Residential Property Price Indices for Austria

*OeNB Workshop, October 9, 2014*
Contents

- Challenges for index construction
- Property price indices in Austria
- Outlook
Challenges for index construction
Measuring “pure“ price changes

• Comparability:
  Taking into account different quality levels (e.g. location, size, age, technical equipment)

• 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

• Change of standards:
  Considering changes in quality standards over time

• Representativeness:
  What is the underlying population we want to describe?
Challenges for index construction

Methods

• Repeated sales method
  • Small share of repeatedly sold properties, particularly for single family homes (SFH)
  • Problem of matching over time, particularly for apartments
  • Possible changes in the building structure over time

• Stratification method
  • Unbalanced / heterogeneous occurrence of transactions over Austria
  • Small sample sizes within strata

• Hedonic regression
  • Overcomes the problems in repeated sales and stratification method
  • However, for quality adjusted comparisons, the underlying data set must cover all relevant attributes to avoid omitted variable bias
Challenges for index construction

Theory of hedonic prices

- Real estate consist of a wide range of characteristics that make each object unique.

- Implicit choice of many different goods and services: If a household buys an object, it selects a set of values for each of the $K$ (structural and locational) characteristics $\mathbf{z} = (z_1, z_2, \ldots, z_K)$.

- Therefore, the price of the house or apartment is a function of the whole bundle of characteristics, or $P = P(\mathbf{z})$ (the hedonic price function), with functional relationships possibly varying over time and space.

- Thus, there is an explicit price for the whole bundle of characteristics, and an implicit price for each single characteristic.

- Implicit prices can be determined e.g., in a multiple regression model.
Challenges for index construction

Data sources in Austria

1. Purchase price collection from land register:
   + Representativeness
     - Only address and purchase price, hardly any additional attributes
     - Probably bias due to special circumstances (e.g. purchase from family members) or tax avoidance
     - Very expensive

2. Data collections by financial institutions:
   + Often very detailed
     - Rather small numbers of observations
     - Probably not representative for the whole market

3. Asking (offer) prices from real estate brokerage platforms:
   + Large number of observations
   + Most relevant variables available
     - Possible “offer mark-up” – is it varying over time?
     - Possible bias in data input, particularly for poor quality

→ Decision in favor of asking price data (3), as it covers space by a sufficient number of observation (“length”) and object characteristics (“width”)
Indices in Austria
Overview

• Price data published by the Austrian chamber of commerce (WKÖ Immobilienpreisspiegel – not in this presentation)

• Two residential property price indices (RPPI) published on the OeNB web page (source: TU Vienna):
  • Time Dummy Index, transaction perspective
  • Spatial Imputation Index, focusing on property stock

• Starting in 3q2014: RPPI of the Austrian statistical office (Statistik Austria)

• For commercial real estate, currently there is no reliable data
Indices in Austria
RPPIs by TU Vienna

• Two RPPIs calculated by TU Vienna for OeNB
  • Time Dummy Index: Transaction perspective
  • Spatial Imputation Index: Stock perspective

• Three groups of explanatory covariates
  • Object characteristics (condition, age, size,…)
  • Location characteristics
  • Time indicators (quarter)

• Data source
  • Internet platform AMETA-NET (EDI-Real, Linz)
  • Approx. 20,000 obs. p.a., partly from 1986
  • Regional information system IRIS, Centre of Regional Science, TU Vienna

• Spatial differentiation: Census tract (~9000) / municipality (~2400) / district (121) / state (9)

• Object types: Single family homes (SFH), apartments
Indices in Austria
Time Dummy Index – Model

- Multiple linear regression model, where (log) price is explained by building attributes and district dummies
- Models for one year with dummy-coded quarters
- Models are overlapping, time effects are chained over the last quarter of the previous model
- Estimation of six separate models, split by object type and region:
  - “Vienna” and “Austria, except Vienna”
  - SFH, apartments (new), apartments (used)
- The total effect is determined by a weighting scheme (see below)
- Problems:
  - “Retrospective” variation of time effects due to model construction
  - Quality changes are not explicitly considered
  - Treatment of unobserved regions
Indices in Austria
Time Dummy Index – Results for submodels

- Used apartments (Vienna)
- Used apartments (Austria, except Vienna)
- Single-family houses (Vienna)
- New apartments (Vienna)
- New apartments (Austria, except Vienna)
- Single-family houses (Austria, except Vienna)

http://www.srf.tuwien.ac.at/feil/immobilienbewertung/Index214.pdf
Indices in Austria

Time Dummy Index – Weighting scheme

Weights are determined by numbers of transactions from land register (2008-2013)

1. Apartments: Weighting of indices for new and used apartments; for Vienna and Austria, except Vienna, respectively

<table>
<thead>
<tr>
<th></th>
<th>Apartments (new)</th>
<th>Apartments (used)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vienna</td>
<td>15%</td>
<td>85%</td>
</tr>
<tr>
<td>Austria, except Vienna</td>
<td>13%</td>
<td>87%</td>
</tr>
</tbody>
</table>

2. Regional indices: Weighting apartments and SFH

<table>
<thead>
<tr>
<th></th>
<th>Apartments</th>
<th>SFH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vienna</td>
<td>93%</td>
<td>7%</td>
</tr>
<tr>
<td>Austria, except Vienna</td>
<td>70%</td>
<td>30%</td>
</tr>
</tbody>
</table>

1. Index for Austria: weighting Vienna and Austria, except Vienna

<table>
<thead>
<tr>
<th></th>
<th>Vienna</th>
<th>Austria, except Vienna</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>27%</td>
<td>73%</td>
</tr>
</tbody>
</table>
Indices in Austria
Time Dummy Index – Overall results

House price developments

Source: OeNB, Prof. Wolfgang Feilmayr, Department of Spatial Planning, Vienna University of Technology.
Indices in Austria
Spatial Imputation Index – Motivation

• Comparability:
  • Space is taken into account by location covariates on census tract and municipality level (“observed” spatial heterogeneity) and a hierarchical structure of state and district (“unobserved” spatial heterogeneity)
  • Modelling potentially nonlinear relationships in object and location variables using semiparametric model specifications

• Time-varying effects:
  • Relatively long “base model”, obtaining robust results
  • Model periods of two years for “comparison model”

• Change of standards:
  • Representative characteristics are determined in each model period over one year
  • Combination in a Fisher-type index

• Representativeness:
  • Imputation in each census tract, with varying census tract characteristics
  • Weighted aggregation using shares of respective state in total building stock
Indices in Austria
Spatial Imputation Index – The approach in detail (1)

1. Definition of subsamples for model construction
   a. Base model: 2007Q1 – 2012Q1 (apartments) and 2005Q1 – 2012Q1 (SFH), with base period 2012Q1
   b. Comparison model: Moving window of two years, with comparison the latest available quarter

2. Determining „average characteristics“ for the last year until the base and comparison period, respectively

3. Regression model for base and comparison period

4. Spatial imputation:
   a. Simulation of an „average characteristics“ object for each census tract in base and comparison period
   b. Leveraging on the similarities modelled by location covariates and the hierarchical structure for spatial heterogeneity
Indices in Austria
Spatial Imputation Index – The approach in detail (2)

5. Index calculation on census tract level:
   a. Laspeyres-Index: Average characteristics of base period
   b. Paasche-Index: Average characteristics of current period
   c. Fisher-Index: Geometric mean of Laspeyres and Paasche
   d. Rescaling to 2007Q1 = 100 using dummy effects from base model

6. Weighting scheme:
   a. For each submodel and state: Averaging over census tracts (except: SFH/Vienna, “inner“ districts)
   b. Average over state/type index values weighted by share of state/type on total stock (based on Household Finance and Consumption Survey/HFCS 2010)
Indices in Austria
Spatial Imputation Index – Method

- Generalized Additive Models (GAM; Wood, 2006): Basic structural and distributional assumptions as in Generalized Linear Models
  \[ E(y_i \mid z_i, x_i) = h(\eta_i) \] with additive predictor \( \eta_i = f_1(z_{i1}) + \ldots + f_q(z_{iq}) + x_i \gamma \)
    - \( x \gamma \) is the parametric part of the predictor
    - \( z_j \) is a continuous covariate, time scale, location- or cluster index
    - \( f_j \) are one- or higher-dimensional, not necessarily continuous functions

- Smoothing is obtained using penalization structures, with automated selection of the smoothing parameter using the Generalized Cross Validation (GCV) criterion
  - Continuous covariate effects are modeled using penalized regression splines (thin plate regression splines, i.e. low rank scale invariant smoothers)
  - Spatial (districts) and time (quarter) indices are modelled using random effects (ridge-type penalty)
Indices in Austria
Spatial Imputation Index – Trend modelling

• For modeling trend effects the following alternatives are checked:
  
  • Dummy approach: Quarterly time dummy effects \(\rightarrow\) rather volatile estimation results
  
  • Smooth trend approach using penalized regression splines \(\rightarrow\) underestimate abrupt jumps
  
  • Random time effect \(\rightarrow\) effect is underestimated if market truly tends up- or downward over time
  
  • Smooth random-effect-model: combination of a nonlinear time trend and random effects \(\rightarrow\) results seem to be dominated by the nonlinear trend.
  
  • Integrates time effects in a hierarchical manner: baseline time effect is estimated as yearly effect, deviations from that effect are captured by random effects (year-random model) \(\rightarrow\) robust trade-off between data fidelity and penalization
  
  • Expert-drive decision in favor of hierarchical time effects (year-random model), supported by AIC
## Indices in Austria

### Spatial Imputation Index

- **SFH**
  - **Parametric coefficients:**
    - Estimate Std. Error  t value Pr(>|t|)
      - (Intercept) 12.307679   0.035462 347.066  < 2e-16 ***
      - year2006 -0.021249   0.020817 -1.021 0.307396
      - year2007 0.031625   0.012357  2.559 0.010505 *
      - year2008 0.025220   0.012185  2.070 0.038503 *
      - year2009 0.031708   0.011852  2.675 0.007477 **
      - year2010 0.053941   0.011473  4.702 2.61e-06 ***
      - year2011 0.074080   0.016927  4.376 1.22e-05 ***

- **Apartments**
  - **Parametric coefficients:**
    - Estimate Std. Error  t value Pr(>|t|)
      - (Intercept) 11.373231   0.112406 101.180  < 2e-16 ***
      - year2008 0.042663   0.012949  3.295 0.000988 ***
      - year2009 0.070320   0.012371  5.684 1.34e-08 ***
      - year2010 0.131047   0.012215  10.728  < 2e-16 ***
      - year2011 0.179753   0.019087  9.417  < 2e-16 ***

- **Approximate significance of smooth terms:**
  - edf Ref.df  F  p-value
    - s(y_q) 8.667 10.641  2.431  0.00564 **
    - s(lnarea) 7.481  8.447 907.079  < 2e-16 ***
    - s(age) 7.537  8.282 276.515  < 2e-16 ***
    - s(ln_census_educ) 5.971  7.201  33.040  < 2e-16 ***
    - s(ln_census_plot_price) 1.703  2.119 101.291  < 2e-16 ***
    - s(mun_no_nights) 7.587  8.191  11.357  < 2e-16 ***
    - s(mun_pot) 4.556  5.601  5.670 1.25e-05 ***
    - s(ln_mun_dens) 2.136  2.545  8.243 6.03e-05 ***
    - s(district) 90.015 98.000  19.312  < 2e-16 ***

- **Signif. codes:** 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

- **R-sq.(adj) = 0.883 Deviance explained = 88.5%
  - REML score = -124.74 Scale est. = 0.054618 n = 15311**
Indices in Austria
Spatial Imputation Index – Model output (base model)
Indices in Austria
Spatial Imputation Index – Imputation for SFH/Austria (w/o Vienna)
Indices in Austria
Spatial Imputation Index – Imputation for apartments/Austria (w/o Vienna)
Indices in Austria
Spatial Imputation Index – Imputation for SFH/Vienna

MV SFH, 1q2010

MV SFH, 2q2014

Index 2q2014 SFH, base 1q2010
Indices in Austria
Spatial Imputation Index – Imputation for apartments/Vienna
Indices in Austria

Spatial Imputation Index – Weighting scheme (derived from HFCS)

<table>
<thead>
<tr>
<th>State</th>
<th>SFH</th>
<th>Apartm.</th>
<th>SFH</th>
<th>Apartm.</th>
<th>SFH</th>
<th>Apartm.</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>90.6%</td>
<td>9.4%</td>
<td>6.7%</td>
<td>2.5%</td>
<td>5.2%</td>
<td>0.5%</td>
</tr>
<tr>
<td>K</td>
<td>90.8%</td>
<td>9.2%</td>
<td>8.2%</td>
<td>2.9%</td>
<td>6.4%</td>
<td>0.6%</td>
</tr>
<tr>
<td>N</td>
<td>84.4%</td>
<td>15.6%</td>
<td>21.2%</td>
<td>13.7%</td>
<td>16.5%</td>
<td>3.1%</td>
</tr>
<tr>
<td>O</td>
<td>88.6%</td>
<td>11.4%</td>
<td>23.1%</td>
<td>10.4%</td>
<td>17.9%</td>
<td>2.3%</td>
</tr>
<tr>
<td>Sa</td>
<td>61.0%</td>
<td>39.0%</td>
<td>5.1%</td>
<td>11.5%</td>
<td>4.0%</td>
<td>2.6%</td>
</tr>
<tr>
<td>St</td>
<td>81.3%</td>
<td>18.7%</td>
<td>18.5%</td>
<td>14.9%</td>
<td>14.4%</td>
<td>3.3%</td>
</tr>
<tr>
<td>T</td>
<td>68.7%</td>
<td>31.3%</td>
<td>8.8%</td>
<td>14.1%</td>
<td>6.9%</td>
<td>3.1%</td>
</tr>
<tr>
<td>V</td>
<td>66.1%</td>
<td>33.9%</td>
<td>4.2%</td>
<td>7.5%</td>
<td>3.2%</td>
<td>1.7%</td>
</tr>
<tr>
<td>W</td>
<td>39.1%</td>
<td>60.9%</td>
<td>4.1%</td>
<td>22.6%</td>
<td>3.2%</td>
<td>5.0%</td>
</tr>
<tr>
<td>AUT</td>
<td>77.8%</td>
<td>22.2%</td>
<td>100.0%</td>
<td>100.0%</td>
<td>77.8%</td>
<td>22.2%</td>
</tr>
</tbody>
</table>
Indices in Austria
Spatial Imputation Index – Overall results

Left:
Weighting by stock (HFCS)

Right:
Comparison for weighting by stock vs. number of transactions
Outlook

• Room for improvement
  • Weighting: More detailed weighting scheme, accounting for share of stock e.g. on district level
  • Average Quality: Determining average quality on a more granular spatial scale (e.g. state or district)
  • Model:
    • Spatially varying effects for object characteristics
    • Including location covariates measured in respective year (currently only “cross-section“ perspective)
    • Including additional covariates measuring fundamental factors for demand (e.g. demographic development) and supply (e.g. available floor space)
  • Data: Obtaining data sources that are not affected by weaknesses of asking price data

• Further applications
  • Disaggregated indices, with expert-driven and/or model-based market delineation
  • Using multilevel models to estimate deviations from fundamental house prices
Thank you for your attention!

Questions, Comments?