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Hedonic house price indices for Malta: A mortgage-based approach

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Abstract

This paper makes use of a novel dataset derived from mortgage contracts granted by the major lending institutions in Malta. This contains information about house prices and a number of important property characteristics. Together with geographic and socio-demographic variables, this information allows the computation of a range of hedonic house price indices for Malta for the period 2010-2017. In general we find that growth in house prices remained relatively muted over the period 2011-2014, ranging between 1.0% and 2.0%. House prices picked-up markedly after 2015, averaging between 4.5% and 7.5%. In particular, house price growth peaked in 2017, at between 10.1% and 11.0%. Although the general evolution of the hedonic house price indices calculated in this study are broadly similar to the indices computed by the contract-based index produced by the National Statistics Office and the advertised-based index produced by the Central Bank of Malta, there are some divergences. These differences can be attributed to changes in property characteristics.

JEL classification: C4, E3, R3, R31.
Keywords: Housing prices; hedonic price models; mortgages; Malta;

Contents

1. Introduction

Due to the limited availability of land and the small size of financial markets, property has over generations served as an important store of wealth for the Maltese population. This is reflected in Malta's relatively high home ownership rate of over 78.0% (NSO, 2018). This high rate of home ownership was also significantly influenced by old rent laws, which limited the supply of dwellings for rent and thereby encouraged new households to purchase property.

There are currently two measures of house prices in Malta, both published on a quarterly basis. The official Property Price Index (PPI) published by the National Statistics Office (NSO) calculates house price growth through actual transaction prices from contracts reported to the Commissioner for Revenue. On the other hand, the Central Bank of Malta (CBM) measures house price growth based on advertised house prices on print media. Growth rates for both indices in recent years confirm a buoyant property market driven by a surge in demand, particularly since 2015.

These indices are based on the median price of property, but do not control for the possible impact of changes in the quality and characteristics of the housing units traded. In recent years, quality adjustment methods applied to house prices have gained a lot of attention among international statistical organisations, particularly Eurostat. These methodologies highlight how differences between dwellings and the changing makeup of houses sold in successive periods need to be taken into account in order to separate the influences of changes in property composition and dwelling quality from pure price movements. This is particularly important in periods where the underlying characteristics that determine the value of the traded housing units are rapidly changing.

Quality adjusted property price indices, also referred to as hedonic price indices, account for these developments by adjusting changes in house prices for variations in the attributes of the properties transacted during a particular time period. With hedonic quality adjustment, a property's price is viewed as the sum of all of the characteristics which define it. The quality of a property is composed of a number of attributes, pertaining to its location and to the structure itself, such as floor area and the availability of external space. Hedonic regression methods are employed to estimate the marginal contributions of these characteristics to the total price, thereby enabling the compilation of quality-adjusted price indices.

This paper makes two main contributions to the housing literature in Malta. The first contribution is the utilisation of a novel dataset of anonymised mortgage contracts, collected from Malta's main mortgage lenders under Banking Regulation VI (BR/06). It is supplemented by a number of ad hoc variables capturing the geographical attributes of the dataset. This is the first time that house prices trends in Malta are being analysed through the use of mortgage contract data.

The second contribution is the application of international methodological standards on hedonic house price indices developed by Eurostat (2017) to this new dataset. We employ three main methodologies, the time-dummy variable (TDV) method, the rolling-window time dummy (RTD) method, and the average characteristics method. Borg (2004) and Falzon and Lanzon (2013) have both constructed hedonic house price indices for Malta, using advertised prices. In this paper, we apply these methods to mortgage contracts for the period 2010-2017, and supplement them with geographic and socio-demographic variables to capture between-region differences.

Using a number of different methods of hedonic adjustment as described in Eurostat (2017), the results of this study suggest that house price growth in Malta remained relatively muted over the period 2011-2014, averaging between 1.0% and 2.0%. House prices picked-up markedly after 2015, averaging between 4.5% and 7.5% and then going to between 7.0% and 13.0% in 2017, depending on the method employed. After narrowing down the number of methods to just two, identified by the literature as ideal for small countries or due to their statistical properties, we obtain a narrower range of growth of between 10.1% and 11.0% for

2017. Although in most periods we observe similar growth rates across the different methods, there are growing divergences among the range of hedonic indices and non-quality adjusted indices. This implies that the housing market has undergone significant changes over the last few years.

This note is structured as follows. Section 2 provides a general overview of the literature on hedonic house price methods, including applications to Malta and to other countries. Sections 3 and 4 then provide an overview of the methodology used in the analysis, which is based on Eurostat (2017), as well as providing some descriptive analysis of the mortgage dataset and the augmenting variables. Section 5 presents the obtained hedonic indices, along with comparison to the official house price indices for Malta. The final section concludes the study and proposes a way forward.

2. Literature Review

In the analysis of price changes, hedonic methods to construct indices are widely used to construct consumer price indices, as well as to measure property prices. The challenge in calculating a real estate price index is that measures of changes in the average or median prices of properties may partly reflect changes in the quality-mix of properties sold (Silver, 2016). Moreover, Palmquist (1980) shows how both average and median measures ignore changes in house characteristics. Indeed, there are significant differences between indices which distinguish and those that do not distinguish between price changes and depreciation or quality differences. Dorsey et al. (2010) also argue that standard house price indices rely on strong constant-quality assumptions, while hedonic price indices overcome many limitations, although they are themselves limited by lack of data.

The idea behind hedonic indices is that the price of a good, for example an apartment, can be approximated by the sum of the values of its constituent parts. In the case of a property this would include the number of bedrooms and its location, for instance.

One of the methods applied in deriving simple hedonic indices is the repeat-sales methodology, first proposed by Bailey et al. (1963). This approach tries to control for housing quality by comparing sales of the same dwellings over time. Its main assumption is that the quality of individual houses remains constant over time (Case and Shiller, 1987). A repeat-sales index[1], however, has a number of drawbacks. Prices are not entered into the index until dwellings experience a subsequent, or repeated, sale. These do not occur very often, meaning that a lot of data is lost. Moreover, houses with repeated sales may not be representative of the whole housing market. Cheaper entry-level homes may sell more often. If differences in composition are systematic over time, this would bias the index. With each new repeated sale, the historic time series for prices would also change, with substantial revisions between

[1] An example of a repeated-sale index is the S&P/Case-Shiller index for the US.

different vintages of the index.

Court (1939) and Griliches (1961) used other hedonic approaches to investigate whether a hedonic price index would take into account product quality changes over time in the automobile industry.[2] These hedonic methods, popularised by Griliches (1971), were further refined in Rosen (1974), who argued that price is some function of the bundle of a product's characteristics. After these seminal studies, several early analyses focused on location effects on house prices.[3] Hedonic quality adjustments to house prices were then adopted extensively.[4]

The literature on hedonic methods is broadly divided into two main variants - the unconstrained and the constrained hedonic approaches (Conniffe and Duffy, 1999).[5] In the constrained approach, a single equation is estimated, with time dummy variables used to distinguish between different time periods, such that each estimated coefficient is restricted to remain the same over time. In the unconstrained approach, multiple equations are used, such that each estimated coefficient varies from one period to another. Hedonic characteristics are included as explanatory variables in both cases.

The first empirical hedonic house price index was the US Census Bureau's 'One-Family Houses Index', which was first published in 1968 (Triplett, 2004). Some examples of studies aiming to construct hedonic house price indices or to look at particular characteristics of properties include Adair et al. (1996) for Northern Ireland, Tse and Love (2000) for Hong

[2]Colwell and Dilmore (1999) argue that Haas (1922) was the first to apply hedonic methods to farm sales in his Master's thesis.

[3]The aim of this study is not to investigate specification selection and estimation methods of hedonic regressions. For details regarding these issues, see: Berndt (1991) and Triplett (2004) for a clear overview of hedonic regression methods and applying these methods to the property market; Sirmans et al. (2006) on selecting explanatory variables for hedonic regressions; and de Haan and Diewert (2013), Coulson (2008), Pace and LeSage (2004), Hill and Scholz (2013), and Silver and Graf (2012) for increasing work on spatial econometric modelling of property prices.

[4]See, for example, Straszheim (1973, 1974). Other more recent studies include Wilhelmsson (2008) and Widlak and Tomczyk (2010). Hill (2013) undertakes a wide ranging literature survey for this topic.

[5]These are termed 'strictly cross-sectional' and 'explicit time variable', respectively, in Gatzlaff and Ling (1994).

Kong, Paz (2003) for Spain, Narwold and Sandy (2010) for San Diego in the United States, O'Hanlon (2011) for Ireland, Ong (2013) for Malaysia, Mallick and Mahalik (2015) for India, Hülagü et al., (2016) for Turkey, and Brécard et al. (2018) for Nantes in France.

In the Maltese case, using an advertised price dataset, Falzon and Lanzon (2013) employ hedonic regression analysis to compute four hedonic house price indices, which span over a relatively long period of thirty-one years. The study also constructs constant weight and chain-linked Laspeyres, Paasche, and Fisher indices for Malta, comparing the results from a total of sixteen different indices. Borg (2004) also constructs a hedonic price index for Malta, using advertised prices for the years 2002 to 2004.

2.1. Housing market developments in Malta

Beyond empirical studies to construct house price indices in Malta, there are also a number of other studies which look at the Maltese housing market. Historically, home ownership was promoted, and such policies were enacted in conjunction with a tightening of rent controls in the 1970s, as highlighted in BICC (2000) and Vakili-Zad (2007). This led to a surge in home ownership over successive years. In Malta, property is often considered as an investment opportunity, and this adds an element of speculation to the price structure (Cordina, 2000).

Studies on the Maltese housing market have focused on affordability, on trying to model long run relationships, and on imputing missing data. The final point is a particular issue, given the lack of timely and accurate data on the housing market in Malta.

Notably, Gatt and Grech (2016) discuss how the compilation of more timely and representative data for house prices in Malta would allow for a quicker and more comprehensive assessment of housing market developments. The study identifies hedonic house price methods as a possible solution to disentangle house price changes which are due to differences in the quality of the units being sold, from house prices movements brought about by changes in demand and supply. Many of these problems, particularly the legal aspects relating to rental, ownership, and property values in Malta are discussed in detail in Xerri (2014).

An analysis on property price misalignment against fundamentals in Malta is carried out in Micallef (2018) for the years 2001 to 2015. Based on the CBM advertised house price index, the misalignment indicator shows a period of overvaluation in house prices which peaked in 2006 - 2007. This disequilibrium began to be corrected following a decline in house prices, reaching a trough in 2013. Starting in 2014, however, the index started to recover such that, by end-2015, house prices were seen to be broadly in equilibrium. An analysis on housing affordability was also carried out in Camilleri (2011), with Malta seen to fit within the Mediterranean housing context in terms of high home-ownership rates and above normal house price growth - while property sizes are closer to northern European countries. Based on the demographic trends and migration patterns of the time, excess housing supply in the early-2010s was expected to lead to a cooling period for house price growth. A more limited study on housing affordability is carried out in Darmanin (2008), with the affordability patterns being confirmed in the later analyses.

The lack of updated data on available housing stock, which is still based on the NSO 2011 Census, has restricted a lot of research on the impact of recent phenomena in Malta - such as migrant worker flows from European countries, new services industries, and a revived rental market.[6] Updated housing stock estimates were computed by Gatt et al. (2018) to build a macro-econometric model of the Maltese housing market.[7] Dwelling investment is seen to be positively related to house prices in the long run. Supply thus responds to increased activity, although this elasticity is less than unity. House prices were found to be negatively related to housing supply per capita, with an estimated elasticity of around -1.3 over the period 1980 to 2017.[8]

[6] Xerri (2017) theorises that the next census may register the first increase in the proportion of rented dwellings following the dramatic increase in Malta's population due to migrant workers.

[7] These estimates are discussed in further detail in Gatt (2019).

[8] Thus, a 1.0% increase in the housing stock per capita decreases real house prices by 1.3% in the long run,

Taken together, it is apparent that lack of data has limited analysis on the Maltese property market over recent years. Moreover, the series of strong changes to the fabric of the Maltese economy and demography appear to have strongly affected property valuations - although it may be too early to disentangle the impacts of these different factors.

holding the other variables in the model constant.

3. Methodology

The paper sets out to apply established methods in the hedonic house price index literature to a mortgage dataset compiled at the CBM. The methodology is based on what is termed the new 'international standard' (Silver, 2016) for hedonic house price indices, namely the Eurostat et al. (2013) Handbook on Residential Property Price Indices (RPPIs). The methods described in the manual are augmented by a set of variables that incorporate hedonic information linked with geography, society, and demography.

The indices computed in this paper are generally presented as a range of estimates, except when comparing between methodologies. Moreover, the band of estimates is also compared with other indices published by the CBM and the NSO. The NSO publishes a quarterly property price index on the basis of the median price for each dwelling type, based on contracted data. The NSO aggregates the indices for apartments, maisonettes, and terraced houses using a Laspeyres-type formula.[9] The weights used to compile the index are based on the value of transactions for the three property types. Moreover, the NSO Index is chain-linked every year. This enables the revision of weights on an annual basis, thus ensuring that the index is relevant at all times.

The CBM publishes an overall advertised property price index, which is a Fisher-chained index, for information purposes as a supplement to the official contract-based index published by the NSO.[10] The CBM Advertised Index has a considerably longer time series, in annual terms starting in the 1980s and in quarterly terms from the year 2000 onward. The NSO index, which has a better coverage of overall properties and uses contracted prices, is only available in its current format from 2005 onward.

[9]For definitions used in the NSO property price index kindly refer to methodological note 3.7 in NSO News Release 105/2018.

[10]Users are advised to exercise caution when using the Bank's index, as in recent years the number of advertised properties on print media account for only a limited portion of available properties, rendering the index less representative over time of the overall market for residential properties in Malta.

3.1. *Hedonic methods*

Three hedonic methods are considered in this study. These are the time dummy variable approach, the rolling time dummy and the average characteristics method. The assumptions behind each method and the similarities and differences between them are discussed here but more details on these hedonic methods can be found in Hill (2013) and Eurostat (2017).

Log-linear functional forms tend to be the most popular methods to construct a hedonic house price index. For example, estimating house prices for a one-period t would mean:

$$ln\ p_{t,h} = Xb_t + u_{t,h} \tag{1}$$

where $p_{t,h}$ refers to the price of dwelling h sold at time t, X is a matrix of hedonic characteristics while the random error term $u_{t,h}$ is the unexplained part of dwelling prices. Since the characteristic variables considered in the models are not changed every time period, (for example, house type, location and land area), the matrix X remains unchanged over time. Each housing unit in the dataset, however, will have its own particular mixture of hedonic characteristics.

The log-linear form in (1) models the natural logarithm of the house price as some linear function of the regressors. The log-linear functional form has a number of advantages in a hedonic context (Diewert, 2003, and Malpezzi, 2003). The hedonic characteristic's shadow price in this functional form is easily interpretable.[11] Using logarithms also reduces skewness and heteroscedasticity. Finally, price indices can be easily constructed in the time-dummy case when the functional form is log-linear. A disadvantage of this functional form is that the hedonic model uses the log of prices, and simply taking the exponent of this estimate

[11] For example, if the coefficient (shadow price) on a hedonic characteristic equals 0.1, it would mean that a one unit increase in the quantity of this characteristic increases a house's price by about 10 percent (note that this simple interpretation does not hold for dummy variables).

will bias the price index. However, this bias is usually assumed to be small.

3.1.1. *Time dummy method (TDV)*

The TDV method estimates a single equation for the period of interest. Time dummy variables are added for each quarter, in contrast to the log-linear hedonic model in (1).

In equation (2), a single hedonic equation is estimated over the whole dataset. The vector b with coefficients for the characteristics represents the average shadow price for the hedonic characteristics over the whole time period in the data set. A matrix D is included to denote the various time dummy variables, along with a vector of time coefficients d:

$$ln\ p_{t,h} = Xb_t + Dd + u_{t,h} \tag{2}$$

This approach has the advantage of simplicity. The construction of price indices under this method requires taking the exponent of the estimated time dummy coefficients. The price index for period t is given by $P_t = e^{d,t*}$. The base period is obviously excluded from the list of dummy variables, and is normalised to 1. This model, however, forces the characteristic shadow price vector b not to be time dependent. This assumption may be unreasonable for housing markets which experience substantial changes to the assumed worth of a characteristic over time.

The TDV method has two principal attractions. It is an easy method to compute hedonic house price indices, while it also works well when using small data sets. This happens because the hedonic model uses all the data and observations which are available, improving statistical significance and robustness.

Assuming fixed parameters for characteristics however is a disadvantage, as it represents a departure from market mechanisms. While the relative valuation of different housing characteristics ought not change too much over a short period of time, these changes do happen, particularly in economies experiencing strong structural change. Localities which were considered to be undesirable become highly demanded, or property types which did not feature strongly in the distribution of house types become prevalent. The TDV method also recalculates the coefficients with the addition of successive periods, leading to potential backward revisions. Both these issues are addressed with the use of rolling time windows.

3.1.2. Rolling-time-dummy (RTD) method

The RTD method is an approach based on the time-dummy method, developed by Shimizu et al. (2010). The procedure behind this method is described in Diewert (2010). The first step is to choose a 'suitable' number of periods for the rolling window - this should be, at least, equal to or greater than two. This will act as the window length (for example, Q quarters) for the sequence of regression models to be estimated over time.

An initial regression model is then estimated, with price indices constructed using the observations for the first Q periods in the data set. Then, a second regression model is estimated with the observations included in the first step - but removing the data for the first period and adding the observations for period $Q+1$. Price indices are calculated for this successive regression model, but only the rate of increase of the index between periods Q to $Q+1$ is used to update the previous sequence of Q index values. This procedure is repeated in each successive regression, with data of the previous earliest period being dropped and data for the next period added, with an update added with each successive regression.

A concrete example can be provided as follows. Assume that one intends to construct a hedonic house price index using this methodology, in quarterly terms. Assume that a rolling window of five periods is chosen, such that:

$$ln\ (P_{\tau,h}) = Xb + D_{t+1}d_{t+1} + D_{t+2}d_{t+2} + D_{t+3}d_{t+3} + D_{t+4}d_{t+4} + u_{\tau,h} \tag{3}$$

The model is estimated using only data for the five quarters ($\tau = t, t+1, t+2, t+3, t+4$). The time dummy variable in (3) for the first period is excluded. The price index for period t is normalised to 1 again. The price indices for the successive periods will equal $\hat{P}_{t+1} = e^{(d^*_{t+1})}$, $\hat{P}_{t+2} = e^{(d^*_{t+2})}$, $\hat{P}_{t+3} = e^{(d^*_{t+3})}$, and $\hat{P}_{t+4} = e^{(d^*_{t+4})}$. The estimates $e^{(d^*_{t+1})}$ and $e^{(d^*_{t+2})}$ are ignored, such that only $e^{(d^*_{t+3})}$ and $e^{(d^*_{t+4})}$ are used. This is because the objective when estimating the coefficient in (3) is to compute the changes in the price index between period $t+3$ to $t+4$.

$$\frac{P_{t+4}}{P_{t+3}} = \frac{e^{(d^*_{t+4})}}{e^{(d^*_{t+3})}} \tag{4}$$

Constructing a property price index following this method would then be a simple case of chaining together ratios as in (4) above, over consecutive periods. This method forces the overall price index to be free from revisions[12], which is a disadvantage of the overall time-dummy method shown above. An important strength of RTD methods over the time-dummy approach is that the vector of coefficients b is time variant. The method is simple to compute, and is well-behaved even with small data sets. The choice on the length of the rolling window is arbitrary. This is an advantage in that it provides flexibility and experimentation, while it is also a weakness as there is no established consensus yet.

For example, O'Hanlon (2011) discusses how Ireland used the RTD method to construct its official house price index, recommending a setting such that the rolling window includes one year of data. However, if it is deemed to be only possible to calculate the house price index on a quarterly basis, a good starting point is a rolling five quarter window. This approach is used in this study, due to the limited number of observations in the dataset, along with a

[12]Unless new observations are included in the dataset for past periods.

rolling window of four and two periods.

A shorter window ensures that the estimated vector of coefficients b is relevant and updated for the time periods being considered. A longer window has the strength of allowing more data to be considered. This increases the robustness and significance of the estimated hedonic model. The optimal window length may be short for larger countries with more data points, and long for smaller countries with considerably less data.

Short term volatility in the index may mean that the sample size in the estimation of each hedonic model is too small - and implicitly the window may be too short. Insignificant coefficients on time-dummy coefficients can also be an indication of a short window length. However, interpretation here should be very careful.

Insignificant time dummy coefficients also occur in periods where prices are stable - such that even if the hedonic model is correctly specified and performing well, as the 'true' underlying coefficient is close to zero anyway, the variable will be insignificant.

The RTD method appears to be a safe and robust way to estimate hedonic house price indices. It appears to be particularly well suited for smaller countries that lack having many observations in each period.

3.1.3. Average-characteristics method

The average-characteristic approach is a type of hedonic imputation method which estimates a separate hedonic model every period. This allows shadow prices estimated for the characteristics to be updated, thus reflecting the situation measured in a particular period. The average characteristics method then imputes a price for the 'average' house. The price index is calculated as the ratio of the imputed price of the average house at time $t + 1$ to the imputed price of the same 'average' house at time t. The Laspeyres version for the average house of period t is calculated as:

$$\frac{P_{t+1}}{P_t} = \frac{\hat{p}_{t+1}, h(\overline{x_t})}{\hat{p}_t, h(\overline{x_t})} = e\Big[\sum_{c=1}^{C}(\hat{b}_{t+1,c} - \hat{b}_{t,c})\overline{x}_{t,c}\Big] \tag{5}$$

where $\overline{x}_{t,c} = \frac{1}{n(t)}\sum_{h=1}^{n(t)} x_{t,h}$ is a vector of average characteristics. Equation (5) also assumes that the hedonic model is log-linear. The average characteristics method can be thought of as the ratio of the weighted shadow prices for the two periods compared. The denominator in (5) is derived by using the average house characteristics of time t estimated at time t. The numerator is obtained by inserting the characteristics of the average house of t into the hedonic model estimated for period $t + 1$.

A Paasche-type price index version, on the other hand, takes an average house of $t + 1$ as the reference:

$$\frac{P_{t+1}}{P_t} = \frac{\hat{p}_{t+1}, h(\overline{x_t})}{\hat{p}_t, h(\overline{x_t})} = e\Big[\sum_{c=1}^{C}(\hat{b}_{t+1,c} - \hat{b}_{t,c})\overline{x}_{t+1,c}\Big] \tag{6}$$

Taking the geometric means of Laspeyres and Paasche in (5) and (6) to ensure the symmetric treatment of both periods will result in a Fisher-type hedonic imputation price index.

4. Data

The CBM collects anonymised mortgage contract data on residential property from the major lenders in the Maltese mortgage market, under Banking Regulation VI. The information is based on the architect's valuation report, which is a prerequisite for property purchases financed through a mortgage.

Mortgages do not cover the sum total of property transactions, such that we estimate that slightly less than half of property transactions are mortgage-based, with the rest being cash transactions. This could lead to some sample biases, in that cash and non-cash transactions can have different characteristics.[13] Moreover, in certain sub-categories the presence of cash transactions can result in a relatively low number of observations. In such cases, outliers can have a significant impact on hedonic regressions, and hence certain transactions are excluded from the dataset. The identified outliers were: (i) properties costing less than fifty thousand euro and more than one million euro; (ii) properties smaller than fifty-five square metres or larger than one thousand square metres[14]; (iii) properties falling under the category of bungalow, villa, or palazzo. After accounting for these outliers, the dataset consisted of just below 29,000 observations, or around 88% of the original amount.

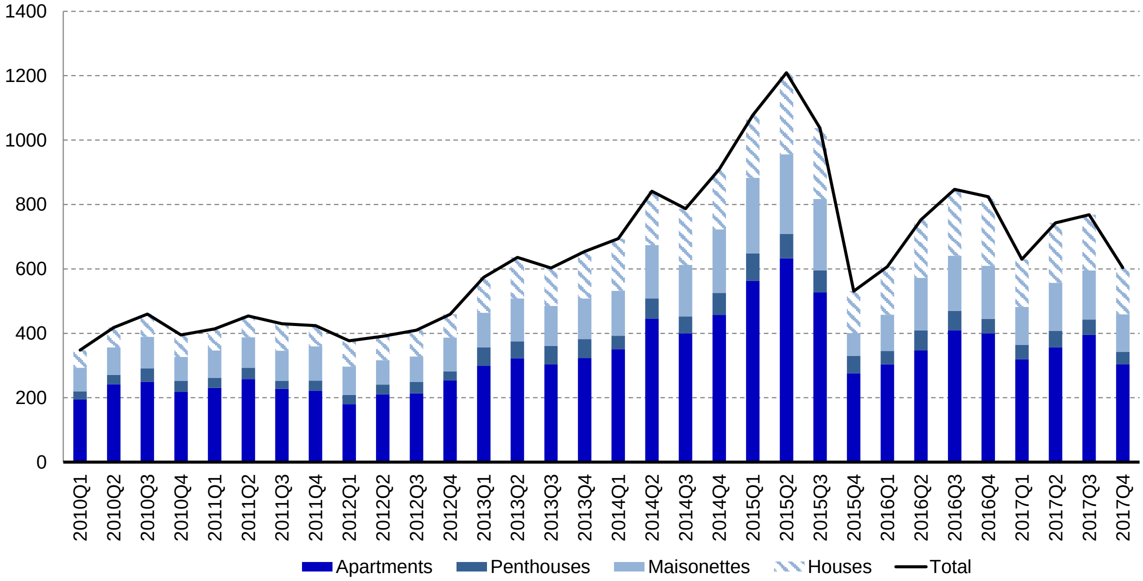
Four categories of property were considered in the analysis, namely apartments, penthouses, maisonettes, and houses, the latter grouping properties listed as terraced houses, townhouses, farmhouses, and houses of character.[15]

[13] This is partly tackled in Section 5.4.

[14] The fifty-five square metres minimum follows MEPA (2015), pp. 101-102.

[15] In this study, flats and apartments are defined as units with a communal entrance, with penthouses being the topmost unit in a block of apartments. Maisonettes are units in a block with an independent access. Houses of character tend to be defined as houses built before 1900, townhouses are usually defined as pre-1968 houses, while terraced houses may be defined as houses built after 1968. In general, farmhouses are the main building on a farm, with combined space originally intended for farm-animals. Dwelling types are self-reported in Bank returns, and definitions may be subjective.

Chart 1
Number of transactions
(Counts in the CBM mortgage dataset)

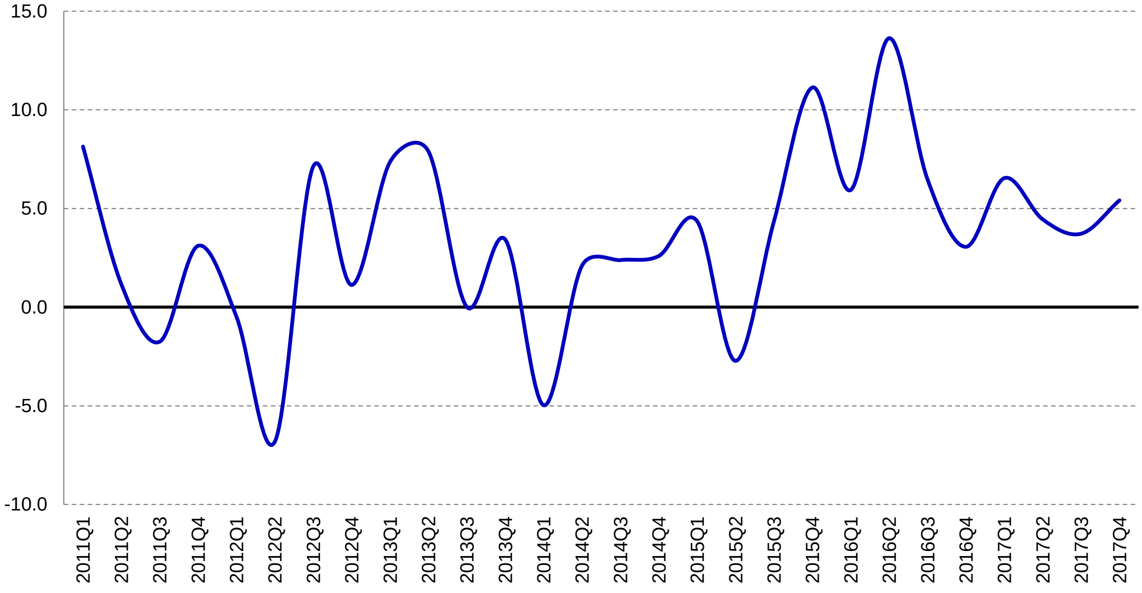


Source: Authors' calculations.

Chart 1 gives a general overview of the dataset, plotting the number of transactions per quarter by property type. The number of transactions has increased considerably over time, reflecting the increased activity in the property market over the sample period. Between 2010 and 2013, the average number of transactions per quarter stood at 512, before rising to 1,177 between 2014 and 2017. Apartments on average comprised 52% of total transactions over the sample period. In particular, 2015 was a plentiful year in terms of property transactions. This probably reflected intertemporal issues relating to the Government's first-time buyer scheme.[16] The scheme, which was first announced in November 2013, and was repeatedly extended until mid-2015, may have led to a number of buyers bringing forward their purchases. In turn, this led to a spike in transactions during the first half of 2015, and a sharp drop thereafter. The scheme was re-introduced in October 2015, and remained in place since then.

[16] The scheme allowed first-time buyers to be exempt from the stamp duty on the purchase of immovable property, up to the first €150,000 spent. This is equivalent to savings of up to €5,000 in stamp duty.

Chart 2
House price growth in mortgage dataset (non-quality-adjusted)
(Annual percentage changes)



Source: Authors' calculations.

The strong increase in property transactions over the years was met by a robust increase in house prices. According to the mortgage dataset, actual house price growth (before quality adjustment) stood at an average rate of 2.0% between 2011 and 2014 (see Chart 2). Growth strengthened thereafter, peaking at 7.3% in 2016 and remaining at a robust 5.0% in 2017. Since the growth in house prices shown in Chart 2 has not been adjusted for quality, there is no way to distinguish whether this acceleration reflects a pure price change or is simply due to changes in the quality and nature of the transacted properties.

Apart from contracted prices and property type, the mortgage dataset also provides several other attributes describing the structure and overall characteristics of each transacted property. These include the size of the property (in square metres), the property state (shell or finished), and its location.

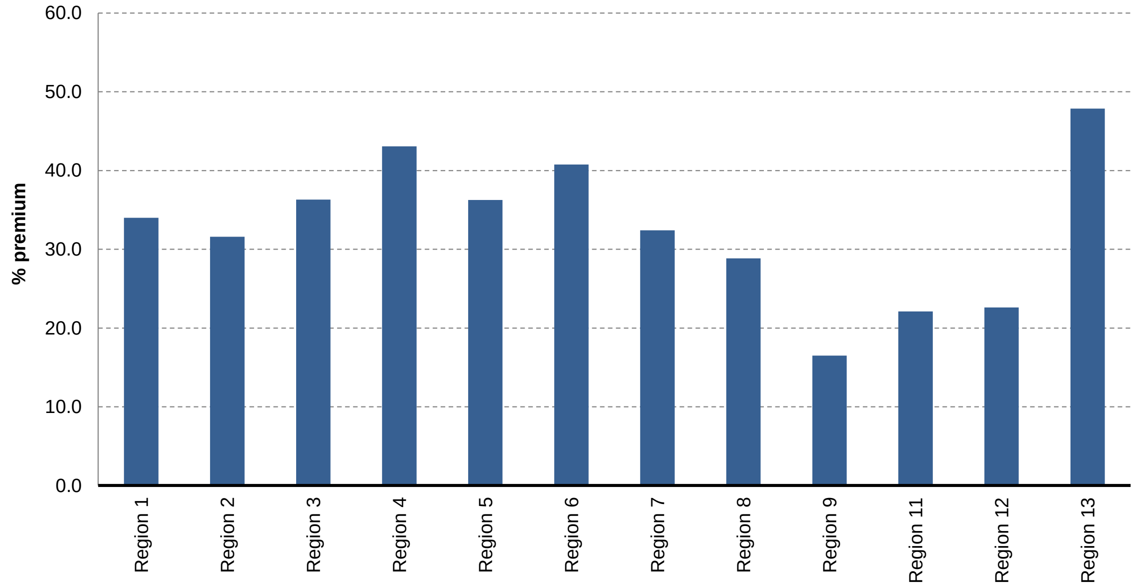
Moreover, a number of other attributes which were not available at the start of data collection have been made available over the years These include characteristics such as a garage/parking space, pool, garden, lift, and view type. Due to the limited span of the time-series, the hedonic regression presented hereunder does not make use of these characteristics. However, going forward, it would be possible to augment the hedonic regression with these variables once more observations become available.[17]

Apart from its structural characteristics, a property's price also depends on its geographic attributes. Data on property location are available in the mortgage dataset, split into 67 different localities. Use of this data would thus entail 66 dummy variables (and one base location), which is too large for a hedonic regression model spanning eight years. Hence, we grouped localities into regions based on the thirteen electoral districts used in the 2017 general election. The advantage of using electoral districts is that these tend to be divided into contiguous geographical areas consisting of broadly equal-sized populations of voters. The tenth region, consisting of Sliema, St. Julian's, Gzira, and Naxxar, was chosen as the baseline region for the analysis, as it is typically the region that garners the highest premium. This is shown clearly in Chart 3, showing that the median price per square metre paid for properties in Region 10 during 2017 was higher than in all other regions. A similar pattern was observed across the entire sample range.

At the same time, a property's price also depends on certain factors relating to the desirability of its location. These include transport links, employment opportunities, the availability of amenities such as shops, entertainment outlets, and schools, and the overall desirability of the neighbourhood in which the property is situated. Although such detailed data are not available for Malta, it was possible to construct a number of proxy variables capturing these geographical attributes, using the 67 property location variables available in the mortgage dataset.

[17] In Appendix B, Chart B, a range of indices is presented with garages, gardens, and pools included in the hedonic regression.

Chart 3
Region 10 premium
(Deviation of median per square metre vis-à-vis Region 10 in 2017)



Source: Authors' calculations.

In order to capture attributes such as the frequency and length of transport links and available employment opportunities, each locality was equated with a specific distance from centre variable. For this purpose, it was necessary to identify an economic and political centre for Malta. This was defined as the localities of Valletta, Floriana, Msida, Pietà, and Ta' Xbiex, as well as St. Julian's, Sliema, Swieqi, and Gzira. The distance from centre attributed to these localities was set to zero. For the remaining localities, the distance from centre was calculated as being the road distance between the centre of each of the remaining 58 localities (in most cases defined as the main parish church, or a convenient centre of a village) and the mid-point of the identified 'centre', set as Manoel Island due to its geographic location between Sliema/Gzira and Valletta. The sign on this variable's coefficient is expected to be negative, suggesting that price and distance from centre are negatively correlated.

At the same time, the distance from centre variable ignores certain instances where a locality may be in high demand for reasons other than its proximity to the economic centre of the island. For example, localities such as St. Paul's Bay, Mellieha, and Marsascala are popular destinations due to the large availability of amenities and leisure activities such as restaurants, shops, and beaches. Such localities also tend to be popular with tourists, leading to the presence of a number of hotels. Data on hotel units by locality ware made available by the Malta Tourism Authority, which proxies the desirability of certain locations due to their entertainment and/or historical heritage. Hence, one would expect the number of hotel units to be positively correlated with property prices. The variable is observed in annual terms for the period 2010 to 2017.

In other instances, a locality may be considered desirable for social reasons. For example, certain localities may be considered as being more socially desirable due to a high concentration of professionals, thereby leading to a premium on property prices. To capture these social effects, data were collected from the NSO's STATAMAP district and locality thematic database on benefits intended to combat social exclusion, such as supplementary assistance. Data were available as a single-point observation for each locality, and is expected to be negatively correlated to house prices.

Apart from residential demand, certain localities are highly popular due to their investment potential, particularly for the buy-to-let market. A good proxy variable to capture this effect is the share of foreign residents residing in a particular location, which acts as a measure of the rent-likelihood of a property. The variable is observed in annual terms for the period 2010 to 2017. The number of foreigners within a locality was obtained as the difference between the total population and the total Maltese population residing in each locality, available from the NSO's Demographic Review. The sign on this coefficient, following Sweeny (1974) and Jackson (1979), is expected to be negative, due to underlying differences in the characteristics of properties rented to expats, and differences between tenant-owner behaviour. Moreover parts of the literature also attribute this negative coefficient to residential segregation, such as Accetturo et al., (2014), Sá, (2015), and Saiz and Wachter (2011).

5. Results

5.1. Regression results

This section presents regression results for the three main methods of hedonic adjustment. Table 1 contains results for three regressions. The first regression outlines the estimated coefficients of the TDV method. The second and third regressions show an output of the five quarter rolling window method, and the average characteristics method. In both the latter cases we show the estimations related to the fourth quarter of 2016. However, the computation of these indices requires the re-estimation of the coefficients multiple of times. In the case of the RTD method, the coefficients are re-estimated every select time period. For example, in the case of the five-quarter rolling window method, coefficients are re-estimated every five quarters. With regards to the average characteristics methods, the coefficients are re-estimated every quarter. The results presented here have to be interpreted with respect to a benchmark property. In our case we have chosen a shell apartment in Region 10, referring to the Sliema/St. Julian's area, as the benchmark property.

The estimated equations are generally a good representation of house prices in Malta, with in-sample fit exceeding 50% in most instances. Moreover, time-dummies in both the TDV method and the RTD method are typically statistically significant, which means that after adjusting for quality we can satisfactorily capture the time series evolution of house prices in Malta.[18] Nevertheless, the RTD method sometimes produces statistically insignificant time-dummies, which can either reflect no significant change in house prices from one quarter to the next, or can represent some estimation biases due to the relatively small sample available. Similarly, the average characteristics method is even more susceptible to small sample biases since estimation is made every quarter, and the probability of statistical insignificance of some coefficients tends to be higher.

[18]We do not show the time-dummy coefficients in Table 1 for brevity, but these can be made available upon request.

Table 1
Regression results

	Time-Dummy Variable method	Five-quarter rolling window method (2016Q4)	Average Characteristics Model (2016Q4)
Constant	9.87***	9.93**	10.34***
Size	0.55***	0.55***	0.50***
Property State			
Shell (benchmark category)			
Finished	0.11***	0.18***	0.19***
Property Type			
Apartments (Benchmark category)			
Penthouses	0.10***	0.08***	0.01
Maisonettes	0.03***	0.00	0.01
Houses	0.18***	0.09***	0.10***
Regions			
Region 1	-0.19***	-0.26***	-0.26***
Region 2	-0.18***	-0.28***	-0.32***
Region 3	-0.23***	-0.30***	-0.36***
Region 4	-0.26***	-0.39***	-0.49***
Region 5	-0.16***	-0.15***	-0.22***
Region 6	-0.14***	-0.21***	-0.23***
Region 7	-0.08***	-0.16***	-0.19***
Region 8	-0.08***	-0.06**	-0.11*
Region 9	-0.10***	-0.08**	-0.07
Region 10 (benchmark category)			
Region 11	-0.04***	-0.11***	-0.09
Region 12	-0.20***	-0.22***	-0.16**
Region 13	-0.19***	-0.21***	-0.2***
Geographic and socio-demographic			
Collective accomodation units	0.06***	0.12***	0.14***
Distance from centre	-0.01***	-0.02***	-0.02***
Social exclusion	-0.17***	-0.16***	-0.16***
Share of foreigners in a locality	-0.24***	-1.12***	-1.70***
Observations	28691	3938	866
Adjusted R-squared	0.53	0.52	0.53

* *significant at the 10% level*
** *significant at the 5% level*
*** *significant at the 1% level*

As expected, the coefficient on the property size variable is positive and statistically significant, which implies that larger properties tend to garner higher prices. The estimated coefficient tends to be very similar across periods and methodologies. In addition, when using shell properties as the benchmark category, the coefficient on finished properties is positive and statistically significant.

The type of property purchased also affects the price. Indeed, using apartments as the benchmark category, the coefficients on other categories have a positive coefficient, meaning that penthouses, maisonettes and houses tend to be purchased for higher prices than apartments. The coefficient on maisonettes is only statistically significant in the case of the TDV method, which implies that in most cases, maisonettes and apartments have similar prices. In Table 1, the estimated equation of the average characteristics method also shows a statistically insignificant coefficient on penthouses. As explained above, this method tends to have the lowest number of observations per estimation, and hence small sample biases tend to be larger and it is not unusual to observe statistical insignificance of certain coefficients in some periods.

With regards to regional variables, we utilise Region 10 as the benchmark category. As expected, the coefficients on all other regions are negative and statistically significant, which implies that housing units in Region 10 typically generate a premium over housing units purchased elsewhere on the island. These negative coefficients become generally larger in absolute values the further away the property purchased is from Region 10. This implies that the premium typically generated by Region 10 tends to decline the closer the property bought is to that area.

Moreover, the coefficients on the geographic and socio-demographic variables are in line with our a priori expectations. The coefficient on the 'distance from centre' variable is negative, which captures the negative premium one would associate with the travel distance of a particular locality from the political and economic centre of the island. Conversely, house prices are positively correlated with the number of collective accommodation units in a particular location. The coefficient on the social exclusion variables is negative, as the desirability of a particular location typically declines when there is a higher concentration of households in a locality who depend on social benefits. This in turn tends to negatively affect the price of housing units.

The coefficient on the foreign share variable is negative and statistically significant. This finding is in line with the literature (see for example Sweeny, 1974 and Jackson, 1979). The foreign share variable captures the rent-likelihood of a location. Rental units and tenants tend to have different characteristics than non-rental units and owner occupied housing, such that they can be expected to be cheaper - from a cross-sectional point of view it is likely to be reflected in lower house prices. Moreover parts of the literature also attribute this negative coefficient to residential segregation, such as Accetturo et al., (2014), Sá, (2015), and Saiz and Wachter (2011). Some caution with the interpretation, however, is necessary. In general, foreigners are not major takers of mortgages. This is because foreigners, particularly those working in Malta for a short period of time, tend not to buy properties. Foreigners are inclined to rent properties, and the characteristics of rental properties may be different from those of non-rental properties. In that sense, this finding may be amplified by the 'property mix' in certain localities. Looking at the impact of the foreign share from a time series perspective, however, foreigner shares have a positive effect on house price inflation: excluding foreigner share lowers house price inflation.[19]

The estimated coefficients using the RTD and average characteristics methods are time dependant, which implies that the contribution of the underlying characteristics of the housing market has changed over time. In particular, we can observe that the coefficients of the state of property and penthouses have increased over time, especially post-2015. This im-

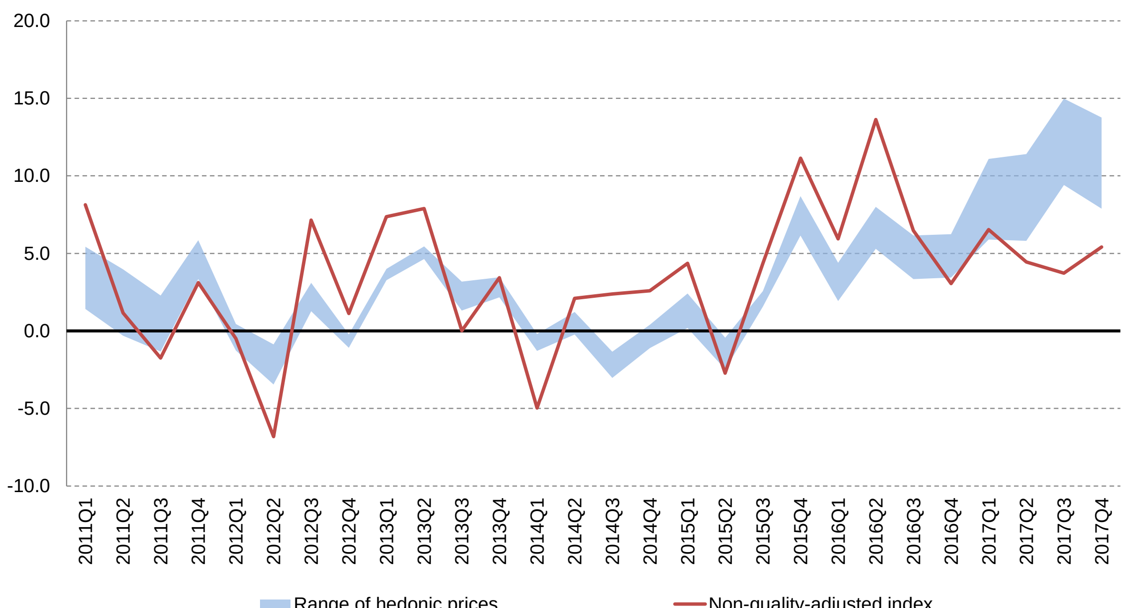
[19] See Appendix A for differences between growth in house prices of a hedonic regression which includes the foreign share and one that excludes this variable. House price growth for the period 2016 and 2017 would be lower if one were to exclude the share of foreigners in the hedonic regression, which implies that from a time-series perspective, the higher the rent-likelihood, the higher the increase in house prices.

plies that those taking a mortgage are attaching a growing premium on the state of finish and penthouses. Furthermore, the coefficients attached to Regions 8, 9, and 11, have been declining, which implies that there seems to be growing price convergence among the central and northern harbour regions. Even more importantly, the coefficient of the foreign share variable has become statistically significant only post-2013, and has been growing in absolute terms, which is consistent with the phenomenon of the sharp rise in the foreign population.

5.2. Indices

This section presents a range of house price indices based on the three different methods of hedonic adjustment explained in previous sections. In general, the time series evolution of the indices is broadly similar, which implies that our results are quite robust to the different hedonic methodologies. On the other hand, the different statistical methodologies, indexing methods, and time-period averaging, tend to create some differences in certain periods.

Chart 4
Range of hedonic house prices compared to mortgage non-quality adjusted index
(Annual percentage changes)



Source: Authors' calculations.

Chart 4 shows the range of house price annual growth rates derived from the different hedonic adjustments, when compared to growth rates that emerge from an index that is not quality-adjusted. Overall, and when considering all indices, the growth in house prices remained quite muted over the period 2011-2014, averaging between 1.0% and 2.0% across the different methods. House price growth picked up markedly in the final three years of the sample period. On average, house price growth stood between 4.5% and 7.5% across the different methodologies.[20]

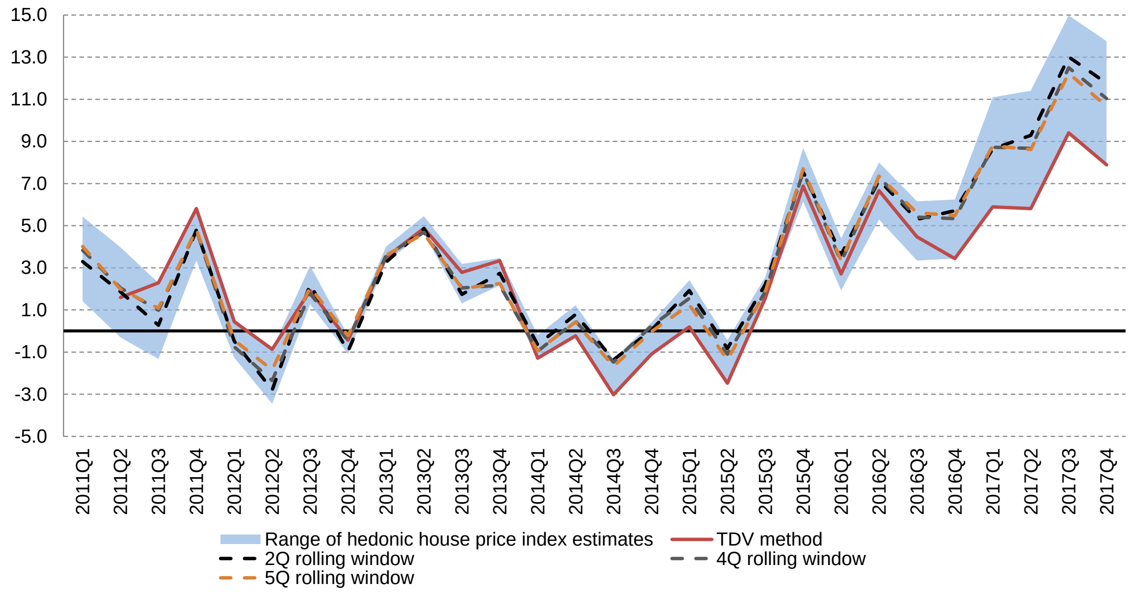
The non-quality-adjusted price index is quite volatile on a quarterly basis, while hedonic indices are generally more stable. However, the dynamics of the quality-adjusted indices and the non-quality-adjusted average price index are broadly similar, except in certain periods. In particular, the average price index shows some positive growth in house prices in 2014, while the range of hedonic indices indicate that house prices were either contracting marginally or experiencing zero growth. These differences were driven by a significant rise in the median square metres of the properties bought using mortgages in 2014. This meant that the price per square metre dropped in 2014, thus leading to some small contraction in house price growth during that year.

Conversely, hedonic house price indices show a much stronger pick-up in house price growth in 2017 when compared to that exhibited by the average price index. Indeed, while house price growth in 2017 stood at around 5.0% according to the non-quality-adjusted house price index, hedonic methods suggest a range between 7.0% and 13.0% during the same year. This was primarily driven by an increase in the share of foreigners in certain localities, which as explained above tends to lead to an increase in hedonically-adjusted house prices. While this does not imply that foreign demand is the sole driver of house prices in Malta, as shown for the various other factors discussed above, its importance can be expected to be higher

[20] As explained in previous sections, we exclude garages, gardens and pools in these indices, since data only starts from 2013. If we were to include these characteristics as part of the hedonic regressions, the range of indices does not change much (see Appendix B, Chart B).

in particular areas of Malta.

Chart 5
Range of time-dummy variable house price growth
(Annual percentage changes)

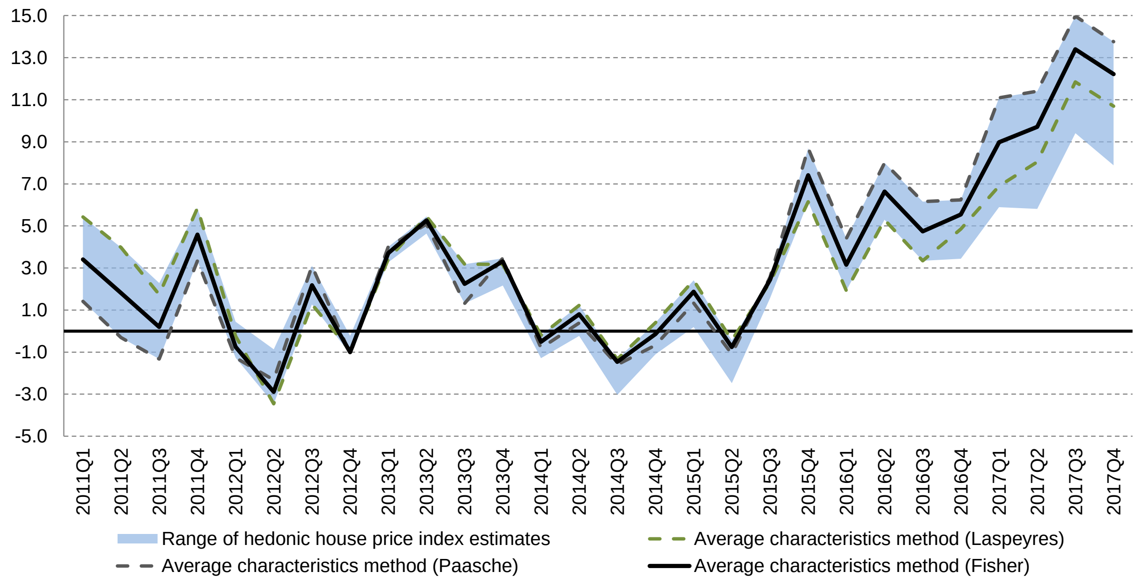


Source: Authors' calculations.

Chart 5 shows the range of house price growth using only the TDV method, and the different rolling windows explained in previous sections. The range is quite narrow over most of the sample period, but widens considerably during the expansionary phase post-2015. The relatively wide range is being primarily driven by the relatively low growth rates derived from the TDV. Indeed, over the period 2015 and 2017, the TDV method exhibits an average growth of around 4.4%, while the RTD methods show average growth of around 6.0% over the same period. Moreover, in 2017, the TDV method shows growth of around 7.2%, while the RTD methods exhibit house price annual growth of around 10.0%.

These growing divergences between the TDV and RTD indices underline the significant evolution of the housing market that took place in Malta in the last few years. Since the TDV method assumes constant implicit prices over time, it is unable to capture the change in the weight of certain hedonic characteristics. Moreover, the TDV method is susceptible to significant revisions as the full index is re-estimated every time a new quarter is added to the sample period. On the other hand, rolling-time window methods re-estimate the coefficients of hedonic characteristics every selected time period, and are hence better equipped at capturing changes in characteristics. Hence, the growing divergence between these two different methodologies indicates that the housing market has been evolving at a rapid pace over the last few years, with certain qualities contributing more to house price movements in Malta.

Chart 6
Range of Average characteristics method house price growth
(Annual percentage changes)



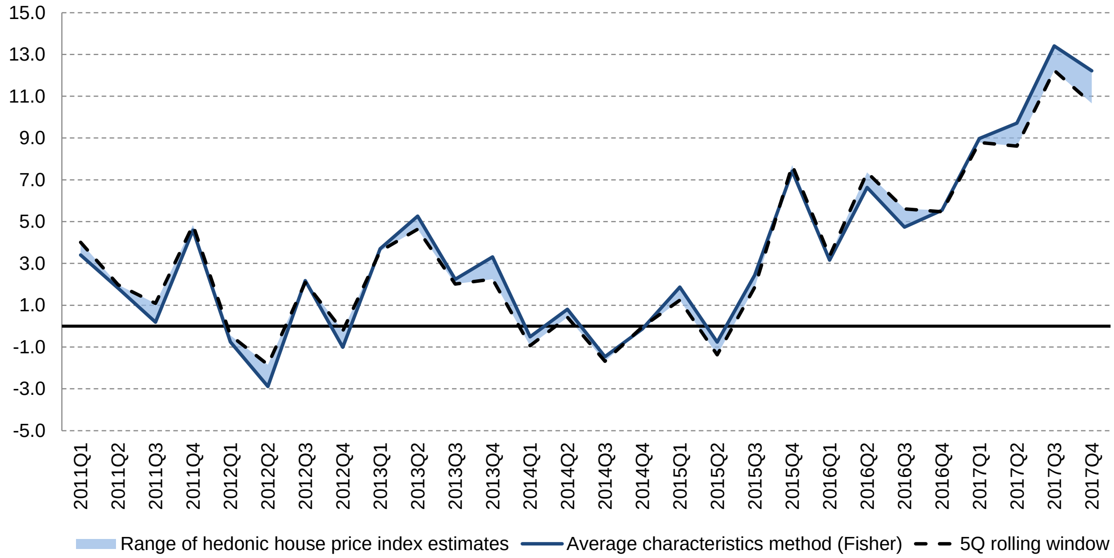
Source: Authors' calculations.

Chart 6 depicts the results derived from the average characteristics method, whereby coefficients are estimated for each time period. As with the TDV and RTD methods, this demonstrates that the general evolution of house price growth tends to be relatively similar across the different statistical averaging methods. Nevertheless, we can observe that the dispersion among these indices is higher than that exhibited by the TDV and RTD methods, especially during 2011 and post-2015. These divergences tend to increase during periods of strong changes in preferences and quality. In particular, the Laspeyres index does not allow for substitution among housing units as it is constructed to achieve constant quality, and hence it tends to overstate inflation. Conversely, the Paasche index allows for continuous changes in preference where agents are assumed to be always willing to purchase lower quality units to achieve affordability. Moreover, ILO et al. (2004) show that when prices and quantities are negatively correlated, the Laspeyres index exceeds the Paasche index, and conversely, when prices and quantities are positively correlated, the Paasche index exceeds the Laspeyres index.

Hence, the growing dispersion among house price growth measures post-2015 can be interpreted as a period in which both prices and characteristics changed markedly. Since 2015, the Maltese housing market experienced both a rapidly increasing housing stock (see Gatt et al. 2018) and strong increases in house prices. Therefore, it is not surprising that post-2015 the Laspeyres index exhibits lower house price growth than the Paasche index. As explained in previous sections, the Fischer chained index is a geometric average of both these indices, and is generally considered among statisticians to behave as an ideal index.

The relatively wide range depicted in Chart 4, especially in the last two years of the sample period, is driven by the TDV method and the Paasche index. Both these indices are less than optimal, for reasons already explained above. Chart 7 shows the two best indices as suggested by the economic literature, that is, the five-quarter RTD, and the Fischer-chained index. The first method is typically suggested for countries with relatively low observations, while the latter is considered to have optimal statistical properties. The range gets much narrower than that shown in previous charts. Indeed, during the period 2015 to 2017, house price growth averaged between 6.0% and 6.3%. In 2017 alone, both indices experience robust growth, ranging from 10.1% to 11.0%.

Chart 7
Range of Five-quarter RTD and Fischer-chained indices
(Annual percentage changes)



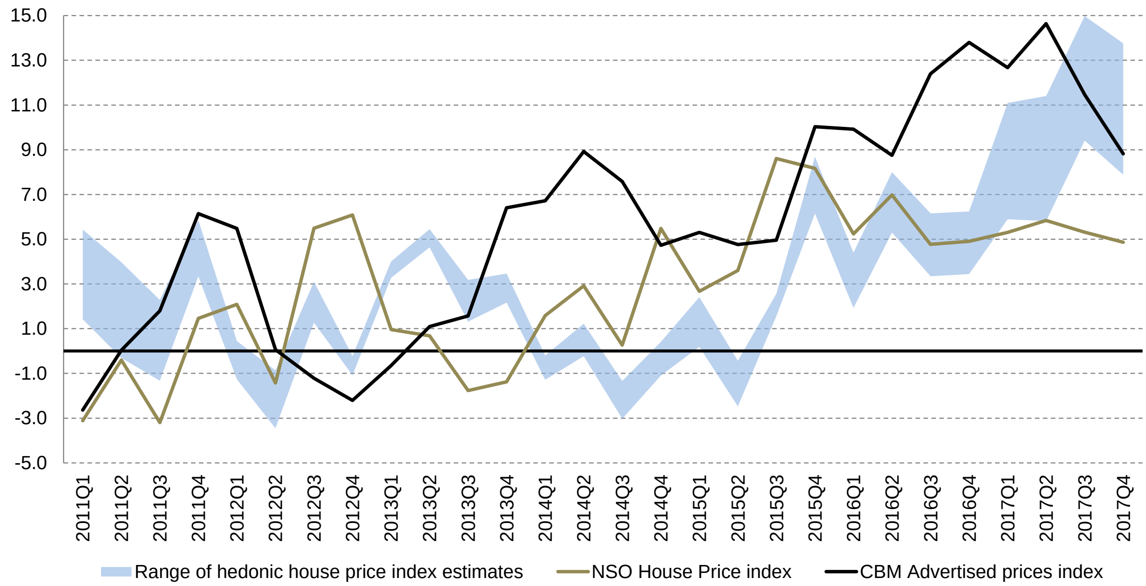
Source: Authors' calculations.

5.3. Comparison with existing indices

In Chart 8 we compare the range of hedonic indices with the house price indices that are published regularly by the NSO and the CBM. As explained in previous sections, the main difference between the mortgage-based hedonic indices presented in this paper and the NSO and CBM indices is the source data. The CBM advertised index is expected to lead both the NSO contract-based index and our range of mortgage-based indices, as purchases of properties typically take place later.

Chart 8 shows that although all indices seem to capture a similar evolution of house prices over time, there are significant differences in certain periods. In particular, the growth in house prices exhibited by the CBM advertised post-2013 is well above that displayed by the NSO contract-based index and the range of hedonic indices estimated in this paper. On the other hand, there is stronger co-movement between the NSO index and the range of hedonic indices, at least until 2015. After 2015, hedonic indices suggest much stronger

Chart 8
Comparison to existing indices
(Annual percentage changes)



Source: Eurostat, CBM, Authors' calculations.

pick-up in house prices than the NSO index. The divergence post-2015 between the range of hedonically-adjusted indices and the NSO index is similar to that observed in Chart 8 between the mortgage-based non-quality adjusted index and the quality-adjusted indices.

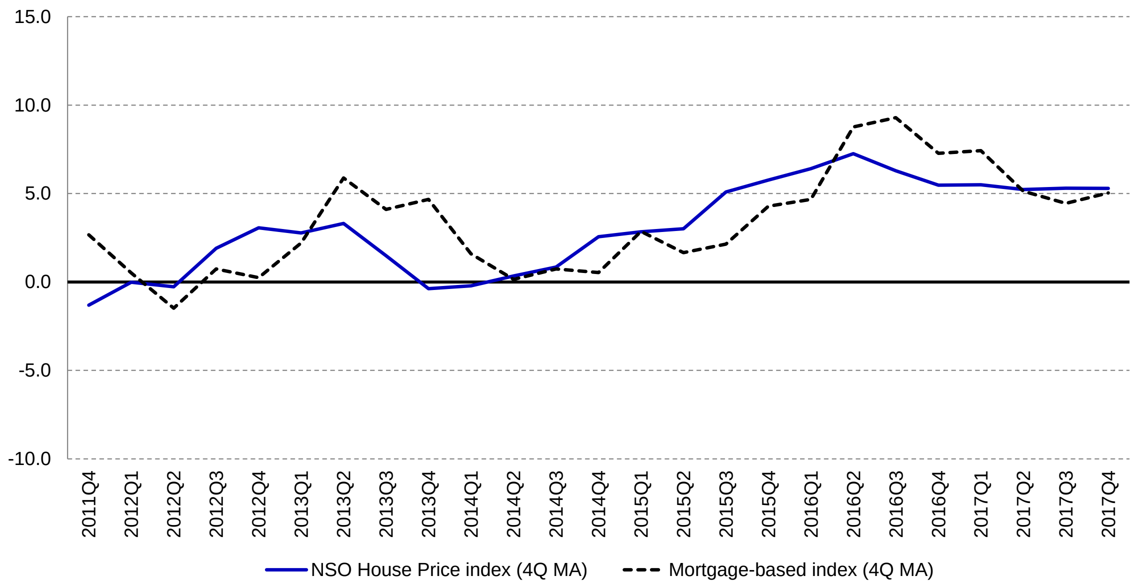
Despite these divergences, all available indices have their own advantages that need to be considered when being used by analysts and researchers. In particular, the CBM advertised index, despite its limitations, has a time series going back to the 1980s, and is hence useful when investigating long-term house price cycles. Conversely, the NSO contract-based index, which has a much shorter time series, is based on contracts and is thus less susceptible to possible divergences between asking and actual prices, which may vary over the house price cycle. With regards to the range of indices presented in this paper, their major advantage is that we control for changes in characteristics, but these indices have the shortest time series and do not include cash transactions in the mortgage dataset.

5.4. Limitations of mortgage-based indices

Although the dataset we have utilised in this study is very rich and allows us to make very useful inferences about the housing market over the last decade, there are some significant limitations which are difficult to fully address without resorting to a different dataset. In particular, our dataset by definition does not include cash transactions. Cash transactions account for around half of the residential property contracts in Malta. In this context, the application of hedonic methods to a much wider contracts dataset may prove to be of particular interest. In addition, the lack of cash data might mean that we lose out on properly observing certain new patterns, such as the buy-to-rent market. Composition effects may also be harder to capture. For example, cash transactions may be more prevalent among the older and richer cohorts, while first-time buyers may be more likely to finance their property purchase using mortgages. As long as the preferences of both markets are similar, then mortgage data will be a good representation of house prices in Malta. However, if preferences significantly diverge, then mortgage data will not be fully representative.

Chart 9 compares the four-quarter moving average of the non-quality-adjusted index derived from our mortgage dataset to the NSO index. The latter has a more complete dataset since it is based on contracts data and hence includes both mortgages and cash transactions. If these indices diverge strongly over time, we can attribute the differences to divergences between the cash and non-cash markets. However, Chart 9 shows that the two indices move closely, which indicate that these two markets did not strongly diverge during the last decade. Hence, despite the limitations of mortgage-based data, it seems that it has been fairly reflective of the property market in general. Indeed, the correlation between the growth rate of the NSO index and the non-quality-adjusted index is strong, at more than 0.7.

Chart 9
Non-quality-adjusted price index compared to NSO index
(Annual percentage changes)



Source: Eurostat, Authors' calculations.

6. Conclusions

During the latest decade, the Maltese housing market went through considerable change, both in terms of the prices at which housing units are traded, but also and more importantly, the underlying characteristics that define the value of a housing unit. This paper introduces a novel dataset that allowed us to gain a deeper understanding of this evolution. The dataset is based on mortgage contracts in Malta for the period 2010-2017, which includes the price of the property being traded and a set of characteristics. These characteristics include the property size, the state of the property, the type of property, and the locality. In addition to this, we included a set of geographic and socio-demographic variables to help us better identify the between-region differences. These characteristics allowed us to create indices of house prices that capture the evolution of both price and quality changes, which ultimately enabled us to build a range of quality-adjusted indices. These quality-adjusted indices - or hedonic indices - capture the pure house price changes over time.

The hedonic indices outlined in this paper are based on the Eurostat et al. (2013) Handbook on Residential Property indices (RPPIs). We have considered three main methodologies: the TDV, RTD, and average characteristics methods. For the case of the RTD method we utilise three time windows, that is, the two-quarter, four-quarter, and five-quarter window. With regards to the average characteristics methods, we calculate three chained indices, that is, the Laspeyres, Paasche, and Fischer chained indices.

Overall, the different hedonic measures outline a broadly similar picture regarding house price growth over the last decade in Malta. House price growth remained relatively muted over the period 2011-2014, averaging between 1.0% and 2.0%. House prices picked-up markedly after 2015, with growth averaging between 4.5% and 7.5%. In particular, house price growth in 2017 stood between 7.0% and 13.0%, depending on the method employed. When taking into account only the two methods considered "ideal" for small economies by the literature, that is the five-quarter time dummy variable method and the Fischer-chained average characteristics index, we obtain a narrower range of growth of between 10.1% and 11.0% for 2017. Although in most periods we observe similar growth rates across the different indices, we have seen growing divergences, especially in the last few years. Indeed, the differences between the range of hedonic measures presented in this paper and the non-quality-adjusted indices become rather stark in the latter period of the sample. This provides evidence that the underlying characteristics of the properties purchased through a mortgage have undergone a significant transformation, suggesting that non-quality-adjusted indices could be misleading.

The main limitation of this study is that with mortgage data we can capture slightly less than half of the market, and we are therefore unable to account for cash transactions. We have provided some evidence that mortgage data have however been quite representative of the overall market during the last decade, and hence the divergences between our results and the official indices can be attributed to the fact that we control for changes in the underlying characteristics of the properties traded.

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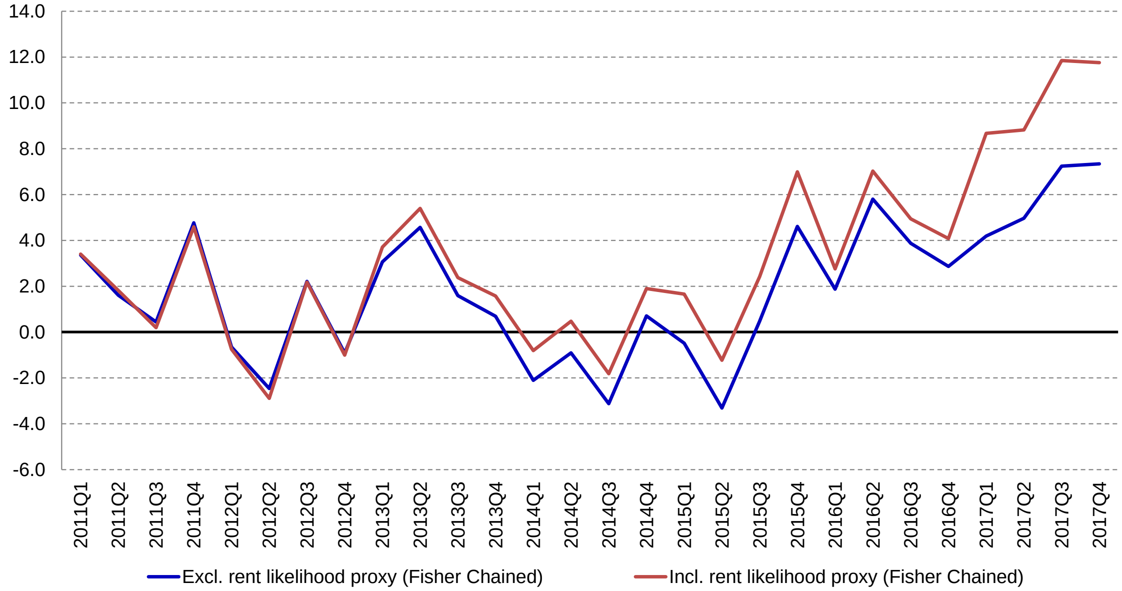
Appendix A

Chart A
Excluding rent likelihood proxy
(Annual percentage changes)

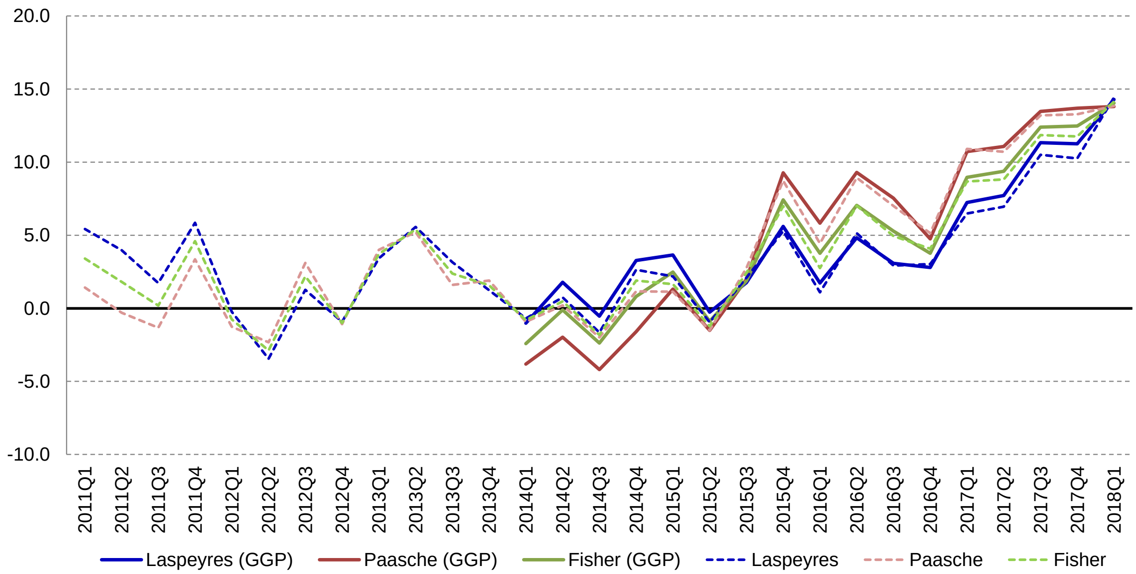


Source: Authors' calculations.

Appendix B

In Chart B hedonic indices are re-estimated using the average characteristics methods when including gardens, garages, and pools, starting from 2013 onward. Each variable has a positive coefficient and is statistically significant. Overall, the range of indices when including gardens, garages, and pools (denoted in the graph as GGP) is not substantially different to the range that excludes these variables. The major difference occurs in 2014, possibly due to some initial sample biases between the two approaches.

Chart B
Including gardens, garages, and pools
(Annual percentage changes)



Source: Authors' calculations.