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Robert J. Hill
(University of Graz, Austria)
robert.hill@uni-graz.at

Norbert Pfeifer
(University of Graz, Austria)
nobert.pfeifer@uni-graz.at

Miriam Steurer
(University of Graz, Austria)
miriam.steurer@uni-graz.at

Radoslaw Trojanek
(Poznań University of Economics and Business, Poland)
radoslaw.trojanek@ue.poznan.pl

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Warning: Some Transaction Prices can be Detrimental to your House Price Index

Robert J. Hill[a], Norbert Pfeifer[a], Miriam Steurer[a], and Radoslaw Trojanek[b]

[a]University of Graz, Department of Economics, 8010 Graz, Austria,
robert.hill@uni-graz.at, nobert.pfeifer@uni-graz.at, miriam.steurer@uni-graz.at

[b]Poznan University of Economics and Business, Poland,
radoslaw.trojanek@ue.poznan.pl

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Abstract

There is a broad consensus in international statistical organizations such as Eurostat and the International Monetary Fund that house price indices (HPIs) should be constructed using transaction data. However, transaction data for newly-built properties lag behind actual market developments as prices are typically set months or years before transactions are finalized. We find that for two Polish cities (Warsaw and Poznan), HPIs for existing properties lead indices for new builds by up to two years. This lag can dramatically distort National HPIs. The lag also has implications for the flagship measure of inflation in Europe, the Harmonized Index of Consumer Prices (HICP), since it is planned to include owner-occupied housing in the HICP using a transactions HPI specifically for new builds. We show that the timeliness issue disappears when preliminary agreements on new builds are used instead of transactions in the compilation of an HPI. (JEL Codes: C43; E01; E31; R31)

Keywords: Hedonic quality adjustment; Dissimilarity metric; HICP; Macroprudential supervision; Timeliness; Primary and secondary housing markets

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1 Introduction

House price indices (HPIs) have multiple purposes; they inform the public, banks, financial markets, and government of developments in the housing market. HPIs are also important for macro-prudential supervision, given that housing booms and busts can undermine financial stability. The state of the housing market can also affect monetary policy.[1]

Transaction prices – the prices registered when transferring ownership between seller and buyer – have long been considered the gold standard for computing price indices. In particular, Article 3(3) of European Union (EU) Regulation No 2016/792 states that only monetary transactions can be used in the Harmonized Index of Consumer Prices (HICP) in Europe (European Commission, 2018).[2]

In a housing context, the need for transaction prices is stressed in the Eurostat Handbook on Residential Property Price Indices (Eurostat, 2013), Eurostat's Detailed Technical Manual on Owner-Occupied Housing for Harmonised Index of Consumer Prices (Eurostat, 2017), and the International Monetary Fund's compilers' guide (International Monetary Fund, 2020). All these publications recommend transaction prices over the alternatives – appraisals, surveys, and list prices.[3]

However, transaction-based HPIs have a problem. They are affected by time lags that can undermine the timeliness, coherence, and usefulness of both an HPI itself and broader consumer price indices that include HPIs as sub-components. Part of the reason for the time-lag is that it takes time for transactions to be recorded and made available to Land Registries. This problem is well-known and has been previously discussed in the literature (Shimizu et al., 2016).

[1]Inflation targeting central banks sometimes raise interest rates to lean against housing booms or lower rates to help the housing market recover after a crash.

[2]The HICP is the flagship consumer price index (CPI) in the EU used by the European Central Bank (ECB) for price stability purposes and for assessing whether countries are ready to join the Euro area. It is jointly compiled by Eurostat (the statistical institute of the European Union) and national statistical institutes of the EU member states following a harmonized statistical methodology.

[3]Appraisal indices tend to be too smooth and backward-looking (Cole et al., 1986; Geltner et al., 2003; Diewert and Shimizu, 2017; Silver, 2016), which is a particular concern for monetary policy and macro-prudential supervision. Survey data likewise tend to be backward-looking and suffer from participation bias as not all sampled households/firms are equally likely to respond. Finally, list prices are typically higher than transaction prices, subject to revision over time, and sometimes do not lead to actual transactions (Shimizu et al., 2016; Anenberg and Laufer, 2017; Lyons, 2019; Kolbe et al., 2021).

Here we focus on a second less appreciated reason why transaction-based indices lack timeliness. In this regard, a distinction needs to be drawn between two sub-categories of residential housing markets: The market for newly-built properties (also called the "primary market") and the market for existing properties (sometimes referred to as the "secondary market"). A timeliness problem exists for new-builds, since prices are typically set when the preliminary agreement is signed. This could be at any stage throughout the building process, and thus months or years before the transaction is completed and entered into deed books. How problematic this lag is for an overall HPI depends on when, in the construction process, contracts for new builds are typically signed and on how large a share new builds have in total housing transactions. Our focus here is on apartments. We use the term "new build" to refer to new apartments that are built and sold by property developers.

In our empirical analysis, we focus on the case of Poland, a country in which around half of the residential property transactions consist of new-builds and which has relatively good micro-level data. We are not the first to explore the relationship between the market for new-builds and existing properties in Poland. Leszczyński and Olszewski (2017) examine the reaction of housing markets in Polish cities to changes in economic fundamentals (e.g., the unemployment rate, income growth, or real interest rates). Our work also relates to Brzezicka et al. (2021), who compare the magnitude of the relative up-and down-movements for new-builds and existing properties for 17 cities in Poland. However, our focus is different to these studies in that we analyze how the time lag between the signing of preliminary agreements for new-builds and their final transactions affects the timeliness (and accuracy) of an overall transaction-based HPI.

Our analysis is made possible by our combining of micro-level data from multiple sources for two major Polish cities (Warsaw and Poznan) (see section 2 for a description of our data). We measure the time-lag between different sub-indices using variants of dissimilarity metrics proposed by Diewert (2002, 2009). While these metrics were initially designed to compare vectors of relative prices across countries, we deploy modified versions of them to measure the similarity between price developments in the new build and existing property sub-categories of the housing market.

Based on these metrics, we find that the price index for new-builds lags that of existing properties by eight quarters in Warsaw and six quarters in Poznan. The lag is very clear during booms and busts, but less apparent during normal market conditions. However, it is precisely during booms and busts that accurate HPIs are most needed. Such long lags imply that transaction-based HPIs will be less useful for macro-prudential supervision purposes, and as a signal to market participants and government regarding current developments in the housing market. Also, the lag has implications for the flagship measure of inflation in Europe – the Harmonized Index of Consumer Prices (HICP) – since it is planned to include owner-occupied housing (HICP) using a transaction-based HPI focused specifically on new builds (Hill et al., 2020).

A potential solution to the timeliness problem with respect to newly-built properties would be to include them in the price index when the preliminary agreement is first signed, rather than when ownership is transferred on completion of the project. However, as Land Registry offices do not currently generally collect information on these preliminary agreements, new EU-wide legislation may be needed to address this data gap. It is also debatable whether such a solution would violate the European Commission's requirement that only market transactions be used in official indices. For an HPI, an alternative solution is to focus only on the market for existing properties, although in countries such as Poland in which new builds have large market shares, this would imply ignoring a significant part of the overall housing market.

The remainder of this paper is structured as follows: Section 2 describes our dataset. In section 3, we develop the methods used in the empirical analysis and present our results. We explore the implications of our results in section 4. Our main findings are summarized in the conclusion in section 5.

2 Data

After the massive restructuring following the political transformation in 1989, Poland today has a high share of owner-occupiers. Eighty-five percent of the population live in self-owned properties, which puts Poland into the group of member states with the highest owner-occupier share within the European Union (Eurostat, 2020).

While the ownership structure changed very quickly after the fall of communism, the change of physical building structure is an ongoing process. Driven by strong economic growth – and the need for updating the communist-era housing stock – the Polish building industry brings a large number of new builds (particularly apartments) onto the market each year. As a result, sales for new builds account for around 50 percent of residential housing transactions in larger Polish cities (and more than 30 percent in Poland as a whole).[4]

This paper concentrates on two cities: Warsaw, the capital and – with 1.794 million inhabitants – also the largest city in Poland, and Poznan, Poland's fifth-largest city with 0.535 million inhabitants. We restrict our analysis to apartments as they account for the vast majority of residential transactions in Polish cities.[5] Table 1 illustrates the differences in price levels between the two cities.

We collected time series of micro-level data for both cities. Collecting such data in Poland is difficult, as the quality of transaction data differs substantially between different regions and across different ownership structures. In particular, access to transaction data differs for properties with outright ownership rights (around 75 percent of apartment transactions) versus properties with cooperative ownership rights (around 25 percent of apartment transactions). Multiple IT systems and 380 different data collection units are involved in registering outright ownership transactions, which – so far – are not combined into one official database in the Property Prices Register (PPR). Finding transaction prices of apartments with cooperative ownership rights is even more difficult. The Polish legal system does not count these transactions as real estate transactions, and they are not recorded in the PPR. Obtaining information on these transactions is very time- and cost-intensive, as they are stored in around 3600 separate cooperatives in Poland. For more information on the data situation in the Polish real estate market, see Trojanek (2018, 2021).

To increase the information content for each transaction, we include multiple data sources.

[4]Precise information on the number of transactions on the Polish residential market is not available but can be estimated based on two sources: a survey by Statistics Poland and information from the Ministry of Justice on the number of notarial deeds concluded (which includes all types of properties). Both of these data sources have some limitations. Statistic Poland estimates are based on data from the Property Price Register, which does not include transactions of cooperatively owned properties. Also, only about 80 percent of real estate transactions are recorded in the Property Price Register. On the other hand, while the Ministry of Justice data counts all property transactions, it is not always clear under which category they fall.

[5]According to the 2011 *National Census of Population and Housing* (https://stat.gov.pl/en/national-census/), apartments account for 80 percent of dwellings in Polish cities. This share is still higher in larger cities, such as Poznan and Warsaw.

The transaction data for Warsaw come from the Property Price Register in Warsaw. It generally contains the following information: accurate location, the transaction date, transaction price, the size of an apartment (in m^2), the story in which the apartment is located, the number and area of any auxiliary premises (e.g., a garage/parking spot in an indoor car park or the cellar/residents' lockup), and whether the property is a new-build. The dataset covers the period 2006Q2 to 2019Q4. The yearly number of unique transactions ranges from 5 960 and 27 360 observations. The number of properties entered into Warsaw's Property Price Register has increased over time due to an increased effort by the authorities.

The transaction data for Poznan comes from the Property Price Register, notarial deeds, and information gathered from housing cooperatives. The Poznan dataset covers the period 2004Q1 to 2019Q4.

The Property Price Register in Warsaw provided the information on preliminary contacts. Preliminary contracts for purchasing an apartment are often signed at the beginning of the construction process, which implies that the transaction price is often set many months before the final transaction occurs (and is registered). The preliminary contract date was available for 61 868 new-built property transactions. The average number of days between the preliminary agreement and final transactions was around 530 days.

We linked the cadastre data to both the transaction and preliminary-agreement datasets, which provided additional information on new-builds, such as the number of stories or the age of the building.[6] For some existing properties in our dataset, no entries in the cadastre dataset existed. In these cases, we estimated the building height and building age via the "street view application" on maps.google.com. The generation of the dataset is described in more detail in (Trojanek and Gluszak, 2018).

Once the transaction dataset was established, we cleaned the raw data. First, we excluded all non-market transactions (e.g., debt collector sales or transactions between family members) as well as apartment sales within buildings with less than four units. We further excluded purchases of multiple apartment units within one building by one buyer as these

[6]Even though these cadastre data are available in electronic form, this step proved to be difficult due to a lack of uniform standards within the cadastre system. It proved impossible to directly link the datasets, so one of the authors collected each property's cadastre information by hand and merged it with our dataset.

sales might be transacted at non-market prices.

Second, we geo-coded the address of each apartment and computed distances to various amenities (e.g., subway stations, schools, and urban green space), which we included as extra variables for each apartment.

Third, to remove outliers in the dataset, we estimated hedonic models of log price separately for each market each year, taking into account the features indicated in Table 2. After that, we removed observations for which the absolute value of standardized residuals was more than 3.[7] Table 1 provides the summary statistics for our dataset before and after cleaning, while Table 2 lists the available variables.

Table 1: Dataset before and after cleaning

	New Builds		Existing Properties		Total	
Warsaw						
	Raw	After cleaning	Raw	After cleaning	Raw	After cleaning
Mean price/m^2	7,677.18	7,666.21	7,899.54	8,117.57	7,807.67	7,925.32
Std price/m^2	2,417.10	1,993.12	2,956.16	2,211.27	2,748.48	2,132.80
Observations	91,718	86,877	129,282	117,090	221,000	203,967
Poznan						
Mean price/m^2	5,531.15	5,747.02	4,680.97	4,689.56	5,050.66	5,126.15
Std price/m^2	1,800.39	1,536.41	1,837.24	1,714.78	1,869.43	1,723.97
Observations	41,464	35,957	53,892	51,133	95,356	87,090

Table 1 shows some descriptive statistics of the datasets used in this study.

[7]The standardized residual is defined as the residual divided by its estimated standard deviation. The threshold of 3 is widely used in statistics for identifying outliers (Dehon et al., 2009).

Table 2: Variables included in the dataset.

Variable	Description
district	factor variable for each district
area	useable area of the apartment in square meters
construction technology	factor variable, apartment either in building with prefabricated technology or with traditional technology
age	age of building in years
floor level	factor variable, apartment either on ground floor, intermediate floor, or above
height of the building	factor variable, up to fifth storey, from 6 - 17 storey, and above
subway	distance to the nearest subway station in meter
park	distance to the nearest park in meter
school	distance to nearest primary school in meter
storage	factor variable indicating whether apartment has a extra storage possibility
garage	factor variable: either own parking space in garage, outside of the building, or other

The table lists the descriptive variables included in the datasets for Warsaw and Poznan.

3 Methods and Applications

3.1 The Rolling-Time-Dummy (RTD) Hedonic Method

To effectively distinguish between genuine price changes and compositional differences, HPIs are typically computed using hedonic methods.[8] The hedonic approach entails estimating shadow prices on the characteristics of properties (such as floor area, age, and location) to ensure that quality is held fixed when measuring price changes from one period to the next. For example, Eurostat recommends that countries in Europe should compute their official HPIs using hedonic methods (Eurostat, 2017).

For each dataset, we construct price indices using the hedonic rolling-time-dummy (RTD) method. The RTD method, which was first proposed by Shimizu et al. (2003) and further developed by Shimizu et al. (2010) and O'Hanlon (2010), is a relatively simple and flexible hedonic method that has become increasingly popular in recent years.[9] In Europe, the

[8]Surveys of hedonic methods for computing HPIs can be found for example in de Haan (2010), Silver (2016) and Hill et al. (2018). An alternative to a hedonic approach is the repeat-sales method – see for example Melser (2017).

[9]For examples of other hedonic methods for constructing HPIs, see for example Rambaldi and Fletcher

RTD method is used by Croatia, Cyprus, France, Ireland, and Portugal in their official national HPIs (Hill et al., 2018). Japan is planning to compute its official residential and commercial property price indices using the RTD method (Shimizu and Diewert, 2019). Brunei Darussalam, Peru, and Thailand are using it, and Indonesia is about to start using it (Hill et al., 2021).

The RTD method estimates a hedonic model with a fixed window length (for example, $m + 1$ periods). Supposing that the first period in the window is period t, the first step is to estimate a semi-log hedonic model as follows:

$$\ln p_{\tau n} = \sum_{c=1}^{C} \beta_c z_{\tau c n} + \sum_{s=t+1}^{t+m} \delta_s d_{\tau s n} + \varepsilon_{\tau n}, \tag{1}$$

where n indexes the housing transactions that fall in the rolling window, $p_{\tau n}$ the transaction price of property n in period τ (where $t \leqslant \tau \leqslant t + m$), c indexes the set of available characteristics of the transacted properties, and ε is an identically, independently distributed error term with mean zero. The characteristics of the properties are given by $z_{\tau c n}$, while $d_{\tau s n}$ is a dummy variable that equals 1 when $\tau = s$, and zero otherwise.

Estimating this model using ordinary least squares, the change in the price index from period $t + m - 1$ to period $t + m$ is then calculated as follows:

$$\frac{P_{t+m}}{P_{t+m-1}} = \frac{\exp(\hat{\delta}^t_{t+m})}{\exp(\hat{\delta}^t_{t+m-1})}, \tag{2}$$

where $\hat{\delta}$ denotes the least squares estimate of δ. A superscript t is included on the estimated δ coefficients to indicate that they are obtained from the hedonic model with period t as the base (i.e., $P_t = 1$). As can be seen from (2), the hedonic model with period t as the base is only used to compute the change in house prices from period $t+m-1$ to period $t+m$. The window is then rolled forward by one period, and the hedonic model is re-estimated. The change in house prices from period $t + m$ to period $t + m + 1$ is now computed as follows:

$$\frac{P_{t+m+1}}{P_{t+m}} = \frac{\exp(\hat{\delta}^{t+1}_{t+m+1})}{\exp(\hat{\delta}^{t+1}_{t+m})}, \tag{3}$$

where now the base period in the hedonic model is period $t + 1$. The price index over

(2014) and Waltl (2019).

multiple periods is computed by chaining these bilateral comparisons together as follows:

$$\frac{P_{t+m+1}}{P_t} = \left[\frac{\exp(\hat{\delta}_{t+1}^{t-m})}{\exp(\hat{\delta}_{t}^{t-m})}\right]\left[\frac{\exp(\hat{\delta}_{t+2}^{t-m+1})}{\exp(\hat{\delta}_{t+1}^{t-m+1})}\right] \times \cdots \times \left[\frac{\exp(\hat{\delta}_{t+m+1}^{t+1})}{\exp(\hat{\delta}_{t+m}^{t+1})}\right]. \tag{4}$$

An important feature of the RTD method is that once a price change P_{t+m}/P_{t+m-1} has been computed, it is never revised. Hence when data for a new period $t+m+1$ becomes available, the price indexes P_t, P_{t+1}, ..., P_{t+m} are already fixed. The sole objective when re-estimating the hedonic model to include period $t+m+1$ is to compute P_{t+m+1}/P_{t+m}.[10]

We run the RTD model separately for new builds and existing properties at a quarterly frequency using a six-quarter rolling window.[11] We use the same variables when estimating the hedonic models for new builds and existing properties. We also estimate an RTD index based on data on preliminary agreements for new builds.

We then compute two aggregate indices – one combines the indices for new builds and existing properties, the other combines the indices for preliminary agreements and existing properties. We follow the standard approach for combining quarterly indices used by NSIs in Europe by updating the weights on an annual basis (Hill et al., 2018).[12] The aggregate indices are calculated as follows:

$$P^{agg}_{(t,q),(t,q+1)} = w^p_{t-1}P^p_{(t,q),(t,q+1)} + w^s_{t-1}P^s_{(t,q),(t,q+1)}, \tag{5}$$

where we have changed the notation so that t now denotes a year, and q denotes a quarter. $P^p_{(t,q),(t,q+1)}$ denotes a price index for the market for new-builds comparing quarter $q+1$ in year t with quarter q in the same year, while $P^s_{(t,q),(t,q+1)}$ is the corresponding index for the market for existing properties.

The weights for new-builds and existing properties are calculated as follows:

$$w^p_{t-1} = \frac{\sum_{n=1}^{Np} p^p_{t-1,n}}{\sum_{n=1}^{Np} p^p_{t-1,n} + \sum_{n=1}^{Ns} p^s_{t-1,n}},$$

[10]More sophisticated versions of the RTD method are considered in Hill et al. (2021).

[11]We chose a six-quarter window, rather than the more common four-quarter window, to stabilize the indices in the first few quarters of the dataset where fewer observations were available.

[12]We observe close to one hundred percent of transactions for both new and existing properties in Poznan. However, in Warsaw, we do not have complete data coverage.

$$w_{t-1}^{s} = \frac{\sum_{n=1}^{Ns} p_{t-1,n}^{s}}{\sum_{n=1}^{Np} p_{t-1,n}^{p} + \sum_{n=1}^{Ns} p_{t-1,n}^{s}},$$

where $\sum_{n=1}^{Np} p_{t-1,n}^{p}$ denotes the value of all new-built properties transacted in year $t-1$, and $\sum_{n=1}^{Ns} p_{t-1,n}^{s}$ the corresponding value of existing properties transacted in $t-1$.

The formula in (5) applies when q is the first, second or third quarter of a year. When q is the fourth quarter, the next quarter with which it is being compared is the first quarter in the following year. In this case the aggregate price index is calculated as follows:

$$P_{(t,4),(t+1,1)}^{agg} = w_{t-1}^{p} P_{(t,q),(t,q+1)}^{p} + w_{t-1}^{s} P_{(t,q),(t,q+1)}^{s}. \tag{6}$$

In other words, the annual weights are updated each year when the first quarter is compared with the second quarter.

3.2 Measuring Lags using Distance Metrics

We use distance metrics to measure the lag (in quarters) between the price index for new builds and existing properties. We estimate the lag length that minimizes differences between the two indices for both Warsaw and Poznan. A distance metric in our context should satisfy the following six axioms:

1. $D(x, \lambda x) = 0$, where λ is a scalar. This axiom implies that if an index is compared with itself or a rebased version of itself, the two indices are interpreted as identical.
2. $D(x, y) = 0$ if and only if $y = \lambda x$. This axiom is a stronger version of (i). It states that two indices are identical only if one is a rebased version of the other.
3. $D(x, y) \geqslant 0$. The metric is strictly non-negative.
4. $D(x, \lambda y) = D(\lambda x, y) = D(x, y)$. This means that the metric is invariant to rebasing one of the indices. For example, if the base year of the index for new-builds is changed from 2010 to 2015, the metric's value is unaffected.
5. $D(x, y) = D(y, x)$. The two indices are treated symmetrically. (Index symmetry)

6. $D(x, y) = D(x^{-1}, y^{-1})$, where x^{-1} refers to a time-reversal of the x index, i.e., where time is run backwards. This axiom is required to ensure that periods with rising index values are treated symmetrically to periods with falling index values (Time symmetry).

Diewert (2002, 2009) proposes three distance metrics for comparing price vectors across countries or periods. As discussed in Steurer et al. (2021), modified versions of these metrics can be used to measure the distance between two indices. Moreover, these modified metrics satisfy all six axioms stated above.[13] The metrics can be used to compare indices both in the same time frame and when one index is lagged. Assuming a predictive relationship exists between the two indices, the objective is to find the lag length that minimizes their dissimilarity.

Let P_t^p and P_t^s denote the levels of the price indices for the new-built and existing property markets, respectively, in period t. DM(k) denotes a modified-Diewert metric with the market for new-builds lagging the market for existing properties by k quarters.

Diewert Metric 1 (DM1):

$$DM1(k) = \frac{1}{T-k-1} \sum_{t=1}^{T-k-1} \left[\frac{P_{t+1}^p}{P_t^p} \Big/ \frac{P_{t+k+1}^s}{P_{t+k}^s} + \frac{P_{t+k+1}^s}{P_{t+k}^s} \Big/ \frac{P_{t+1}^p}{P_t^p} - 2 \right].$$

Diewert Metric 2 (DM2):

$$DM2(k) = \frac{1}{T-k-1} \sum_{t=1}^{T-k-1} \left[\left(\frac{P_{t+1}^p}{P_t^p} \Big/ \frac{P_{t+k+1}^s}{P_{t+k}^s} - 1 \right)^2 + \left(\frac{P_{t+k+1}^s}{P_{t+k}^s} \Big/ \frac{P_{t+1}^p}{P_t^p} - 1 \right)^2 \right].$$

Diewert Metric 3 (DM3):

$$DM3(k) = \frac{1}{T-k-1} \sum_{t=1}^{T-k-1} \left[\ln \left(\frac{P_{t+1}^p}{P_t^p} \Big/ \frac{P_{t+k+1}^s}{P_{t+k}^s} \right) \right]^2.$$

Diewert (2009) shows that these three metrics approximate each other to the first order.

Three other possible metrics are 1-PCC, where PCC is the Pearson Correlation Coefficient in log form, and the Hellinger and Euclidean distances.

[13] A more detailed discussion of related metrics can be found in Steurer et al. (2021).

Pearson Correlation Coefficient in Log Form (PCC):

$$PCC(k) = \frac{\sum_{t=1}^{T-k-1} \ln\left(\frac{P_t^p}{\bar{P}_G^p}\right) \ln\left(\frac{P_{t+k}^s}{\bar{P}_G^s}\right)}{\sqrt{\sum_{t=1}^{T-k-1} \left[\ln\left(\frac{P_t^p}{\bar{P}_G^p}\right)\right]^2 \sum_{t=1}^{T-k-1} \left[\ln\left(\frac{P_{t+k}^s}{\bar{P}_G^s}\right)\right]^2}},$$

where $\bar{P}_G^p$ and $\bar{P}_G^s$ denote the geometric mean of the new-built and existing property price indices included in the PCC calculation.

$$\bar{P}_G^p = \left(\prod_{t=1}^{T-k-1} P_t^p\right)^{1/(T-k-1)}, \quad \bar{P}_G^s = \left(\prod_{t=1}^{T-k-1} P_{t+k}^s\right)^{1/(T-k-1)}.$$

Hellinger Distance (HD):

$$HD(k) = \frac{1}{\sqrt{2}} \sqrt{\sum_{t=1}^{T-k-1} \left(\sqrt{\frac{P_{t+1}^p}{P_t^p}} - \sqrt{\frac{P_{t+k+1}^s}{P_{t+k}^s}}\right)^2}$$

Euclidean Distance (ED):

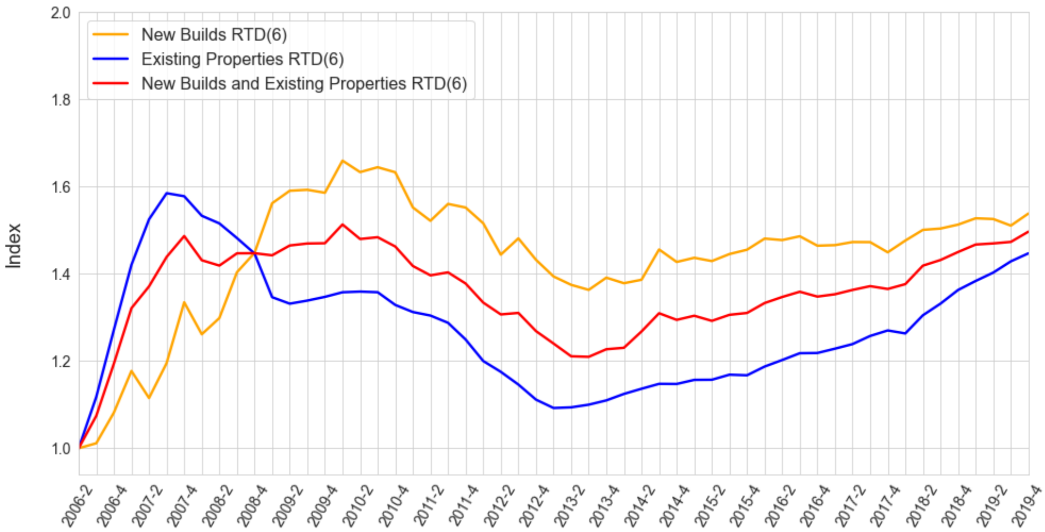
$$ED(k) = \sqrt{\sum_{t=1}^{T-k-1} \left(\frac{P_{t+1}^p}{P_t^p} - \frac{P_{t+k+1}^s}{P_{t+k}^s}\right)^2}$$

The metric, 1-PCC, satisfies all the axioms except (ii). To see that it violates (ii), consider the following two index series: $\{3, 9, 1, 3\}$ and $\{4, 8, 2, 4\}$. We obtain a value of PCC=1, which implies that 1-PCC=0, and yet it is clear that the second index is not a rescaled version of the first. Both the Hellinger and Euclidean distance metrics violate axiom (vi). In other words, they do not treat rising and falling indices symmetrically. However, if the Euclidean distance defined on the price relatives is rewritten in log form, we obtain a metric closely related to DM3 that does satisfy all six axioms.

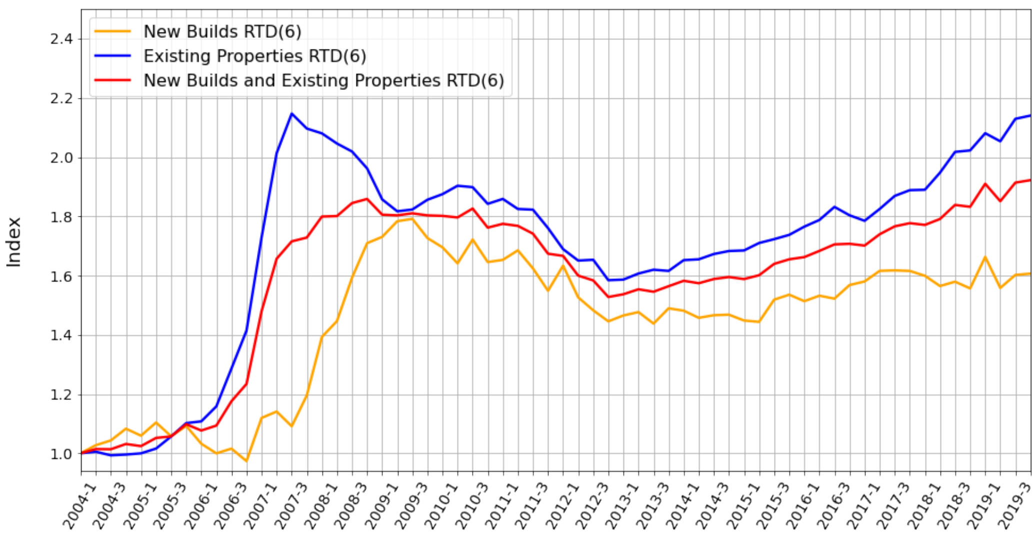
3.3 Results

The price indices for new-builds and existing properties for Warsaw and Poznan are graphed in Figure 1. The indices are constructed using the RTD hedonic method (subsection 3.1). Also shown are the aggregate indices for new builds and existing properties combined calculated using the weights in (5) and (6). Given that we have only partial coverage of transactions in the new-build market in Warsaw, we apply the weights obtained from Poznan – where we have almost complete coverage – to Warsaw. Figure 1 strongly suggests that the price indices for new-builds in both cities lag those for existing properties by multiple quarters. Given that the new-builds price index has a weight of around 40 percent in the aggregated index, this lag significantly distorts the aggregate index.

Figure 1: Real House Price Indices



(a) Warsaw



(b) Poznan

Figure 1 shows the price indices for new-builds and existing properties for Warsaw (a) and Poznan (b), as well as an overall index for the whole market. Prices were deflated using the Polish CPI (see Figure A1 in Appendix A), and all indices were constructed using the Rolling Time Dummy (RTD) method with a 6-quarter window length.

3.4 Granger Causality Test

We use a Granger causality approach to test whether the price index for existing properties predicts the price index for new-builds. More specifically, we test the null hypothesis that the index for existing properties cannot predict the index for new-builds. To implement the test, we construct the following two autoregressive models:

$$y_t^p = \alpha_0 + \alpha_1 y_{t-1}^p + \alpha_2 y_{t-2}^p + \cdots + \alpha_m y_{t-m}^p + \varepsilon_t \tag{7}$$

$$y_t^p = \gamma_0 + \gamma_1 y_{t-1}^p + \gamma_2 y_{t-2}^p + \cdots + \gamma_m y_{t-m}^p + \beta_1 y_{t-1}^s + \cdots + \beta_m y_{t-m}^s + \epsilon_t, \tag{8}$$

where y^p and y^s are the corresponding stationary time series (first differences of the log price indices) for new-builds and existing properties. We determine the number of lags for the new-builds market in (7) by using the autocorrelation function (see Figure B2 and Figure B3). The number of lags for the existing property market in (8) are determined using the Akaike information criterion (see Table B1). We then run an F-test (9) to test whether the price index for existing properties can add additional explanatory power to the model specified in (7).

$$F = \frac{(RSS_1 - RSS_2/(q_2 - q_1))}{(RSS_2/(n - q_2))}, \tag{9}$$

where RSS_1 denotes the residual sum of squares of the restricted model in (7) with the optimal number of lags, and RSS_2 is the corresponding residual sum of squares from the more general model in (8) that includes the secondary market, again with optimal lags. q_1 and q_2 denote the number of parameters in the restricted and more general models, respectively, and n is the number of data points. The test static follows an F distribution with $(q_2 - q_1, n - q_2)$ degrees of freedom.

The model results for Warsaw and Poznan are shown in Figure B4 and Figure B5. The result of the F-test statistic (9) for Warsaw (Poznan) is 24.587 (4.4305), yielding a p-value less than 0.001 (0.03965) and hence the null hypothesis that the price index for existing properties does not Granger-cause the price index for new-builds is rejected for both cities at the 95% significance level.

3.5 Measuring the Time Lag

We use the distance metrics described in subsection 3.2 to measure how many quarters the index for new-builds lags that for existing properties. The results for Warsaw are shown in Table 3. Independently of which metric is used, we find an estimated lag for Warsaw of eight quarters. This long time lag still holds when the first and second half of our data sample are analyzed separately. In other words, the price dynamics of an index for new-builds is most similar to an index for existing properties from two years earlier. If, however, we replace new build transaction dates with preliminary agreement dates, the time lag between the indices disappears. These results are shown in Table 3. It follows that an aggregate index constructed by combining an index for new builds based on preliminary agreement dates with an index for existing properties using (5) and (6) would cover the whole market without having a time lag. This can be seen in Figure 2.

It should be noted though that the difference in the dissimilarity metrics for new build and existing property indices are much smaller for the second half of the sample than for the first half (shown in the last column of Table 3 and denoted by Δ). In other words, in the second half of the sample, any tendency of an index for new builds to lag an index for existing properties is less pronounced.

Table 3: Estimates of the lag between price indices for new builds and existing properties - Warsaw

		Quarters Lagged											
Time	Metric	0	1	2	3	4	5	6	7	8	9	10	Δ
2006-Q2 –2019-Q4	ED	0.322291	0.301150	0.316026	0.315085	0.286432	0.285711	0.278631	0.225813	**0.207451**	0.232671	0.259395	0.1148
	DM1	0.001835	0.001636	0.001843	0.001882	0.001592	0.001589	0.001547	0.001039	**0.000883**	0.001138	0.001454	0.0010
	DM2	0.003690	0.003292	0.003716	0.003788	0.003207	0.003206	0.003115	0.002082	**0.001771**	0.002281	0.002918	0.0019
	DM3	0.001833	0.001635	0.001841	0.001880	0.001590	0.001587	0.001545	0.001039	**0.000883**	0.001138	0.001453	0.0010
	HD	0.112542	0.105226	0.110518	0.110400	0.100446	0.099760	0.097350	0.078936	**0.072262**	0.081085	0.090498	0.0403
	1-PCC	0.893741	0.815482	0.746859	0.661109	0.551372	0.465249	0.382675	0.297460	**0.286216**	0.368467	0.497925	0.6075
2006-Q2 –2012-Q4	ED	0.310755	0.286076	0.304319	0.298690	0.268366	0.264212	0.256014	0.188852	**0.174555**	0.202955	0.227166	0.1362
	DM1	0.003535	0.003121	0.003696	0.003741	0.003167	0.003150	0.003110	0.001764	**0.001561**	0.002253	0.003017	0.0020
	DM2	0.007113	0.006284	0.007456	0.007534	0.006386	0.006363	0.006269	0.003535	**0.003131**	0.004516	0.006061	0.0040
	DM3	0.003531	0.003118	0.003691	0.003737	0.003163	0.003145	0.003106	0.001764	**0.001561**	0.002252	0.003015	0.0020
	HD	0.108449	0.099880	0.106367	0.104587	0.094039	0.092088	0.089267	0.065695	**0.060444**	0.070419	0.078931	0.0480
	1-PCC	0.911577	0.815349	0.749268	0.657993	0.511637	0.436830	0.334184	0.147936	**0.108369**	0.212241	0.417553	0.8032
2013-Q1 –2019-Q4	ED	0.085456	0.094019	0.083612	0.097119	0.083546	0.092245	0.086325	0.057868	**0.049172**	0.054252	0.057758	0.0363
	DM1	0.000256	0.000322	0.000264	0.000371	0.000284	0.000363	0.000332	0.000159	**0.000121**	0.000155	0.000185	0.0001
	DM2	0.000512	0.000643	0.000528	0.000743	0.000569	0.000726	0.000664	0.000318	**0.000242**	0.000309	0.000370	0.0003
	DM3	0.000256	0.000322	0.000264	0.000371	0.000284	0.000363	0.000332	0.000159	**0.000121**	0.000155	0.000185	0.0001
	HD	0.030075	0.033090	0.029422	0.034196	0.029371	0.032456	0.030359	0.020438	**0.017386**	0.019170	0.020406	0.0126
	1-PCC	0.100483	0.102373	0.113530	0.132201	0.127686	0.147156	0.132947	0.092091	**0.090600**	0.118081	0.166613	0.0098
		Preliminary agreement											
2006-Q2 –2019-Q4	ED	**0.184759**	0.235226	0.245887	0.277539	0.299050	0.314288	0.305036	0.325515	0.349900	0.348919	0.299385	0.0000
	DM1	**0.000627**	0.001032	0.001126	0.001458	0.001726	0.001964	0.001893	0.002182	0.002567	0.002617	0.001930	0.0000
	DM2	**0.001257**	0.002071	0.002262	0.002936	0.003483	0.003955	0.003811	0.004416	0.005210	0.005304	0.003890	0.0000
	DM3	**0.000627**	0.001032	0.001126	0.001456	0.001724	0.001962	0.001890	0.002178	0.002561	0.002612	0.001927	0.0000
	HD	**0.065160**	0.082872	0.086185	0.097181	0.104701	0.110308	0.107120	0.114048	0.122472	0.122226	0.104354	0.0000
	1-PCC	**0.030419**	0.081580	0.200781	0.335271	0.476133	0.586087	0.679863	0.822648	0.917967	0.952438	0.936023	0.0000

The final column denoted by Δ shows how much higher the metric score is with a zero period lag as compared with the minimizing lag. The top three sub-sections show the dissimilarity between the price indices of new builds and existing properties in Warsaw for various time lags for the entire dataset and separately for 2006 to 2012 and 2013 to 2019. All metrics indicate that an 8-quarter lag minimizes the difference between the two price index series. The last section of Table 3 indicates that a lag of 0 quarters minimizes the difference between the price index for existing properties and a price index for new-builds compiled using the dates of preliminary agreement rather than of the actual transactions.
Note, ED stands for Euclidean distance, DM1, DM2, and DM3 stand for Diewert measure 1, 2, and 3, HD stands for Hellinger distance, and 1-PCC stands for 1 - Pearson Correlation Coefficient.

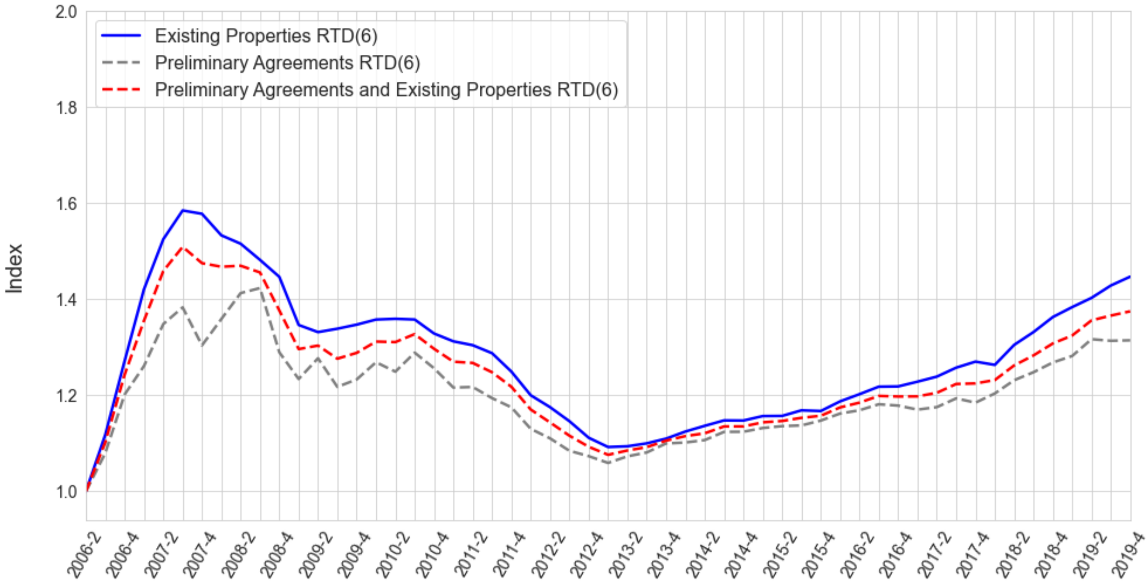
Equivalent results for Poznan are presented in Table 4. The metrics are almost in complete agreement that the index for new-builds lags behind the index for existing properties by six quarters. When splitting the dataset into two sub-samples, the first half indicates a six-quarter lag while the second half has a five-quarter lag. Again, the gap between the dissimilarity metrics in the second half of the dataset is much smaller than in the first half, implying that any lagging trends are weaker. Indeed, in the second half not all of the metrics agree on the lag, although the Diewert metrics (DMs) still agree.

Table 4: Estimates of the lag between Price Indices for new-builds and existing properties - Poznan

		Quarters Lagged											
Time	Metric	0	1	2	3	4	5	6	7	8	9	10	Δ
2004-Q1 –2019-Q4	ED	0.456320	0.501780	0.437231	0.381388	0.375772	0.361538	**0.324406**	0.396296	0.426765	0.421899	0.465360	0.1319
	DM1	0.003092	0.003737	0.002884	0.002276	0.002255	0.002075	**0.001698**	0.002541	0.002982	0.002956	0.003668	0.0013
	DM2	0.006220	0.007549	0.005838	0.004571	0.004533	0.004170	**0.003405**	0.005107	0.006012	0.005953	0.007408	0.0028
	DM3	0.003089	0.003731	0.002878	0.002274	0.002253	0.002074	**0.001697**	0.002539	0.002978	0.002953	0.003662	0.0013
	HD	0.158550	0.173574	0.151215	0.132609	0.130791	0.125066	**0.112188**	0.136556	0.146826	0.145008	0.159981	0.0463
	1-PCC	0.241634	0.193087	0.136907	0.086207	0.048586	**0.030465**	0.033312	0.068995	0.125948	0.202168	0.301799	0.2111
2004-Q1 –2012-Q4	ED	0.420380	0.458756	0.406837	0.333443	0.321598	0.306302	**0.279027**	0.348294	0.377786	0.381501	0.423856	0.1413
	DM1	0.005271	0.006352	0.005181	0.003649	0.003524	0.003205	**0.002774**	0.004428	0.005408	0.005775	0.007487	0.0024
	DM2	0.010610	0.012854	0.010508	0.007333	0.007091	0.006449	**0.005566**	0.008907	0.010921	0.011644	0.015152	0.0050
	DM3	0.005265	0.006340	0.005169	0.003646	0.003520	0.003202	**0.002772**	0.004423	0.005399	0.005767	0.007472	0.0024
	HD	0.145627	0.158042	0.140216	0.115313	0.111257	0.104996	**0.095720**	0.119011	0.128915	0.130246	0.144797	0.0499
	1-PCC	0.271137	0.213816	0.150065	0.089720	0.044338	0.020508	**0.018431**	0.047339	0.097537	0.164895	0.249426	0.2527
2013-Q1 –2019-Q4	ED	0.149870	0.181066	0.146282	0.156658	0.172340	**0.137540**	0.138451	0.148472	0.150808	0.134935	0.125721	0.0123
	DM1	0.000725	0.001088	0.000739	0.000875	0.001098	**0.000720**	0.000766	0.000920	0.000985	0.000818	0.000748	0.0000
	DM2	0.001451	0.002181	0.001480	0.001755	0.002202	**0.001443**	0.001534	0.001845	0.001975	0.001639	0.001498	0.0000
	DM3	0.000725	0.001088	0.000739	0.000875	0.001098	**0.000720**	0.000766	0.000920	0.000985	0.000818	0.000748	0.0000
	HD	0.052985	0.063939	0.051737	0.055355	0.060890	0.048497	0.048926	0.052508	0.053254	0.047555	**0.044377**	0.0086
	1-PCC	0.243511	0.188139	**0.172815**	0.191483	0.198553	0.177997	0.188387	0.220142	0.277500	0.313184	0.366894	0.0707

The final column denoted by Δ shows how much higher the metric score is with a zero period lag as compared with the minimizing lag. The dissimilarity between price indices for now builds and existing properties in Poznan are shown for the entire dataset and separately for 2006 to 2012 and 2013 to 2019. All metrics indicate that a 6-quarter lag minimizes the difference between the two price index series overall and in the sub-sample between 2006 and 2012. For the sub-sample between 2013 and 2019, four measures indicate that a five quarter lag minimizes the difference between the two series.
Note: ED stands for Euclidean distance, DM1, DM2, and DM3 stand for Diewert measure 1, 2, and 3, HD stands for Hellinger distance, and 1-PCC stands for 1-Pearson Correlation Coefficient.

Figure 2: Real House Price Indices including Preliminary Agreement (dashed) for Warsaw



The figure compares the price index for existing properties with one for the whole market constructed by combining existing properties with preliminary agreements on new builds. Both indices are constructed using the Rolling Time Dummy (RTD) method with a 6-quarter window length.

4 The Time Lag in the Index for New-Builds and its Implications

4.1 Explaining the Lag

The time lag in price indices for new-builds depends on at least three factors:

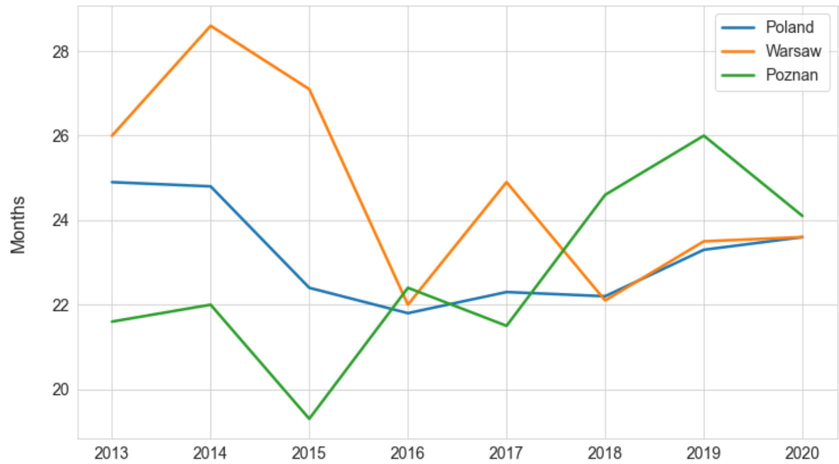
(i) How long it takes to build an apartment block.

(ii) How far into the building process are preliminary agreements signed.

(iii) How well buyers and sellers anticipate future price movements.

We consider each of these in turn. The average building times for Warsaw and Poznan are shown in Figure 3, starting from 2013. For Warsaw, we find that the apartment building process takes about 25 months, while in Poznan, it takes around 23 months. The result for Warsaw fits almost exactly with the eight-quarter time lag identified in Table 3. The 23 month building time in Poznan is slightly longer than the six-quarter lag identified in Table 4.

Figure 3: Average Building Time in Months



The figure illustrates the mean time lag between building approval and completion for Poland, Warsaw, and Poznan between 2013 and 2020.

At which stage during the construction process preliminary agreements are signed will depend partly on the state of the housing market. If buyers commit sooner during booms than at other times, there should be a cyclical component in the time lag of the new builds price index. Even though we found that the overall time lag stayed stable over our 23-year sample period in both Warsaw and Poznan, the gap between the dissimilarity metrics with no lag versus the metric minimizing lag (shown by Δ in the last column of Tables 3 and 4) is much smaller in the second half of our sample, implying that the evidence for a lag is much weaker then.

From the indices in 1 we can see that the Warsaw market for existing properties peaked in 2007Q2, while the market for new-builds peaked in 2009Q4. The lag can be attributed to buyers of new-builds after the market peaked still being locked into their earlier contracts.

More generally, the price agreed by the buyer and seller in the preliminary agreement will be influenced by expectations of how future prices will develop. When the market is calmer, market participants will be more able to anticipate future price developments. Hence the lag between the price indices for new and existing properties should be less pronounced. This is indeed what we observe in the last column of Tables 3 and 4.

The length of the lag may also vary over the housing cycle, although we do not see this in our results. During a market upturn, contracts on new builds could be signed at the very initial stage while in a downturn they may not get signed until the project is complete. Other factors, such as the introduction of first home-buyers' grants, changes in the mix of owner-occupiers and investors, and better information (e.g., the introduction of the National Bank of Poland's HPI in 2010) can also affect the lag.

4.2 Implications for National House Price Indices (HPIs) and their users

New-builds are often bought off the plan with prices agreed on months or years before the transaction. As a result, the prices stated in purchase contracts can be stale at the time of the transaction. For countries in which a significant part of the property market consists of new-builds, including these stale transaction prices can undermine the timeliness of the HPI. This situation is particularly problematic when the HPI is being used for macro-prudential supervision or as an input for monetary policy decisions, as the timeliness of the index is crucial in this context.

One way to avoid the time lag in an HPI would be to exclude new-builds. The drawback of this approach is that the resulting HPI would not provide a complete picture of over-all housing market developments. Thus, a trade-off exists between market coverage and timeliness.

A second way to avoid the time lag in the HPI would be to replace transactions for new-builds with preliminary agreements. Our results for Poland show that an index based on preliminary agreements does not show any lag. The main problem with this solution is that preliminary agreement data are not currently collected by most EU Land Registries. Also, even in the Polish case where multiple registries collect these information, information on preliminary agreements are only released together with the transaction data. If these preliminary agreements were to be used as a proxy for new-build transactions, they would need to be made available sooner. A further concern is that there is a strong preference in statistical circles for using only actual transaction prices to compute HPIs. This is the position of Eurostat (Eurostat, 2017), the European Union (European Commission, 2018), and the International Monetary Fund (International Monetary Fund, 2020).

4.3 Implications for the Harmonized Index of Consumer Prices (HICP) and its Users

The European Commission, in its Article 3(3), requires that the HICP is constructed using only data on actual transactions (European Commission, 2018). In a housing context, the approach agreed although not yet implemented for including OOH in the HICP – the net acquisitions method – goes further by requiring that the owner-occupied-housing price index (OOHI) should be constructed using only transaction data for newly-built properties (Hill et al., 2020). This is the case as the net acquisitions approach aims to treat housing in the HICP like it treats other consumer durables. For example, the sale of a newly produced car enters the HICP, while that of a second-hand car does not. In the same way, purchases of newly built properties are included, while purchases of existing properties are not.

However, real estate is different from other consumer durables. In particular, the time lag between committing to buy a property and when it is finally transacted is generally much longer than with cars or refrigerators. As a result, the prices for new-builds can be stale by the time transactions happen, resulting in a price index that lags the current state of the housing market. In the case of Poland, this lag is two years.

Given OOH's considerable weight in the HICP (about 9 percent according to Eiglsperger and Goldhammer (2018)), a two-year lag in the OOHI would be highly problematic. Indeed, combining a two year (24-month) lag in the OOHI with a 9 percent expenditure weight in the HICP implies that the inclusion of OOH would cause a lag of about 2.2 months (24×0.09) in the HICP (over and above any lags arising from delay in recording and transmitting transaction prices to national Land Registries). When evaluating the significance of such a delay, it is worth remembering that the HICP is the flagship measure of inflation used by the ECB for setting monetary policy and that there is about a two and a half year time lag until the full impact of monetary policy decisions is felt in the economy (Havranek and Rusnak, 2013). Therefore, effective monetary policy requires the HICP to capture the very latest price trends in the economy. Again, it should be emphasized that OOH is currently included in the HICP only on an experimental basis. So the time lag in the OOHI is not yet actually affecting monetary policy decisions.

Ironically, a significant reason OOH has not yet been integrated into the official HICP is not because of the time lags associated with new builds, but rather because many EU countries cannot supply the housing data quickly enough to meet HICP guidelines. These guidelines state that all data each month must be provided to the ECB not more than 15 days after the end of the month (European Commission, 2018). This strict deadline exists to ensure that the HICP is released quickly based on the most up-to-date data available. However, in the case of Poland at least, the timeliness issue related to the data release is a far smaller problem than the lags arising from the time interval between preliminary agreements on new builds being signed and the transactions being finalized.

How then should the OOHI be constructed? One option is to replace a transaction-based index with an index based on preliminary agreements for new builds. As noted above, our results for Poland show that an index for new builds constructed in this way does not lag behind the price development for the market of existing properties. For a practical implementation of this option, authorities would need to collect data on preliminary agreements (at the time they are signed). Still, there remains the question of whether an index that substitutes prices and dates of preliminary agreements for those of final transactions could fall within the rules of Article 3(3) of EU Regulation No. 2016/792 regarding the HICP (European Commission, 2018).

There are, however, two further problems with the OOHI. First, in some smaller EU countries, the number of transactions for new builds each month is so low that it is problematic to construct a quality-adjusted index. Switching from transactions to preliminary agreements helps with the timeliness of the index but does not increase the number of observations available for index compilation. From the point of index stability, it would thus be better to use an index that includes new builds (via preliminary agreeements) and transactions of existing properties to measure house price inflation in the HICP.

5 Conclusion

Timeliness is essential for house price indices (HPIs), especially when they are used for macro-prudential supervision or as inputs into consumer price indices (CPIs). A distinction can be drawn between two sources of delay in HPIs, one of which has received some attention in the literature, while the other hardly any. The widely recognized source concerns delays in recording transactions by notaries and transferring and transcribing these transactions by national Land Registries.

In this paper, we highlighted a second and so far under-appreciated source of delay, which arises from the time lag between signing preliminary agreements and final transactions for new-builds. We showed that Warsaw's price index for newly-built apartments lags that of existing apartments by eight quarters. For Poznan this lag is slightly lower at six quarters. The lag is most pronounced during periods of market turmoil, when accurate HPIs are most needed.

Delays of this magnitude are not only problematic for HPIs. The Harmonized Index of Consumer Prices (HICP) in Europe is also affected. This is because the European Central Bank/Eurostat are planning to bring owner-occupied housing (OOH) into the HICP using a transaction-based HPI for new builds. This would reduce the timeliness of the HICP.

We discussed two possible ways to deal with this time lag problem. One way is to focus exclusively on the market for existing properties when creating an HPI. However, if price dynamics in the new and existing housing markets differ, the resulting index may give a misleading picture of developments in the overall housing market, especially in countries, such as Poland, in which new builds have a large market share.

A second way to improve the timeliness of an HPI could be to replace transactions for new builds with preliminary agreements. Our results with Polish data show that an index for new builds compiled in this way does not lag a price index for existing properties. However, for this to work it is crucial that Land Registries or other government authorities collect information on preliminary agreements.

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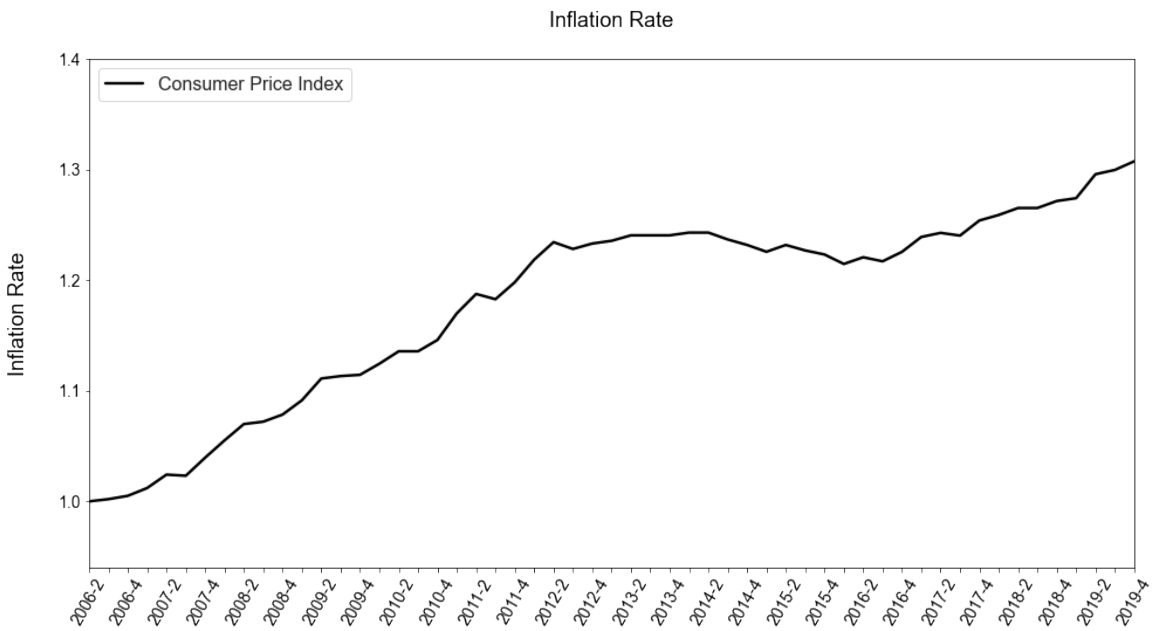
Appendix

A Inflation and Nominal House Price Indices

A.1 Inflation rate for Poland

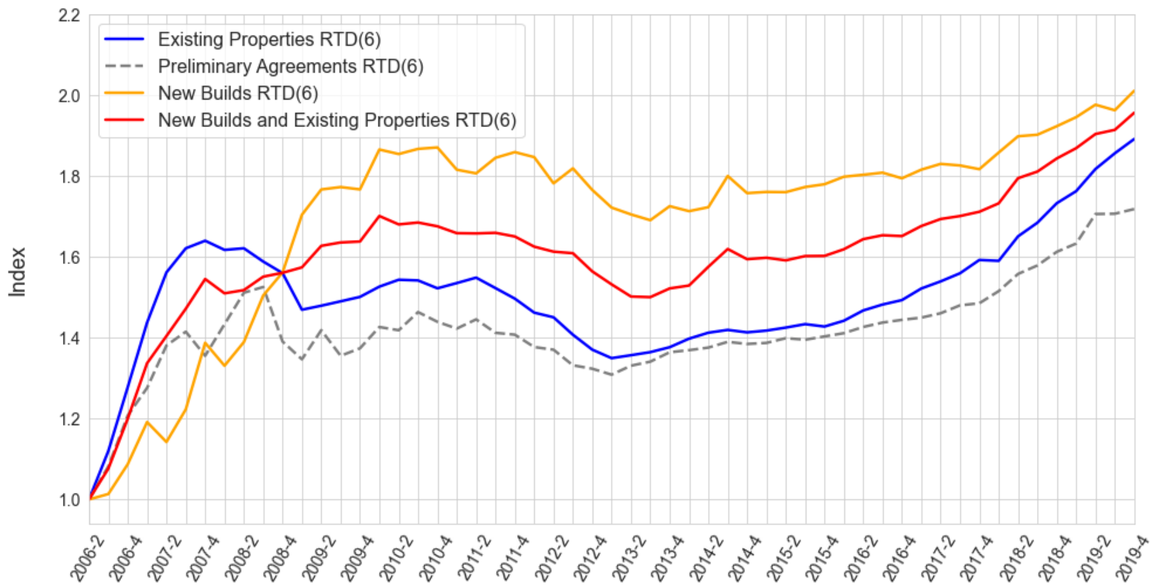
Figure A1: Level of the Polish Consumer Price Index (2006-Q2=1)



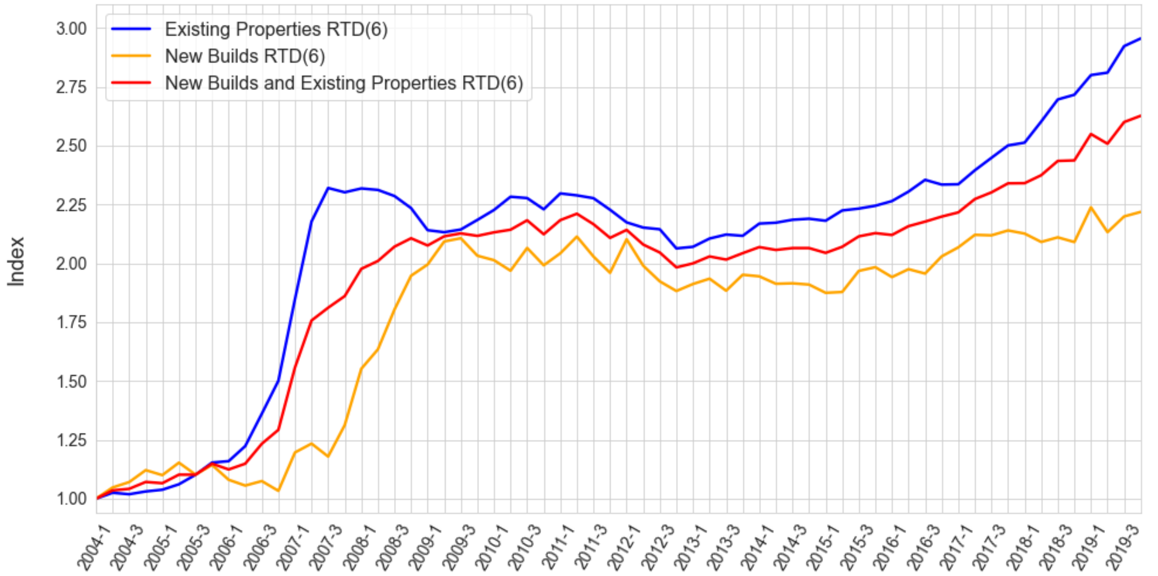
The figure depicts the official consumer price index (CPI) for Poland (source Statistics Poland (`https://stat.gov.pl/en/topics/prices-trade/price-indices/`). This CPI series is used to deflate the various house-price indices in section 3.

A.2 Nominal house price indices (HPIs)

Figure A2: Nominal House Price Indices (HPIs)



(a) Warsaw

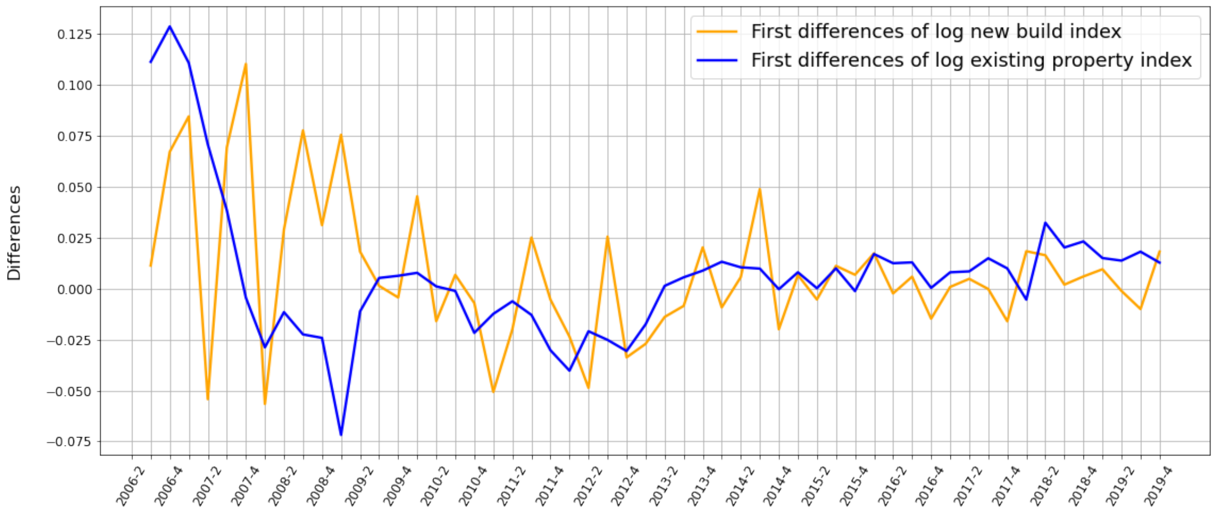


(b) Poznan

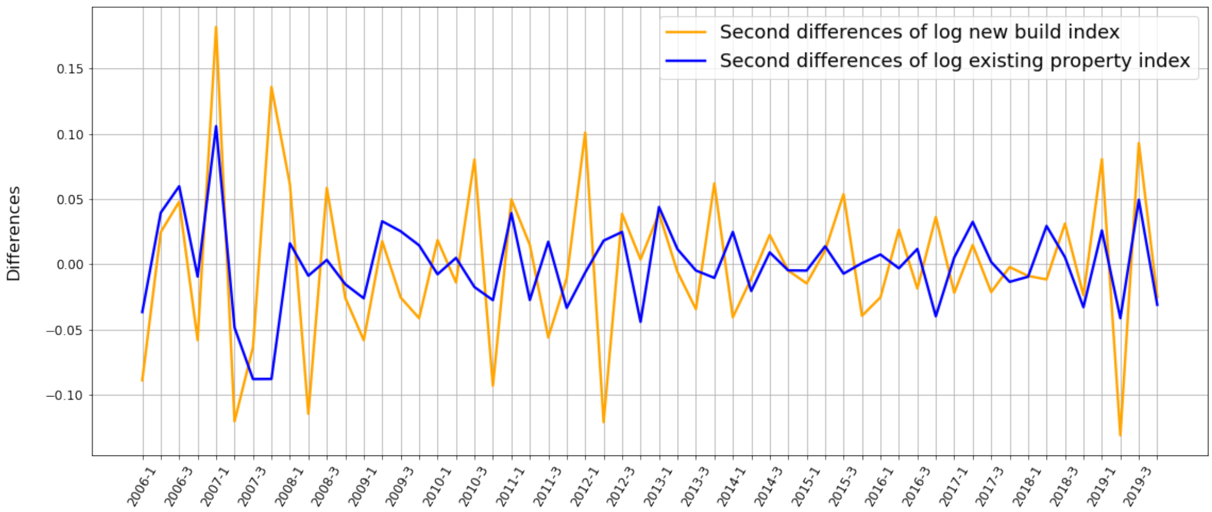
Figure A2 illustrates the development of nominal house-price indices for new and existing properties as well as a weighted combination of the two indices for Warsaw (a) and Poznan (b). The indices were constructed using the Rolling Time Dummy (RTD) method with a 6-quarter window length.

B Granger Causality

Figure B1: Stationary Price Indices



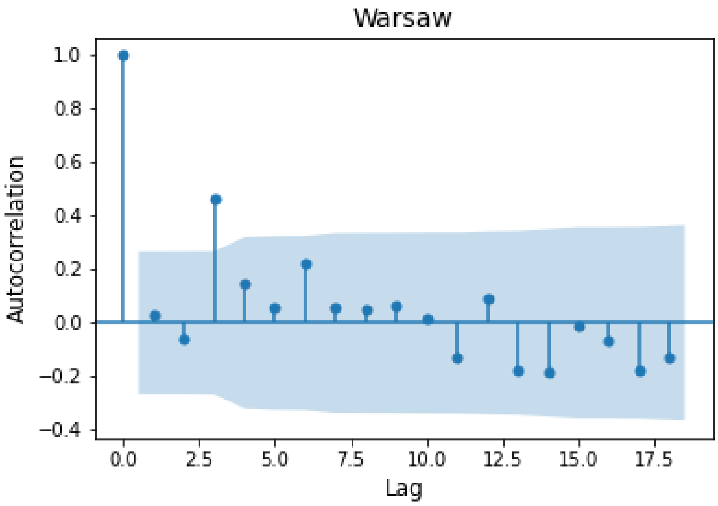
(a) Warsaw



(b) Poznan

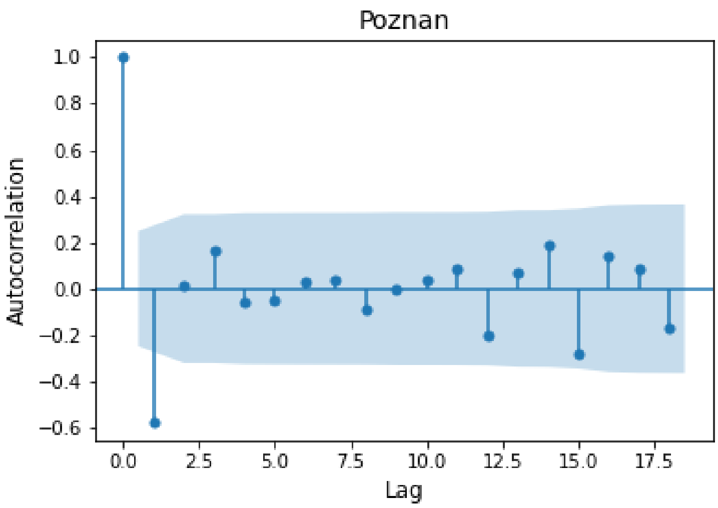
Figure B1 depicts the stationary (i.e, log first differenced) price indices for new and existing properties in Warsaw (a) and Poznan (b).

Figure B2: Autocorrelation function for the market for new-builds in Warsaw



The figure illustrates that a lag of 3 quarters (in log first differences) is the only significant auto-correlation lag for the new-build market price index for Warsaw.

Figure B3: Autocorrelation function for the market for new-builds in Poznan



The figure illustrates that a 1-quarter lag (in log second differences) is the only significant auto-correlation lag for the new-builds price index for Poznan.

Table B1: Model selection with the Akaike Information Criterion (AIC)

Akaike Information Criteria (AIC)		
Lag	Warsaw	Poznan
1	-216.9	-180.3
2	-214.9	-181.8
3	-213.1	**-183.2**
4	-215.3	-179.8
5	-212.5	-174.6
6	-221.2	-170.0
7	-221.2	-172.0
8	**-223.6**	-168.5
9	-221.8	-166.2
10	-218.2	-160.8
11	-215.0	-168.9
12	-212.7	-164.7

The table shows AIC criterion results for models predicting market prices for new builds for Warsaw (Poznan) including a three-quarter (one-quarter) auto-regressive lag as well as lags between 1 and 12 quarters for the market for existing properties.

Figure B4: Model Summary for Warsaw including only new builds – equation (7)

```
                            OLS Regression Results
=======================================================================================
Dep. Variable:            New Builds   R-squared (uncentered):                   0.276
Model:                           OLS   Adj. R-squared (uncentered):              0.261
Method:                Least Squares   F-statistic:                              19.05
Date:               Mon, 14 Feb 2022   Prob (F-statistic):                    6.38e-05
Time:                       11:55:36   Log-Likelihood:                          110.38
No. Observations:                 51   AIC:                                     -218.8
Df Residuals:                     50   BIC:                                     -216.8
Df Model:                          1
Covariance Type:           nonrobust
==================================================================================================
                                coef    std err          t      P>|t|      [0.025      0.975]
--------------------------------------------------------------------------------------------------
New_Builds_lagged_by_3_quarters     0.4777      0.109      4.365      0.000       0.258       0.698
==============================================================================
Omnibus:                       0.668   Durbin-Watson:                   1.921
Prob(Omnibus):                 0.716   Jarque-Bera (JB):                0.269
Skew:                          0.167   Prob(JB):                        0.874
Kurtosis:                      3.123   Cond. No.                         1.00
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Figure B5: Model Summary for Warsaw including only existing properties – equation (8)

```
==============================================================================
Dep. Variable:                      y   R-squared (uncentered):              0.536
Model:                            OLS   Adj. R-squared (uncentered):         0.423
Method:                 Least Squares   F-statistic:                         4.753
Date:                Mon, 14 Feb 2022   Prob (F-statistic):               0.000310
Time:                        11:58:46   Log-Likelihood:                     120.81
No. Observations:                  46   AIC:                                -223.6
Df Residuals:                      37   BIC:                                -207.2
Df Model:                           9
Covariance Type:            nonrobust
=========================================================================================================
                                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------------
New_build_index_lagged_by_3_quarters    0.1939      0.099      1.956      0.058      -0.007       0.395
Existing_property_index_lagged_by_1_quarters  0.2862  0.223   1.284      0.207      -0.166       0.738
Existing_property_index_lagged_by_2_quarters  0.3017  0.239   1.263      0.215      -0.182       0.786
Existing_property_index_lagged_by_3_quarters  0.0286  0.232   0.123      0.903      -0.441       0.498
Existing_property_index_lagged_by_4_quarters -0.5051  0.230  -2.192      0.035      -0.972      -0.038
Existing_property_index_lagged_by_5_quarters  0.2095  0.234   0.895      0.377      -0.265       0.684
Existing_property_index_lagged_by_6_quarters  0.0493  0.225   0.219      0.828      -0.407       0.506
Existing_property_index_lagged_by_7_quarters -0.1461  0.240  -0.608      0.547      -0.633       0.341
Existing_property_index_lagged_by_8_quarters  0.5382  0.175   3.072      0.004       0.183       0.893
==============================================================================
Omnibus:                        3.403   Durbin-Watson:                   2.393
Prob(Omnibus):                  0.182   Jarque-Bera (JB):                2.628
Skew:                           0.580   Prob(JB):                        0.269
Kurtosis:                       3.158   Cond. No.                         6.65
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Figure B6: Model Summary for Poznan including only new-builds – equation (7)

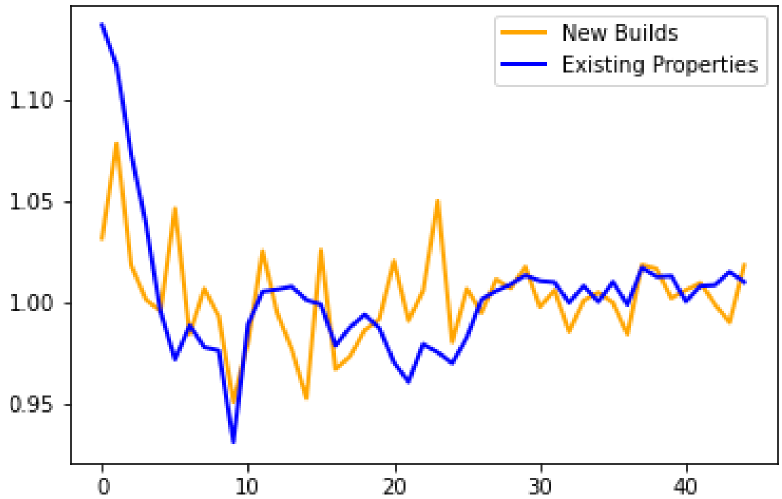
```
                                 OLS Regression Results
==============================================================================
Dep. Variable:        New_build_index   R-squared (uncentered):              0.335
Model:                            OLS   Adj. R-squared (uncentered):         0.323
Method:                 Least Squares   F-statistic:                         29.17
Date:                Mon, 14 Feb 2022   Prob (F-statistic):               1.29e-06
Time:                        12:01:53   Log-Likelihood:                     92.110
No. Observations:                  59   AIC:                                -182.2
Df Residuals:                      58   BIC:                                -180.1
Df Model:                           1
Covariance Type:            nonrobust
=========================================================================================================
                                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------------
New_build_index_lagged_by_1_quarter   -0.5748      0.106     -5.401      0.000      -0.788      -0.362
==============================================================================
Omnibus:                        6.280   Durbin-Watson:                   2.521
Prob(Omnibus):                  0.043   Jarque-Bera (JB):                5.799
Skew:                           0.525   Prob(JB):                       0.0551
Kurtosis:                       4.120   Cond. No.                         1.00
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Figure B7: Model Summary for Poznan including only existing properties – equation (8)

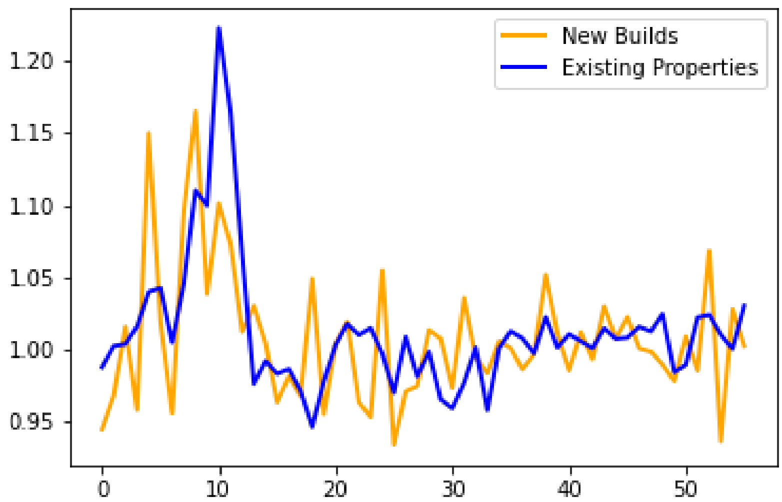
```
                            OLS Regression Results
=======================================================================================
Dep. Variable:                      y   R-squared (uncentered):                   0.409
Model:                            OLS   Adj. R-squared (uncentered):              0.366
Method:                 Least Squares   F-statistic:                              9.523
Date:                Mon, 14 Feb 2022   Prob (F-statistic):                    6.35e-06
Time:                        12:05:19   Log-Likelihood:                          95.616
No. Observations:                  59   AIC:                                     -183.2
Df Residuals:                      55   BIC:                                     -174.9
Df Model:                           4
Covariance Type:            nonrobust
=========================================================================================================
                                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------------
New_build_index_lagged_by_1_quarter1      -0.5950      0.120     -4.967      0.000      -0.835      -0.355
Existing_property_index_lagged_by_1_quarters   -0.2883      0.232     -1.244      0.219      -0.753       0.176
Existing_property_index_lagged_by_2_quarters    0.0292      0.315      0.093      0.926      -0.603       0.661
Existing_property_index_lagged_by_3_quarters    0.4386      0.240      1.825      0.073      -0.043       0.920
==============================================================================
Omnibus:                        4.413   Durbin-Watson:                   2.467
Prob(Omnibus):                  0.110   Jarque-Bera (JB):                5.198
Skew:                           0.063   Prob(JB):                       0.0744
Kurtosis:                       4.449   Cond. No.                         4.22
==============================================================================

Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

C Shift of the primary market

Figure C1: Stationary (first differenced log) price indices in Warsaw and Poznan with the price index for new builds lagged by eight quarters compared with existing properties in Warsaw and by six quarters in Poznan



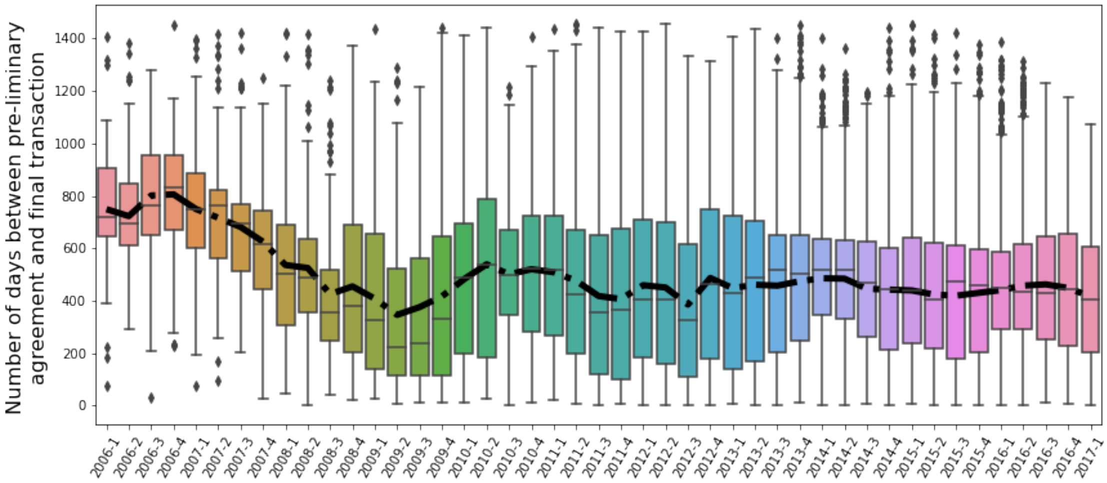
(a) Stationary Price Index for Warsaw lagged by eight quarters



(b) Stationary Price Index for Poznan lagged by six quarters

These figures illustrate the first-difference of the log price indices for new and existing properties in Warsaw and Poznan. We find the best overlap with an eight quarter lag for Warsaw and a six quarter lag for Poznan.

Figure C2: Average Number of Days between Pre-Agreement and Final Transaction



The figure illustrates the average number of days between signing preliminary agreements and transaction for apartments in Warsaw.

Note: the quarterly Box-Whisker-Plots shows the distribution of the individual time spans between preliminary agreement and final transaction in the market for new builds in Warsaw. The solid black lines in Figure C2 indicate the arithmetic mean over time.