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House Price Indexes for Warsaw: An Evaluation of Competing Methods

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Abstract

Using a detailed micro-level dataset we compute house price indexes (HPIs) for Warsaw over the period 2006 to 2018. We find that when a hedonic approach is used, the resulting index is reasonably robust to the choice of method. Nevertheless, the hedonic HPIs computed by the National Bank of Poland (NBP) and Statistics Poland (SP) both have some weaknesses. More problematic than hedonic indexes are HPIs computed using the repeat-sales method, which is widely used in the US. We find that such indexes are unreliable, suffering from sample selection bias, and prone to significant revisions when new periods are added to the dataset. Overall we recommend using either the hedonic time-dummy or rolling time dummy (RTD) methods. These methods when applied to our dataset provide the most reliable HPIs for Warsaw.

Keywords: The residential real estate market in Warsaw; Hedonic house price index; Repeat-sales price index; Sample selection bias; Robustness to revisions; Robustness to deletion of data

1. Introduction

Banks and international financial organizations have become more interested in house price indexes in the last decade. This issue is largely a result of recessin which started in the US real estate market. The financial crunch of 2007-2008 demonstrated the relevance of collecting and processing important statistical data for maintaining financial stability. Studies conducted in different countries suggest close links between price fluctuations in the housing market and changes in economic activity in individual countries. In particular, economic recessions that follow sharp increases in housing prices tend to be especially long and severe (Claessens, Kose, & Terrones, 2012; Hirata, Kose, Otrok, & Terrones, 2012; Liu, Wang, & Zha, 2013; Reinhart & Rogoff, 2008).

Better statistical data, including on residential properties, could have mitigated the negative consequences of the recession. Earlier studies (Hilbers, Lei, & Zacho, 2001) emphasised how sudden changes in housing markets may affect the stability of the financial sector. Unfortunately, there was a lack of up-to-date data concerning the real estate market, such as prices, rents, vacancy rates, and construction costs (Sundararajan et al., 2002).

Following the recommendations of the Financial Stability Board (FSB) and the International Monetary Fund (IMF) (FSB and IMF, 2009) , Eurostat, under the patronage of the IWGPS (Inter-Secretariat Working Group on Price Statistics), prepared a Handbook on residential property price indexes (Eurostat, 2013). Moreover, since 2013, European Union member states under Regulation (EC) No. 93/2013 have been obliged to publish house price indexes (HPIs). Provisions are also included in Regulation (EC) No. 2016/792 of the European Parliament and of the Council of 11 May 2016 on harmonised indexes of consumer prices and HPIs.

The unique characteristics of each property make it difficult to construct an unbiased HPI. The literature provides comparisons of indexes based on different methods, indicating the superiority of hedonic and repeat-sales methods (see sectiosn 3 and 4) over mean or median methods (Bourassa, Hoesli, Scognamiglio, & Sormani, 2008; Case & Shiller, 1987; Hansen, 2009; Prasad & Richards, 2008).

Eurostat suggests computing HPIs using a hedonic approach, but has not given guidance to the National Statistical Institute (NSIs) as to which hedonic method should be used. This has resulted in countries implementing different approaches (Hill, Scholz, Shimizu, & Steurer, 2018).

By contrast, repeat-sales methods are more widely used than hedonic methods in the US – the best known example being the S&P CoreLogic Case-Shiller indexes. The greater use of repeat sales methods in the US may be at least partly due to the higher turnover rate for properties there. Nevertheless, a number of concerns have been raised about repeat sales methods in the literature. In particular, they are more sensitive than hedonic methods to changes in the structure of sold properties (Francke, Vos, & Janssen, 2000), and are prone to sample selection bias. For example, Shimizu, Nishimura and Watanabe (2010) find that repeat-sales indexes for Tokyo fail to correctly identify turning points in the housing market. In the context of our Warsaw dataset, we find that repeat-sales methods exhibit a number of unattractive features. Hence we strongly recommend using a hedonic approach.

The National Bank of Poland (NBP) produces an HPI for Warsaw using the hedonic imputation method, while Statistics Poland (SP) produces one based on the average price per square metre. The NBP and SP HPIs also differ in their underlying source data. While these HPIs have reasonable properties, we find that both have some weaknesses. Overall, we argue for using the time-dummy or rolling time dummy (RTD) hedonic methods for computing HPIs for Warsaw over the 2006-2018 period.

2. Data

This paper compares competing methods for constructing HPIs using micro-level transaction data for Warsaw from the secondary housing market (with full private accommodation ownership rights). This study focuses on dwellings in multi-family buildings (the majority of dwellings in Warsaw are of this type).

The data covering the period Q2 2006 to Q3 2018 was collected from the Board of Geodesy and Municipal Cadastre in Warsaw. All non-market sales (e.g. debt enforcement transactions), transactions with more than one apartment, as well as dwelling located in single-family buildings were removed from the final dataset. Notarial contracts include the following information: date of purchase, price, area of a dwelling, the floor of a dwelling and area of any auxiliary premises (e.g. garage/parking spot in an indoor car park or cellar/storage). On the other hand, notarial contracts do not include information on various price determinants such as construction technology, architecture, building quality. Additional information on the height of buildings and the year of construction was obtained employing cadastral data. Finally, the missing height and most importantly building technology data were added using the Street View application on maps.google.com. The addresses were geocoded through google maps API. The vector layer of parks, Limited Use Area, was designed with Warsaw City Hall WMS servers. 101182 geo-coded apartments sold between Q2 2006 and Q3 2018 were included in the final data collection. The choice of qualitative and quantitative data was limited by the availability of information in the database. Table 1 presents the variables used in the study. The resulting dataset has a more detailed list of characteristics than are available in either the NBP or SP datasets.

Table 1. Qualitative and quantitative variables applied in the models

Variable	Symbol	Description
quarter	q1, …., q50	50-time dummy variables used in the global model. If the dwelling was sold in a given year-quarter, it takes the value 1; otherwise, it takes 0.
district	d1-Bemowo, d2-Białołęka, d3-Bielany, d4-Mokotów, d5-Ochota, d6-Praga Południe, d7-Praga Północ, d8-Rembertów, d9-Śródmieście, d10-Targówek, d11-Ursus, d12-Ursynów, d13-Wawer, d14-Wesoła, d15-	18 dummy variables. If an apartment is located in a given district, it takes the value 1; otherwise, it takes 0.

	Wilanów, d16-Włochy, d17-Wola, d18-Żoliborz	
Area	area	area of dwelling
construction technology	technology	1 - if the dwelling is located in a building made with a prefabricated technology, 2 - if the dwelling is located in a building made with traditional technology.
Age	age	6 dummy variables. If the dwelling is located in a building built in a given period, it takes the value 1; otherwise, it takes 0.
Floor	floor1 - ground and top floor floor2 - intermediate floors floor3 - first and second floor	3 dummy variables. If the dwelling is located on a given floor, it takes the value 1; otherwise, it takes 0
Height	height	0-buildings up to 4 floors 1-buildings above 5 floors
basement	basement	A dummy variable, it takes the value 1 if the apartment has a basement or storage room; otherwise, it takes 0
Garage	garage	It takes the value 1 if the apartment has an individual parking space in the garage or a parking space outside the building. Otherwise, it takes 0
Park	park	distance to the nearest park in m
school	school	distance to nearest primary school in m
Limited Use Area	LUA around Okęcie airport	time dummy variable takes 1 if the dwelling was located in the LUA or 0 otherwise

3. Hedonic methods

The hedonic regression method dates back at least to 1922, when G. A. Hass built a hedonic model of agricultural land prices. Given his findings appeared in a technical report, its impact on the literature was limited (Colwell & Dilmore, 1999). Credit is typically given to Andrew Court (Court, 1939), who used hedonic methods to study the price changes of cars over time by taking into account their characteristics. Ridker and Henning (1967) were probably the first to use the hedonic method to study the housing market (Hill, 2013). They tried to determine the impact of air pollution reductions on average house prices (they analyzed statistical areas, not individual properties). The theoretical principles of the hedonic method were developed by Lancaster (1966) and Rosen (1974).

The hedonic method assumes that the price of a heterogeneous good can be described by its features. In other words, the method may be used to quantify the value of particular characteristics of a given good. In order to determine the influence of individual chacteristics on the value of a given good, econometric equations are built, in which the explained variable is the price (or log price) of a given good, and the explanatory variables are its quantitative and qualitative attributes, which can be written as follows:

$$P = \alpha + \sum_{i=1}^{K} \beta_i C_i + \varepsilon$$

where: P – the price of a good, β – regression coefficients, C – explanatory characteristics, and ε – error term.

The application of the hedonic regression method requires the resolution of several issues. The most important are the following: the choice of the functional form (Diewert, 2003; Malpezzi, 2008; Lisi, 2013), the variable choice (Crompton, 2005; Dubin, 1988; Malpezzi, 2008), consideration or not of spatial effects (Anselin, 1988; Osland, 2010), collinearity and heteroscedasticity (Xiao, 2017).

The use of the hedonic method requires information on the price of properties and all the associated characteristics, as well as their condition. In the absence of a sufficiently abundant database of reliable information on the characteristics, the hedonic method may not provide a reliable HPI for the period under analysis. This is the most severe practical obstacle to the use of hedonic regression.

Table 2. Advantages and disadvantages of the hedonic method

Advantages	Disadvantages
• possibility of controlling changes in the structure as well as qualitative and quantitative changes (to the extent allowed by the information describing the statuses of property characteristics in the database) over time, • exploiting the full potential of data, • price indexes can be built for different types of dwellings as well as for different specific locations, • allow the value of the land to be distinguished.	• stringent data quality requirements, • difficulties with effective location control in the event of price changes vary from region to region, • the sensitivity of the results to the set of explanatory variables as well as to the selected functional form of the model.

Source: Own conclusions based on the literature

3.1 Hedonic indexes

Hedonic HPIs are computed here using a median quantile regression approach. Quantile regression is preferred to a least squares approach, as it can better manage heteroscedasticity, outliers and unobserved heterogeneity (Liao & Wang, 2012). The explanatory variables are described in Table 1. In this research, we constructed hedonic HPIs using several different hedonic methods:

- Time dummy (TD) – The standard procedure was followed.

- Rolling time dummy (RTD) – The 2 quarters window was assumed.
- Repricing (RP) – The log-linear model of prices was estimated for the 2017 year. The quality adjustment factor was estimated taking into account the estimated coefficients regression and the average characteristics of apartments in each quarter.
- Average characteristics method (AVC) – For all quarters a semi-log equation was estimated. Then the average attributes of flats in the 3rd quarter of 2018 were calculated. Then this average flat was priced using the characteristic shadow prices obtained from the estimated hedonic models. Price indexes are obtained by tracking the change in the price of this reference average dwelling over time.
- Hedonic imputation method (IMP) - Each property sold in 3rd quarter of 2018 is priced in every period using the characteristic shadow prices obtained from the estimated hedonic models. This is similar to the method used by the National Bank of Poland.

To address the research questions, hedonic regression equations using median quantile regression were estimated. The dependent variable was the log transaction price. Then, Gretl software was used to estimate the model parameters. The explanatory variables were as follows: the location, construction technology, floor, time of construction, area of dwelling, basement, garage, location in outside zone of LUA, distance to the urban green areas and school were estimated. Table 3 presents the results of the estimations for TD hedonic method. All the coefficients are statistically significantly different from zero.

Table 3. Results of estimation for time-dummy hedonic model

Variable	Coefficient	Std. Error	t-ratio	p-value	Variable	Coefficient	Std. Error	t-ratio	p-value
const	11.6047	0.00689819	1682	<0.0001	q41	0.364888	0.00535582	68.13	<0.0001
q2	0.118445	0.00580682	20.40	<0.0001	q42	0.382508	0.00536680	71.27	<0.0001
q3	0.268678	0.00567911	47.31	<0.0001	q43	0.389997	0.00539195	72.33	<0.0001
q4	0.372542	0.00617852	60.30	<0.0001	q44	0.407254	0.00529567	76.90	<0.0001
q5	0.461235	0.00609340	75.69	<0.0001	q45	0.429627	0.00530991	80.91	<0.0001
q6	0.487981	0.00611869	79.75	<0.0001	q46	0.442593	0.00528441	83.75	<0.0001
q7	0.499607	0.00643177	77.68	<0.0001	q47	0.460935	0.00530704	86.85	<0.0001
q8	0.484788	0.00611976	79.22	<0.0001	q48	0.472094	0.00525394	89.86	<0.0001
q9	0.484105	0.00583485	82.97	<0.0001	q49	0.499959	0.00516130	96.87	<0.0001
q10	0.465518	0.00585327	79.53	<0.0001	q50	0.519559	0.00538839	96.42	<0.0001
q11	0.445488	0.00594459	74.94	<0.0001	d1	−0.313215	0.00333255	−93.99	<0.0001
q12	0.388761	0.00650113	59.80	<0.0001	d2	−0.506809	0.00293133	−172.9	<0.0001
q13	0.390371	0.00618631	63.10	<0.0001	d3	−0.277640	0.00299363	−92.74	<0.0001
q14	0.394892	0.00593071	66.58	<0.0001	d4	−0.160222	0.00223264	−71.76	<0.0001
q15	0.401065	0.00585993	68.44	<0.0001	d5	−0.200952	0.00276704	−72.62	<0.0001
q16	0.418074	0.00582220	71.81	<0.0001	d6	−0.318132	0.00249738	−127.4	<0.0001
q17	0.433839	0.00574027	75.58	<0.0001	d7	−0.365170	0.00338578	−107.9	<0.0001

q18	0.433105	0.00561897	77.08	<0.0001	d8	−0.507294	0.00667017	−76.05	<0.0001
q19	0.421645	0.00562366	74.98	<0.0001	d10	−0.395634	0.00330406	−119.7	<0.0001
q20	0.422515	0.00565744	74.68	<0.0001	d11	−0.381245	0.00425479	−89.60	<0.0001
q21	0.436821	0.00564560	77.37	<0.0001	d12	−0.183423	0.00361734	−50.71	<0.0001
q22	0.415544	0.00560942	74.08	<0.0001	d13	−0.433966	0.00522880	−83.00	<0.0001
q23	0.400763	0.00581969	68.86	<0.0001	d14	−0.520699	0.00669742	−77.75	<0.0001
q24	0.380339	0.00579252	65.66	<0.0001	d15	−0.271234	0.00427260	−63.48	<0.0001
q25	0.368041	0.00588728	62.51	<0.0001	d16	−0.354162	0.00481553	−73.55	<0.0001
q26	0.342440	0.00586123	58.42	<0.0001	d17	−0.233368	0.00249993	−93.35	<0.0001
q27	0.312957	0.00595445	52.56	<0.0001	d18	−0.106485	0.00402701	−26.44	<0.0001
q28	0.301008	0.00591484	50.89	<0.0001	area	0.0241593	5.84942e-05	413.0	<0.0001
q29	0.298266	0.00565777	52.72	<0.0001	area2	−6.17957e-05	3.05610e-07	−202.2	<0.0001
q30	0.303959	0.00548642	55.40	<0.0001	age	−0.00675741	8.51850e-05	−79.33	<0.0001
q31	0.315560	0.00541735	58.25	<0.0001	age2	5.44494e-05	8.65424e-07	62.92	<0.0001
q32	0.321629	0.00553543	58.10	<0.0001	technology	0.0841863	0.00166874	50.45	<0.0001
q33	0.341027	0.00561004	60.79	<0.0001	basement	0.0228622	0.00115765	19.75	<0.0001
q34	0.341759	0.00555453	61.53	<0.0001	grarage	0.0322998	0.00162728	19.85	<0.0001
q35	0.336534	0.00562101	59.87	<0.0001	height	0.0130113	0.00141341	9.206	<0.0001
q36	0.342661	0.00549372	62.37	<0.0001	floor2	0.0177685	0.00152821	11.63	<0.0001
q37	0.347312	0.00547686	63.41	<0.0001	floor3	0.0221642	0.00138569	16.00	<0.0001
q38	0.357014	0.00544188	65.60	<0.0001	school	−4.03461e-05	2.30404e-06	−17.51	<0.0001
q39	0.343576	0.00542710	63.31	<0.0001	park	−2.04291e-05	1.62432e-06	−12.58	<0.0001
q40	0.353571	0.00541198	65.33	<0.0001	LUA	−0.0283419	0.00267593	−10.59	<0.0001

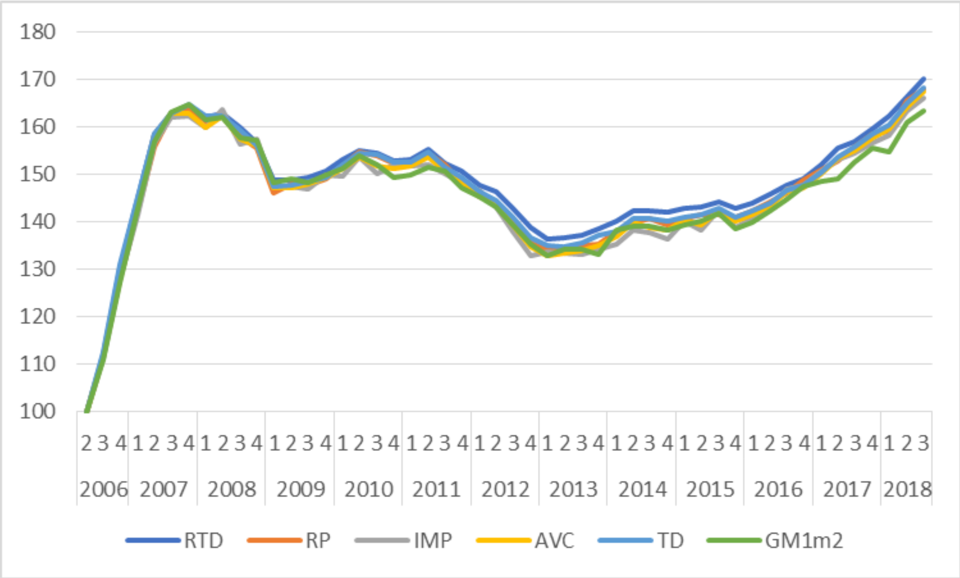
Source: own calculations

The regression coefficients on the district dummy variables can be viewed as district values. In this study, the base variable was d9 relating to the district of Downtown. Statistically significant negative regression coefficients for other districts confirm that consumers are willing to pay more for apartments in the city centre.

The relationships between apartment physical characteristics and sales prices are consistent with expectations. In the case of a primary school and urban green areas, the negative relationship between distance and property price was also observed (Trojanek, Gluszak, & Tanas, 2018). Moreover, there is a significant negative association between house prices and location in LUA compared with apartments outside this zone, confirming earlier studies concerning Warsaw Okęcie International Airport (Trojanek & Huderek-Glapska, 2018; Cellmer, Bełej, & Konowalczuk, 2019).

In Figure 1 the HPIs and additionally an index based on the geometric mean price per square meter (GM1m2) in Warsaw for the period from 2006 (2^{nd} quarter) to 2018 (3^{rd} quarter) are presented. GM1m2 is the method used by Statistics Poland. It can be viewed as a simple case of a hedonic method, where the only characteristic is floor area.

Figure 1. Hedonic price indexes



Source: own calculations

Note: RTD = Rolling time dummy; RP = repricing; IMP = Hedonic imputation; AVC = Average chaarcteristics; TD = Time-dummy; GM1m2 = the geometric mean of price per square metre

HPIs in Warsaw constructed on the basis of different hedonic models are very similar. For the GM1m2 index slight differences arise. The overall price increase in the analysed period varies as follows:

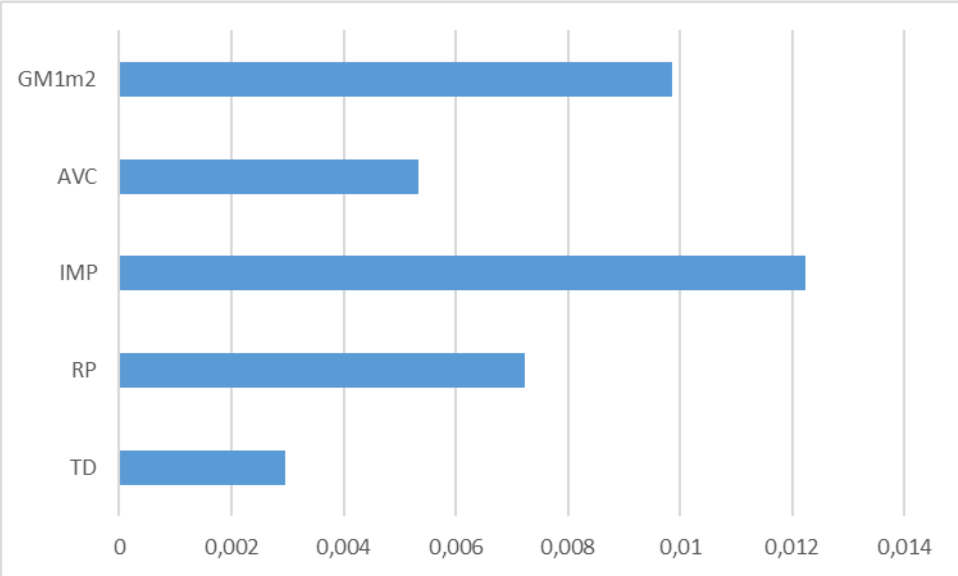
- about 68.12 % based on TD,
- about 69.98 % based on RTD,
- about 67.96 % based on RP,
- about 66.11 % based on IMP,
- about 67.34 % based on AVC,
- about 63.48% based on GM1m2.

In Figure 2 we estimated the root mean squared error (RMSE) between the log changes in the RTD index (reference time-series, as it is the smoothest) and the log changes in the other indexes. The RMSE is calculated as follows:

$$RMSE_k = \frac{1}{49}\sqrt{\sum_{t=2006,q2}^{2018,q2}\left[\ln\left(\frac{p_{k,t+1}}{p_{k,t}}\right) - \ln\left(\frac{p_{RTD,t+1}}{p_{RTD,t}}\right)\right]^2},$$

where k indexes the other methods being compared with RTD. The log transformation is included so that price rises and price declines are treated symmetrically.

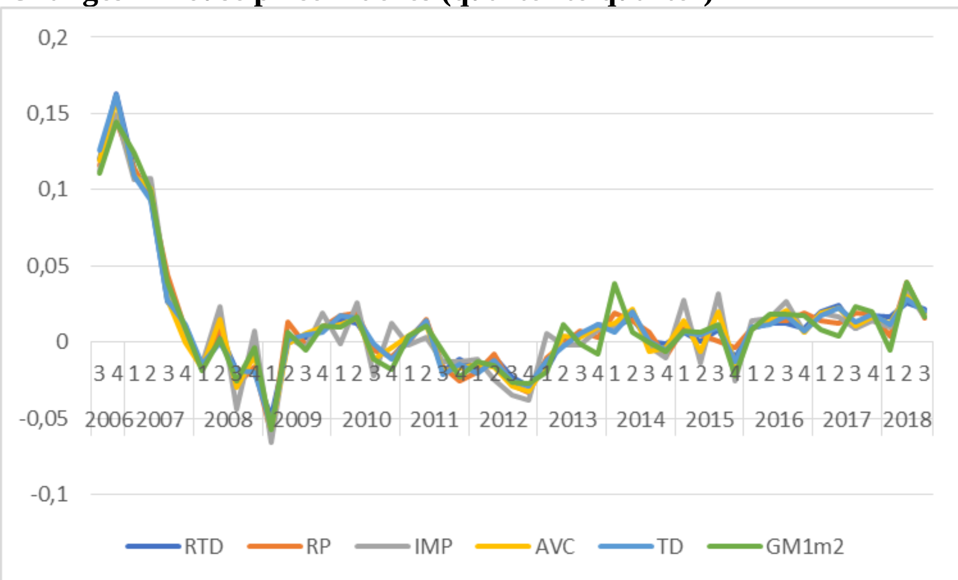
Figure 2. RMSE distance from the RTD method



Source: own calculations

The results suggest that TD is the most similar to RTD and the least similar is imputation method. In Figure 3 the house price changes (quarter to quarter) were computed.

Figure 3. Changes in house price indexes (quarter to quarter)



Source: own calculations

The courses of price changes (q/q) show very similar patterns. Estimated Euclidean distances for these time series based on the same assumptions as for indexes provided slightly different results – in this case IMP is the least similar to RTD. Linear correlation coefficients for changes in house prices quarter to quarter are presented in Table 4 below.

Table 4. Correlation coefficients, using the observations 2006:3 - 2018:3
5% critical value (two-tailed) = 0.2816 for n = 49

RTD	RP	IMP	AVC	TD	GM1m2	
1.0000	0.9802	0.9482	0.9900	0.9969	0.9640	RTD
	1.0000	0.9514	0.9786	0.9824	0.9816	RP
		1.0000	0.9787	0.9498	0.9460	IMP
			1.0000	0.9887	0.9683	AVC
				1.0000	0.9633	TD
					1.0000	GM2

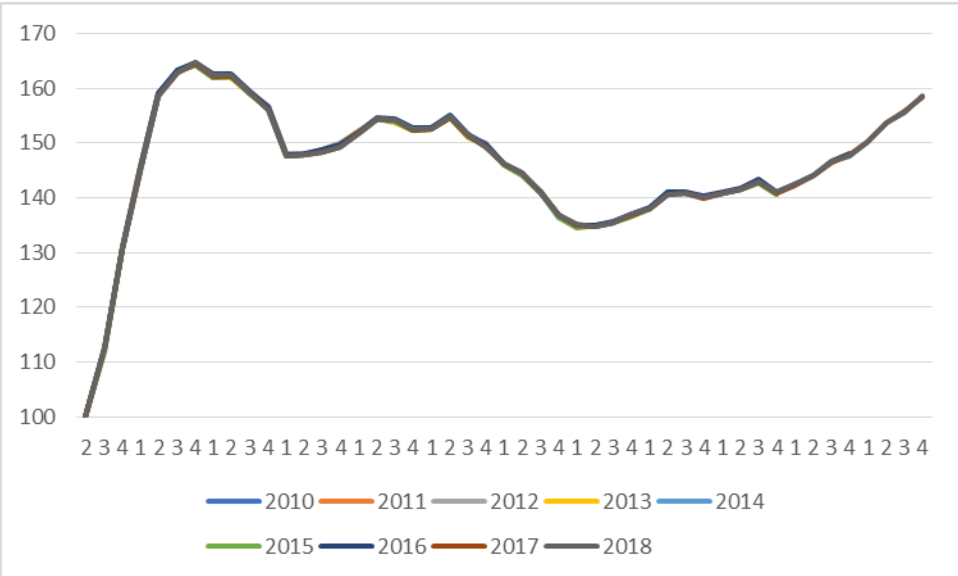
Source: own calculations

The correlation coefficients confirm the earlier results.

3.2 Revision bias in time-dummy indexes

Just like in the case of repeat sales models, the time dummy hedonic method is often criticized for being vulnerable to the influence of transaction revisions in later periods. In order to vcheck this for the case of Warsaw, we tested the resistance of the established price indexes to the inclusion of new time periods. We computed HPIs with the time dummy method for the periods from 2006 to 2010, and then lengthened the temporal sample to include other years. The results are shown in Figure 4.

Figure 4. Time dummy index based on different time scope



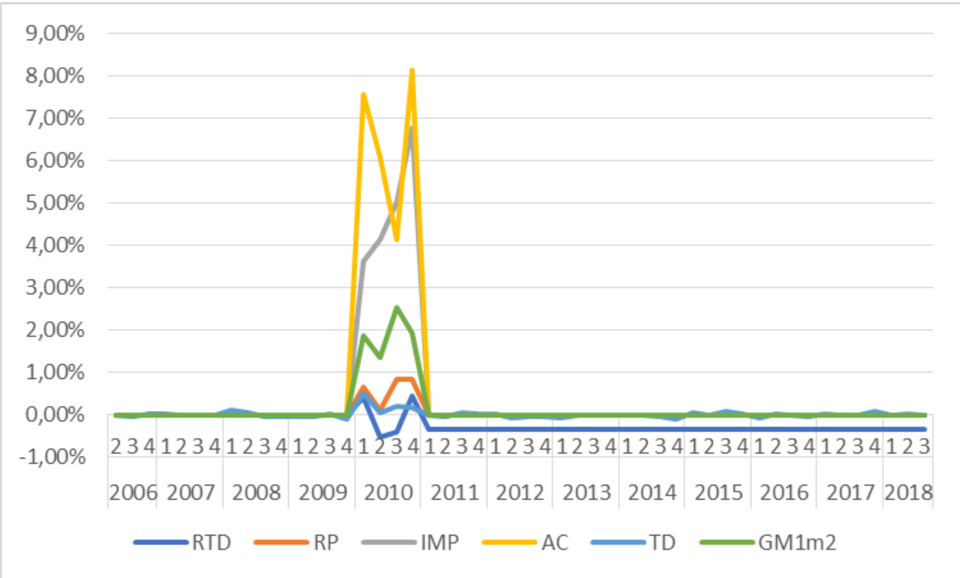
Source: own calculations

We observe no significant changes in the prices of residential properties across quarters depending on the temporal scope of the model, regarding both the size and direction of changes. In other words, adding new quarters does not led to significant variations in the previously identified rates of changes in the prices of apartments The results of the investigation show that for the time-dummy method the problem of revision is of limited significance. Moreover, the established short-term price changes are much more stable than in case of the repeat sales method (see section 4).

3.3 Robustness test on hedonic methods

The results presented in section 3.1 indicate that HPIs constructed with hedonic methods are quite similar. To further check this, we carried out some robustness tests of the sensitivity of selected methods to changes in the structure of sold dwellings. We deleted 3745 observations from the sample – dwellings aged up to 25 years and sold in 2010. After that, we reestimated the hedonic methods. In the next step, we compared the impact of the deletions on the hedonic indexes. The differences in % between indexes are presented in Figure 5.

Figure 5. The differences between indexes based on full sample and subsample in %

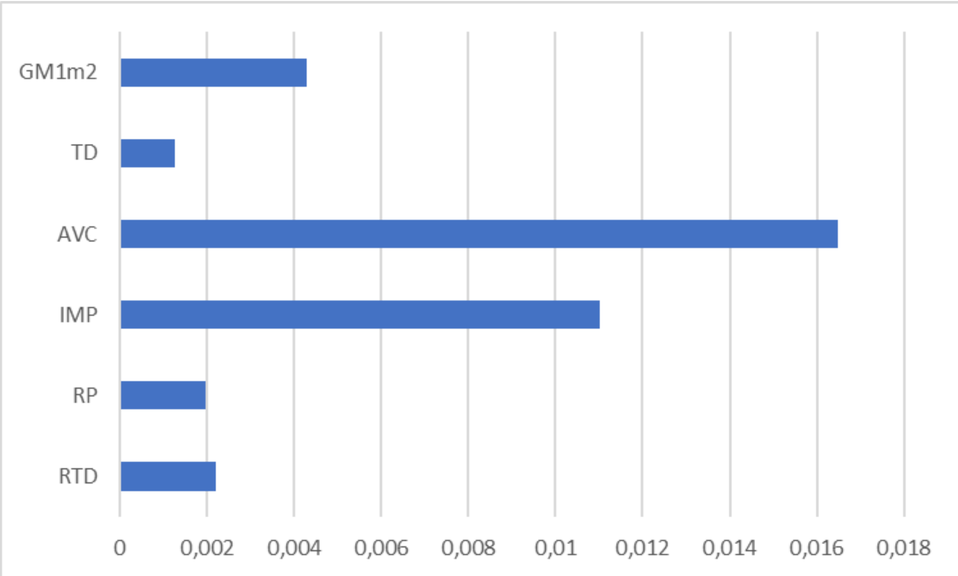


Source: own calculations

Figure 5 reveals that TD, RP and RTD indexes are least affected in 2010 by the deletions. However, it must be stated that the TD and RTD indexes after 2010 are affected as well. In Figure 6, the RMSE between the original and new sample indexes were estimated following the formula:

$$RMSE = \frac{1}{49}\sqrt{\sum\nolimits_{t=2006,q2}^{2018,q2}\left[\ln\left(\frac{p_{new,t+1}}{p_{new,t}}\right) - \ln\left(\frac{p_{old,t+1}}{p_{old,t}}\right)\right]^2}.$$

Figure 6. RMSE between indexes constructed with different samples



Source: own calculations

The results suggest that the TD index is the most robust to changes in structure, although the new TD index is slightly affected in all subsequent quarters. Surprisingly the GM1m2 index performs better than IMP and AVC indexes. The reason is that in the new subsample some districts have no observations in quarters of 2010 year, which distorts the IMP and AVC results. Hence, the GM1m2 method (which only controls for quality with one characteristic) is in this case more robust than some hedonic methods to deletions of data. GM1m2 is similar to a time-dummy hedonic method with area of the apartment as the only explanatory variable. When the other characteristics are reasonably stable from one quarter to the next, GM1m2 performs quite well. This seems to be the case here. In each quarter, there were about 2000 observations, and these subsamples (quarters) did not differ a lot with regard to the average characteristics of dwellings.

4. Repeat-sales methods

The repeat-sale regression method focuses on transaction prices of real estate traded at least twice in the analysed period. This method assumes that in the period between transactions, there were no changes in the qualitative and quantitative characteristics of the analysed properties (Zabel, 1999). Usually, this method is applied to large databases that lack detailed descriptions of the properties.

4.1 Methods considered and potential biases

Bailey, Muth and Nourse (1963) first used the repeat-sales sales (BMN) method to compute residential HPIs. Each pair of properties and, prices and indexes can be presented as follows:

$$\frac{P_{it'}}{P_{it}} = \frac{B_{t'}}{B_t} U_{itt'};$$

where:

P_{it} – the selling price of the *i* house in *t* period,

t – for each pair, the period in which the first sale took place,

t' – for each pair, the period in which the second sale was made ($t' > t$),

$B_t, B_{t'}$ – the price of the period t and t',

$U_{itt'}$ – error term.

By logging both sides, the analysed model can be reduced to a linear auxiliary model:

$$\ln(P_{it'}) - \ln(P_{it}) = \beta_{t'} - \beta_t + lnU_{itt'};$$

where the parameters $\beta_t = \ln(B_t), \beta_{t'} = \ln(B_{t'})$ are estimated using linear least squares regression. The HPI is then obtained by exponentiating $\beta_t, \beta_{t'}$. Further researchers made modifications to the BMN method to improve its results. One of the most significant and widely used improvements was proposed by Case and Shiller (Case & Shiller, 1987, 1989). The authors rejected the assumption of residual variance constancy - they assumed that variance is related to time intervals between transactions. In the BMN model, properties re-sold after a long time (e.g. 8 years) have a strong impact on the index level compared to properties re-sold after a short time (e.g. 2 years between transactions). According to the authors, less importance should be given to repeat transactions after a longer time period (smaller weights in the index). Hence they assume that the longer the time between transactions, the higher the variance of the log price. In the Case-Shiller (C-S) model, the logarithm of a random component $2\sigma_u^2 + (t' - t)\sigma_v^2$ contains the following elements (Nagaraja, Brown, & Wachter, 2014):

- a random error related to the i-th property $(\sigma_u^2 + \sigma_u^2)$,
- random error due to time between transactions for this property $\left((t - t')\sigma_v^2\right)$.

The application of the repeat sales method entails some difficulties. The most frequent criticism is that the repeat sales sample includes only those properties which have been sold more than once. Thus this method is subject to sample selection bias (Case & Quigley, 1991). The repeat sales method is often also criticized for its inefficiency. If we assume that we use only those properties with repeat transactions, and no changes occurred, this method rejects a lot of the data. For example, taking this criterion into account, Case and Shiller (1987) had to reject almost 96% of all available observations. Moreover, frequently sold properties often have worse sets of attributes. The causes of such a situation may be as follows (Bourassa, Hoesli, & Sun, 2006; Costello & Watkins, 2002):

- purchasing a property in order to have it renovated and resold,
- the so-called “first flats” are often smaller, having a lower standard and being characterised by more frequent rotation,
- residential properties which do not meet new buyers’ expectations,
- hidden troubles related to a given property, which were not identified during purchase or which did not occur then (e.g. a troublesome neighbour).

Another possible problem may be so-called fast sales, i.e. the situation in which a flat becomes the subject of a transaction in a short period between two consecutive sales. This may be the result of speculative behaviours, forced sales, or purchase with the intent to improve the condition of a flat and then resell it. In the literature on the subject, it is recommended that such pairs of transactions should be removed because they lack free market characteristics and the criterion of the unchanged standard of a residential property is not fulfilled. Moreover, such transactions offer high rates of return, much higher than is the case for other transactions (Jansen, De Vries, Coolen, Lamain, & Boelhouwer, 2008).

Table 5. Studies in which the repeat sales method was applied and the percentage of repeat sales in total.

Id	Authors	Location	Time scope	Number of transactions	Number of repeat-sales	The share of repeat-sales in total transactions (%)
1	(Mark & Goldberg, 1984)	Fraser, Kerrisdale (Canada)	1957-1979	8488	2723	32.08%
2	(Englund, Quigley, & Redfearn, 1998)	8 region (Sweden)	1981-1993	533.894	109.931	20.59%
3	(K. E. Case & Shiller, 1987)	Atlanta, Chicago, Dallas and San Francisco (USA)	1970-1986	952.606	78.420	8.23%
4	(B. Case & Quigley, 1991)	Kahala region (USA)	1980-1987	408	108	26.47%
5	(Nagaraja et al., 2014)	20 cities (USA)	1985-2004	3.691.274	1.948.001	52.77%

6	(X. Liu, 2014)	Sydney (Australia)	2001-2009	338.526	114.217	33.74%
7	(R. C. Hill, Knight, & Sirmans, 1997)	Baton Rouge (USA)	1985-1990	3723	694	18.64%
8	(Meese & Wallace, 1997)	Oakland and Freemont (USA)	1970-1988	51.014	6747	13.23%
9	(Leishman & Watkins, 2002)	Aberdeen, Dundee, Edinburgh, Glasgow (Great Britain)	1983-1999	402.405	200.780	49.90%
10	(Bourassa et al., 2006)	Region Auckland, Wellington and Christchurch (New Zealand)	1989-1996	167.645	36.571	21.8%
11	(Mcmillen, 2012)	Chicago (USA)	1993-2008	168.842	51.658	30.63%
12	(Shimizu, Nishimura and Watanabe, 2010)	Tokyo (Japan)	1986-2008	157.627[1] 315.791[2]	67.436 19.428	42.78% 6.15%
13	(Jansen et al., 2008)	The Netherlands	1993-2006	2.476.726	736.041	29.71%
14	(Głuszak, Czerski, & Zygmunt, 2018)	Cracow (Poland)	2002-2015	58.739	5998	10.21%
15	(Trojanek, 2018)	Poznań (Poland)	2000-2015	38.798	6972	17.9%

Source: Own assessment based on the literature

Another problem connected with the repeat sales method is that the index is revised as new periods become available (Clapp & Giaccotto, 1999). The research conducted by Abraham and Schauman (1991), which involves a large number of transactions, reveals considerable differences. Similar conclusions were reached by, among others, Hoesli et al. (1997).

Studies of the causes of price differences in the case of revisions (Clapp & Giaccotto, 1999; Steele & Goy, 1997) emphasise the need to remove the so-called "fast transactions" from a database. The prices of properties sold twice within one or two years behave differently from other repeat sales (prices have increased more). What is more, a short time between sales might indicate that properties were purchased to be renovated and sold quickly (or that no investment was made to improve the standard of property, and that it was bought below its market value).

Another possible concern is the assumption that location quality does not vary over time. However, the literature shows that different phenomena affecting the housing market may make some locations more attractive and others less attractive. Changes in legal rules, construction of new subway lines, environmental pollution all may happen between two sales and cause changes in the perceived attractiveness of a location.

The repeat-sales method uses only data related to the transaction prices and dates of two consecutive transactions, not requiring data on the qualitative and quantitative attributes of a

[1] listings of dwellings in multi-family buildings
[2] listings of houses

property. The main advantages and disadvantages of the repeat sales method are presented in Table 6 (Eurostat, 2013; Haurin, Hendershott, & Kim, 1991; Hill, 2013).

Table 6. Advantages and disadvantages of the repeat-sales method

Advantages	Disadvantages
• it does not require detailed information concerning the sets of attributes of property; • location is directly controlled; • standard specifications of the method are easy and quickly estimated.	• it uses only the information about those properties that were the subject of a transaction more than once in the period under study • new properties are automatically rejected from the analysis; • no possibility of building separate indexes for buildings and land; • as the result of a revision, it does not take into consideration changes in the surroundings of property (both positive and negative changes in the neighbourhood); • difficulty in building indexes with a frequency lower than one quarter (e.g. due to too few pairs of properties sold at least once); • no possibility of building regional price indexes, because the same house cannot be sold in two locations; • the assumption that the quantitative and qualitative sets of attributes are controlled is not always met. • properties which are frequently sold are not a good representative sample.

Source: Own assessment based on the literature

4.2 Sample selection issues

The existing body of literature on the subject provides an extensive discussion on the deficiencies of the repeat sales method, such as a different structure of apartments sold or the so-called fast transactions. Using the Warsaw database from the second quarter of 2006 to the third quarter of 2018 (total number of transactions: 101182), we identified 20853 cases of repeat transactions (20% of the total). The frequency of repeat sales for dwellings is shown in Table 7.

Table 7. The frequency of repeat sales

Number of sales	Number of dwellings	Number of transactions
7	1	7
6	1	6
5	10	50
4	70	280
3	712	2136

2	9187	18374
1	80329	80329

Source: own calculations

In order to verify the problem of fast sales in the case of Warsaw, we identified the monthly rates of return of all pairs of transactions, taking into consideration the number of months between transactions. To this end, we used the following formula (Jansen, De Vries, Coolen, Lamain, & Boelhouwer, 2008):

$$R = \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) * \left(\frac{1}{d}\right) * 30 * 100\%$$

where:

R – monthly rate of return,

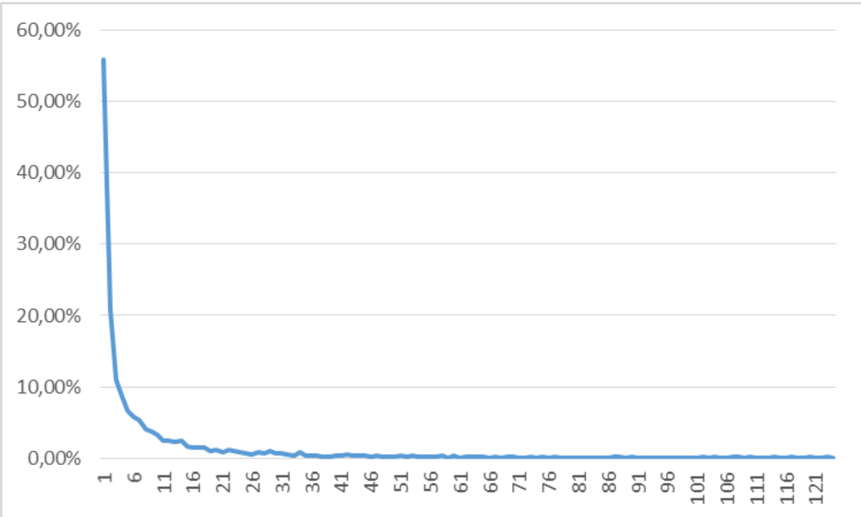
P_t – the transaction price for a given property in the later period,

P_{t-1} – the transaction price for a given property in the earlier period,

d – the number of days between the two transactions.

Figure 7 shows monthly rates of return on the sale of residential properties between transactions.

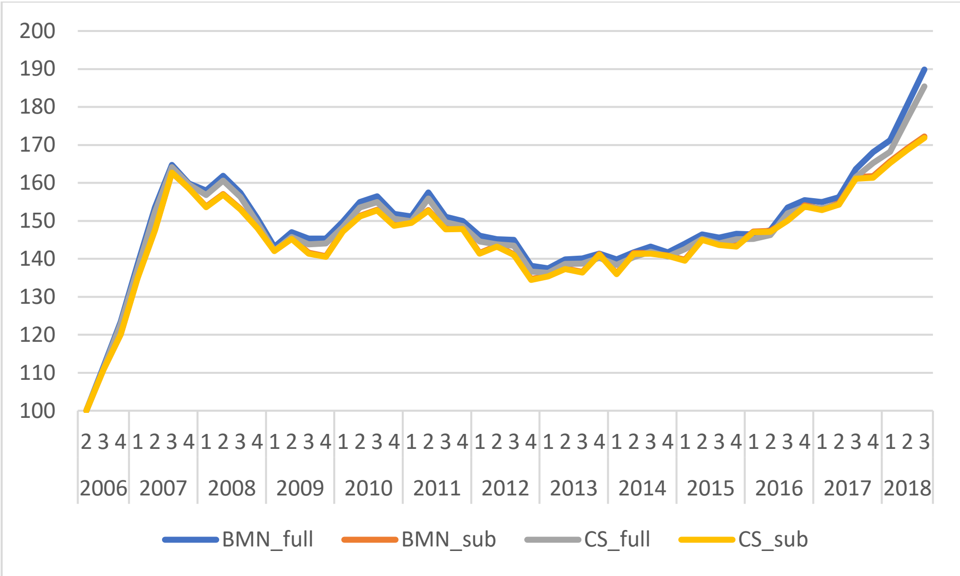
Figure 7. Monthly rates of return on the sale of residential properties taking into consideration the number of months between the transactions



Source: Own calculations.

The results confirm the high variability of the rates of return on the residential properties resold within the period of up to a dozen or so months. For example, a mean rate of return was 55.8 %, 15.64%, 10.93%, 3.58% and 0.46% in the case of flats resold within the period of, respectively, up to one month, six months, 12 months, all periods in total, and in the period from the 13th month to the last period. The rates of return presented above show that if we take into account residential properties bought for “fast sale”, the index based on the repeat sales method may be biased. In Figure 8, HPIs based on the BMN and C-S methodologies using all repeat sales (BMN_full, CS_full) and subsamples excluding repeat transactions in the same year (BMN_sub, CS_sub) are presented.

Figure 8. Comparing repeat-sales indexes



Source: own calculations

The indexes based on the same methodological assumptions are very similar in terms of both direction and strength. The indexes based on all repeat transactions showed the highest increase of 190% (BMN specification), 185% (CS specification) compared to an increase of about 172% based on the subsamples excluding repeat transactions in the same year (BMN and CS specifications). The results confirm that fast transactions may distort the repeat sales index.

In the next step Table 8 below presents the structure of residential properties sold in Warsaw in the years 2006-2018, divided into repeat and single transactions, taking into consideration location and mean sets of attributes (the height of a building, the age of a building at the time of a transaction, construction technology, floor size).

Table 8. The structure of residential properties sold in Warsaw in the years 2006-2018

Variable	Single sales	Repeat sales
d1-Bemowo	5,41%	4,02%
d2-Białołęka	9,61%	7,94%
d3-Bielany	5,48%	5,25%
d4-Mokotów	15,78%	16,43%
d5-Ochota	6,13%	7,28%
d6-Praga-Południe	9,76%	10,08%
d7-Praga-Północ	3,44%	3,78%

d8-Rembertów	0,80%	0,60%
d9-Śródmieście	10,40%	13,96%
d10-Targówek	4,47%	3,87%
d11-Ursus	4,02%	3,25%
d12-Ursynów	6,10%	4,62%
d13-Wawer	1,28%	1,46%
d14-Wesoła	0,83%	0,64%
d15-Wilanów	2,82%	2,37%
d16-Włochy	1,77%	1,61%
d17-Wola	9,66%	10,68%
d18-Żoliborz	2,23%	2,16%
Mean of LUA	13,15%	10,39%
Mean of garage	27,91%	25,78%
Mean of basement	42,07%	49,47%
Mean of area	53,75	50,16
Mean of age	31,87	36,80
Mean of height	0,52	0,51
Mean of technology	1,77	1,76
Mean of park	549,90	528,17
Mean of school	453,84	426,61
Mean of price	431 798,69	421 669,24
Mean of price1m2	7897,20	8164,54
N	80329	20853

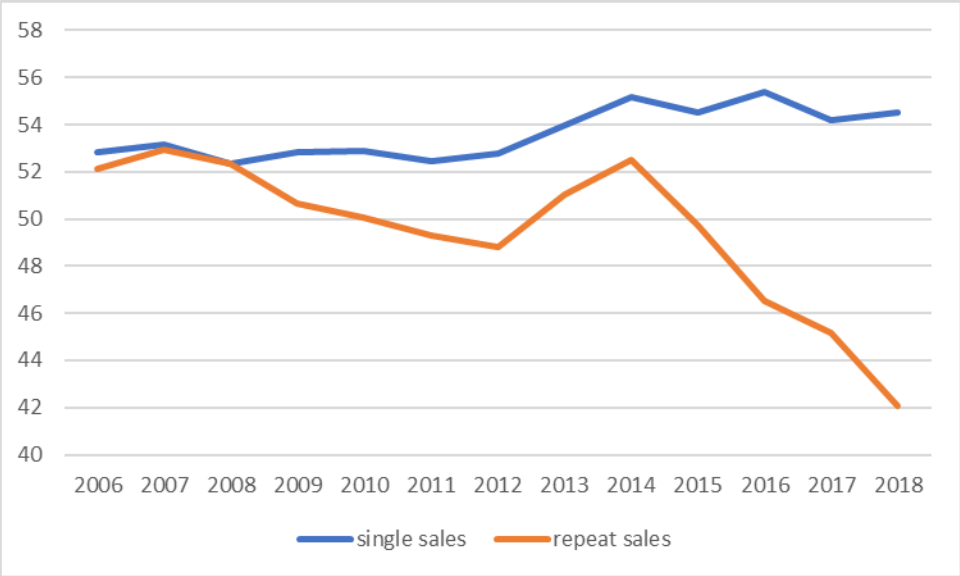
Source: own calculations

Table 8 reveals some differences in the structure of residential properties sold. The flats that had been sold more than once had:

- worse sets of attributes than the other properties in case of the average age (older) and the average area of flats (smaller),
- better sets of attributes than the other properties in case of location in better districts (e.g. district 9 – the most valuable or location in LUA).

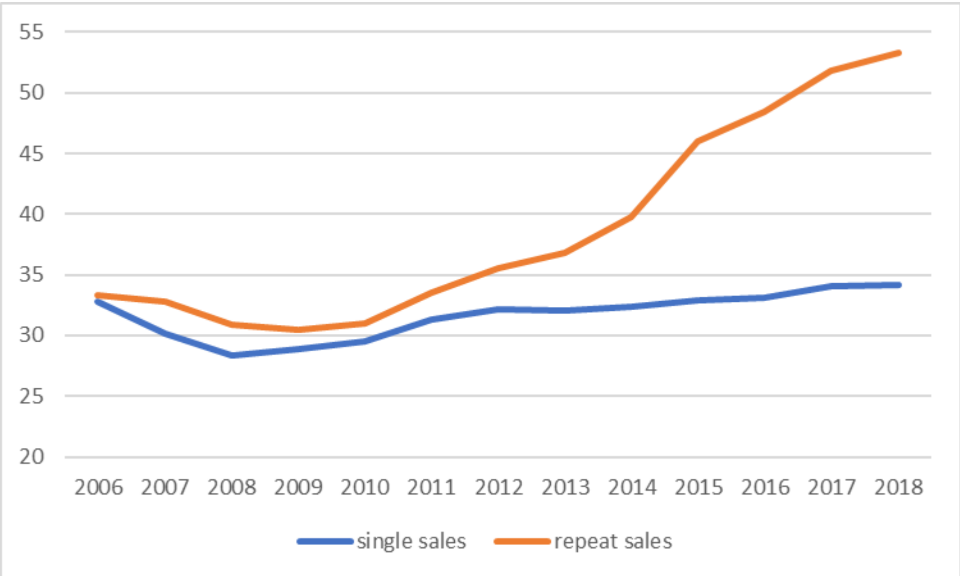
The difference in the structure of sold dwellings have grown over time, as can be seen from Figures 9 and 10.

Figure 9. Average area of a dwelling



Source: own calculations

Figure 10. Average age of a dwelling

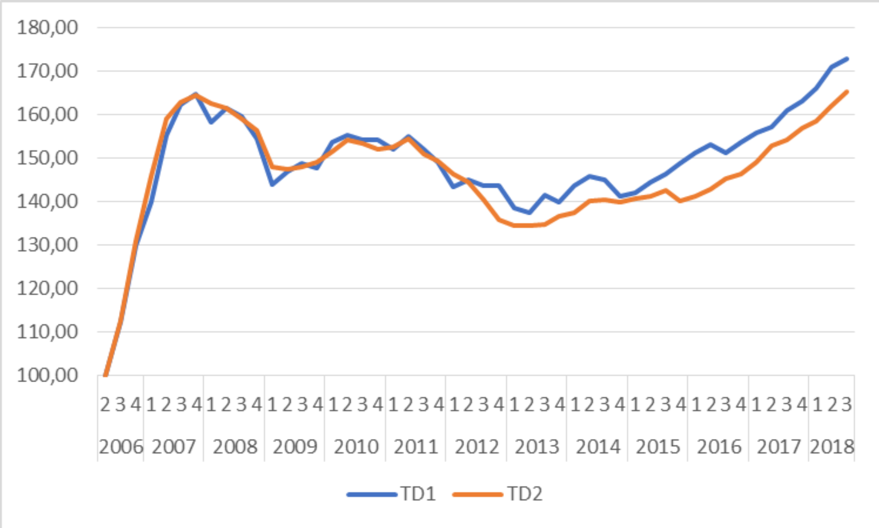


Source: own calculations

On the other hand, it must be noted that these differences were not huge. In order to check the sample selection bias we computed two time-dummy indexes as shown in Figure 11, one based on repeat sales observations (without repeat transactions that took place in the same year)

– TD1 and the other based on single sales – TD2. If there is no sample selection bias the indexes should be similar.

Figure 11. Time-dummy indexes computed using the full sample and repeat-sales sample



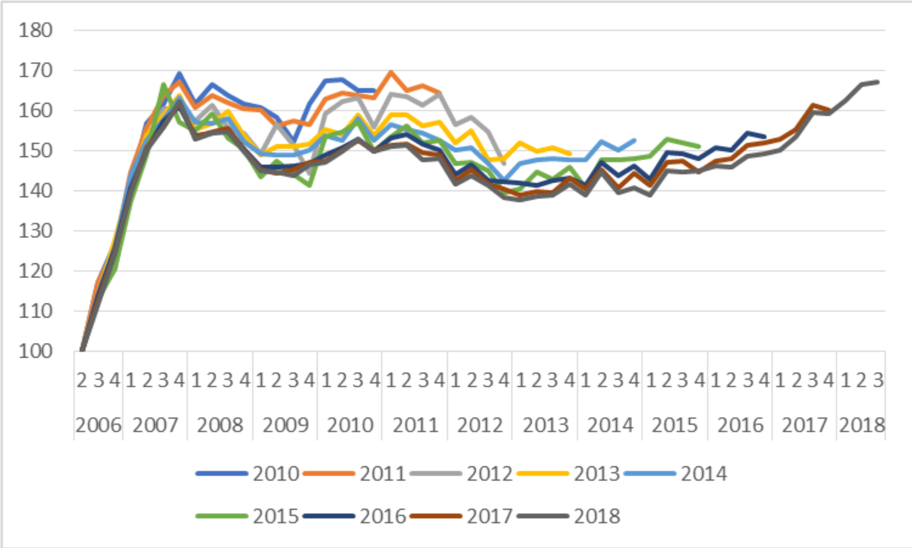
Source: own calculations

The presented time-dummy indexes show different trends confirming the sample selection differences and potential bias in the use of the repeat sales method. The presented comparison therefore supports some of the criticisms of repeat sales methods from earlier studies.

4.3 Revision issue

The repeat sales method is often criticized for being vulnerable to the influence of transaction revisions in later periods. In order to verify this phenomenon in the case of Warsaw, we tested the impact on an HPI of the inclusion of new time periods. We computed price indexes with the repeat sales method (BMN_sub) over the period 2006 to 2010, and then lengthened the temporal scope to include more years.

Figure 12. Repeat sales index based on different time scope



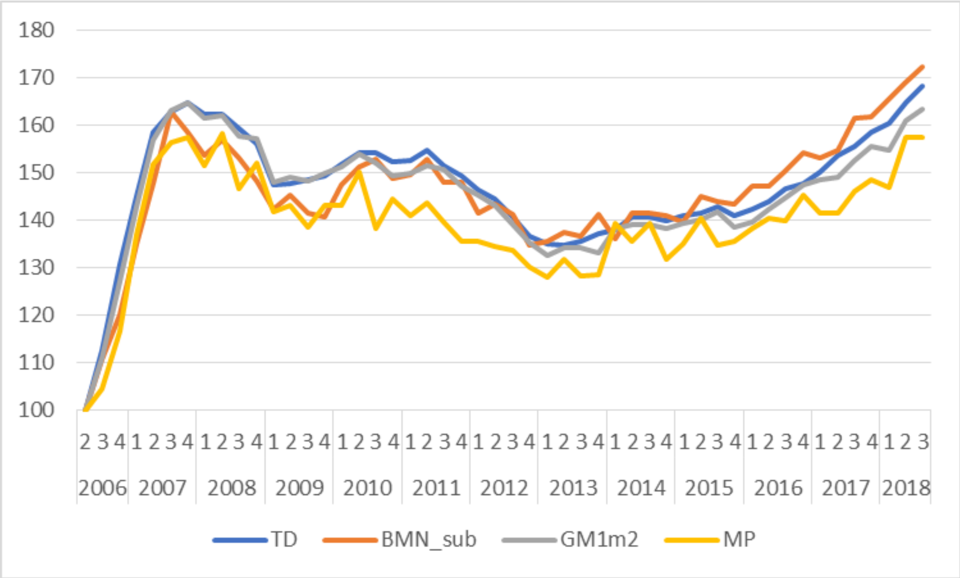
Source: own calculations

We observe significant changes in the prices of residential properties across quarters depending on the temporal range of the model, both in the size and direction of changes. A comparison of Figures 4 and 12 reveals that the repeat-sales method is much more sensitive to revisons than the hedonic ttime-dumy method. In other words, for the repeat-sales method, adding new quarters of observations led to significant variations in the previously identified rates of changes in the price of flats. This raises the possibility that, in the case of Warsaw in the years 2006-2018, the measured short-term price changes obtained from a repeat-sales model are unreliable and unstable.

5. Comparison of hedonic with repeat-sales methods

Due to the specific nature of real estate as an object of trading, its physical and economic characteristics, market transparency in terms of transactions, and delays in access to information on price or value, the construction of HPIs is a real challenge. In Figure 13 we compare the theoretically weakest index – a simple geometric mean price (MP) – with: time dummy index (TD), BMN repeat-sales index excluding repeat sales within the same year (BMN_sub) and geometric mean of 1 square meter (GM1m2).

Figure 13. A comparison of price indexes



Source: own calculations

HPIs based on the same data, although differing in methods and assumptions, show similar trends for Warsaw between 2006 and 2018. This is also confirmed by the linear correlation coefficients in Table 9. The price increase in the analysed period was different and ranged from 57% to 72%.

Table 9. Correlation coefficients, using the observations 2006:2 - 2018:3
5% critical value (two-tailed) = 0.2787 for n = 50

TD	BMN_sub	GM1m2	MP	
1.0000	0.9352	0.9927	0.9531	TD
	1.0000	0.9103	0.9089	BMN_sub
		1.0000	0.9646	GM1m2
			1.0000	MP

Source: own calculations

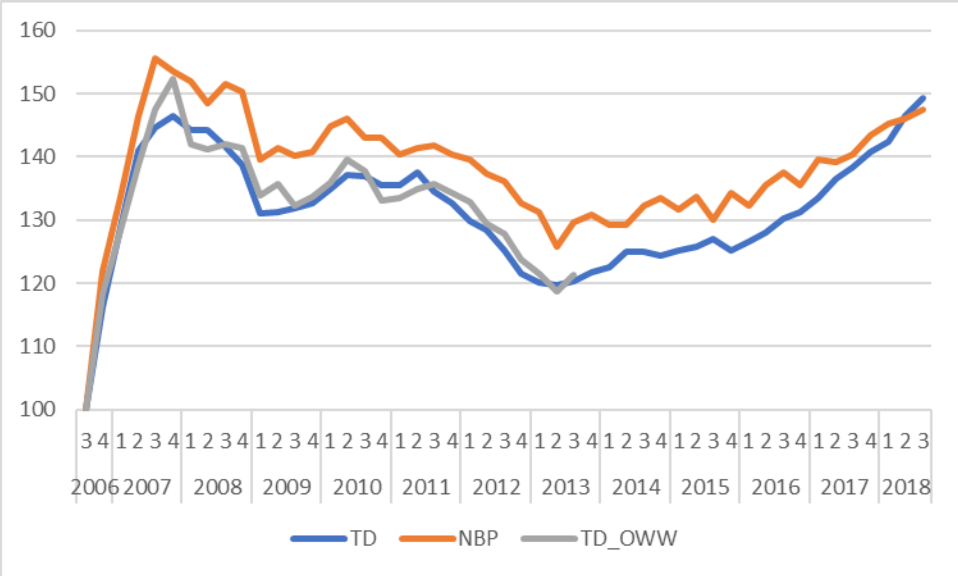
An interesting aspect of the results is that GM1m2 quite closely approximates the time-dummy method. Given that GM1m2 requires less data (only price and floor area) and is easier to compute, one might legitimately ask whether the greater accuracy of time-dummy is worth the cost. One answer is that while GM1m2 performs adequately when the other characteristics (especially location) are reasonably stable from one period to the next, when something unexpected happens it may generate quite misleading results. For example, suppose that the proportion of properties traded in expensive locations rises in period *t*+1. In this case, GM1m2 will have an upward bias from period *t* to *t*+1.

With regard to the choice between time dummy and RTD, it should be remembered that we only consider the two-quarter RTD method. The rolling window could be extended to include 3, 4, 5 or indeed any number of quarters. As the window length increases, in the limit the RTD method onverges on the time dummy method. Also, although we find that the time dummy method is more robust to the deletion of data, the RTD method (with a relatively short window) has the advantage of being more responsive to the latest developments in the hosuing market. In particular, it may more accurately detect turning points.

6. A Comparison with the National Bank of Poland (NBP) index

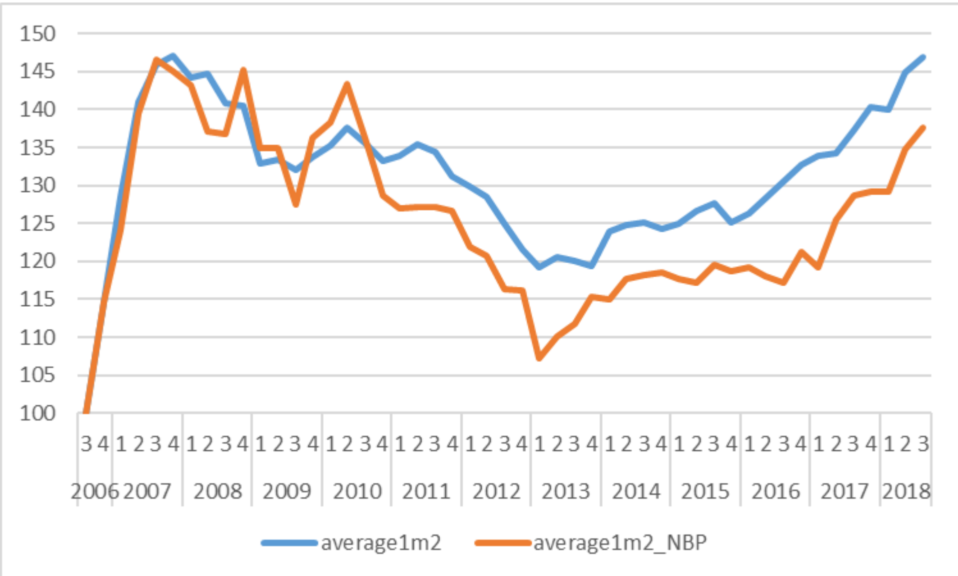
The NBP index is compared with our time-dummy index and the index constructed by Olszewski, Waszczuk and Widłak (OWW) (2013) in Figure 14 below. We include the OWW index because it was constructed using the hedonic time-dummy method from the same dataset as the NBP index (4037 transactions for the years 2006-2013). We do not attempt a comparison with the Statistics Poland index since that index only begins in 2015. One thing both the NBP index and our index agree on is that real estate prices rose very rapidly in 2006-7 before then falling until the end of 2012, since when they have again risen quite strongly. However in 2006-7 prices did not rise as much according to our index, while since the end of 2012 prices have risen faster than indicated by the NBP. The differences between the our time-dummy index and the NBP index arise from both the different hedonic methods (the NBP uses the hedonic imputation method) and differences in the underlying datasets. Our dataset is larger, particularly for the earlier years in the sample. Our index is quite similar to the OWW index. This suggests that time-dummy indexes are quite resistant to the problem of sample size (representativeness). Differences arising from the underlying data are further explored in Figure 15 which plots average 1m2 indexes computed from each dataset.

Figure 14. Comparison of our time-dummy hedonic index with the NBP index



Source: own calculations

Figure 15. Comparison of average 1m2 indexes for our dataset versus the NBP dataset



Source: own calculations

As can be seen from Figure 15, when the same average 1m2 formula is used the two indexes track each other reasonably closely for most of the sample period, although big differences emerge in 2010. All the hedonic indexes in Figure 14, however, control for these differences in 2010. Hence the divergence between the NBP index and our index in 2006-7 observed in Figure 14 seems to be driven more by formula differences than differences in the underlying data.

7. Conclusions

In this research different methods for computing HPIs have been examined using a large dataset of apartment transactions in Warsaw over the period 2006-2018. Taking into account that gathering data, cleaning and adding additional information on property sales is expensive and time consuming, the aim of the paper was to check the pros and cons of each method. Mark and Goldberg (1984) defined features that HPIs should have: the concept of the index should be directly related to theory, it should not be excessively complicated or expensive to compute, and it should maintain relative stability and be resistant to changes in the structure and characteristics of transacted real estate in subsequent periods. We have carried out different tests in order to indicate the strengths and weakness of competing methods.

The repeat sales method performs poorly for two reasons. Firstly, there were significant differences in growth rates of residential prices in the quarters depending on the time scale of the model, both in terms of magnitude and direction of change. In other words, the addition of subsequent quarters of observation caused significant changes in the previously determined rates of changes in the prices of apartments. The short-term price changes determined with repeat sales are unreliable and unstable over time. Secondly, we have identified sample selection and fast transactions as the main causes. We did not find noticeable differences between the BMN and CS versions of the repeat sales method. Hence giving lower weight to repeat sales with longer time intervals does not help to reolve these probelms

As far as hedonic methods are concerned, our results show that the repricing method, rolling time dummy (2 quarters window) and the time dummy model performed best. Revisions to time-dummy indexes arising from the inclusion of new time periods were minimal, and hence this was not a problem.

Moreover, these models are more robust to structural changes in sold apartments, irrespectively of whether the change in the sales structure results from the actual situation on the market or from shortages in the database (e.g., not all information has been collected).

Even though the imputation and average characteristic methods (the former of which is used by the National Bank of Poland) showed similar price changes to the other hedonic indexes, they turned out to be the most vulnerable to changes in the structure of transacted apartments. Moreover, the large variations in the ranges of regression coefficients for the same variable that arise when models are estimated separately for each quarter is a cause for concern. In reality such differences may occur for legitimate reasons (e.g. opening a new metro line or establishing a limited use area). In other cases, such differences may be spurious.

Our results were based on a large dataset of information on transaction prices (101182 observations) and detailed descriptions of each property (in the hedonic models 31 variables were used). The results show the superiority of hedonic methods that control for quality and quantity changes. With a large number of observations, the risk of large changes in the structure or location of sold apartments is relatively low. It seems that the greater risk is the lack of representativeness of the collected data. Overall, we recommend using either the time dummy or RTD methods. While the time-dummy method may be more robust to shocks, the RTD may better capture current trends in the real estate market.

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