July 19, 2012.
- Knight, J. 2002.** Listing Price, Time on Market, and Ultimate Selling Price: Causes and Effects of Listing Price Changes. In: *Real Estate Economics* 30(2). 212–237.

- Wood, S. 2006a.** An Introduction to Generalized Additive Models with R. Boca Raton: Chapman and Hall.
- Wood, S. 2006b.** Low-Rank Scale-Invariant Tensor Product Smooths for Generalized Additive Mixed Models. In: Biometrics 62(4). 1025–1036.