European Commission

ISSN 2443-8022 (online)

Assessing House Price Developments in the EU

Nicolas Philiponnet, Alessandro Turrini

DISCUSSION PAPER 048 | MAY 2017

EUROPEAN ECONOMY

Economic and Financial Affairs

European Economy Discussion Papers are written by the staff of the European Commission's Directorate-General for Economic and Financial Affairs, or by experts working in association with them, to inform discussion on economic policy and to stimulate debate.

Authorised for publication by Mary Veronica Tovsak Pleterski, Director for Investment, Growth and Structural Reforms.

Luxembourg: Publications Office of the European Union, 2017

KC-BD-17-048-EN-N (online)
ISBN 978-92-79-64887-8 (online)
doi:10.2765/232500 (online)

KC-BD-17-048-EN-C (print)
ISBN 978-92-79-64888-5 (print)
doi:10.2765/540742 (print)

European Commission
Directorate-General for Economic and Financial Affairs

Assessing House Price Developments in the EU

Nicolas Philiponnet and Alessandro Turrini

Abstract

Booms and busts in house prices may have major macro-financial implications. Accordingly, monitoring developments in house prices plays an important role in the assessment of macroeconomic risks. This paper provides a methodology to estimate benchmarks for the assessment of developments in house prices in the EU context. A number of approaches are developed, based on (i) long-term averages for price-to-income ratios, (ii) long-term averages for price-to-rent ratios (iii) predictions from cointegration relationships between real house prices and their demand and supply determinants. With the latter approach, cointegration analysis is carried out both on individual countries' time series and on a panel of EU countries. The paper makes alternative proposals for computing long-term averages for price-to-income and price-to-rent ratios with a view to combining cross-country comparability with representativeness. The various benchmarks are combined to define a single synthetic benchmark based on model averaging techniques.

JEL Classification: R21, R31, C32, E37.

Keywords: House price, Housing market, Panel cointegration.

Acknowledgements: We would like to thank Jean-Charles Bricongne, Leonor Coutinho, Stefan Zeugner and Matteo Salto for their useful comments and suggestions.

Contact: Nicolas Philiponnet, European Commission, Directorate-General for Economic and Financial Affairs, nicolas.philiponnet@ec.europa.eu.

CONTENTS

LIST OF TABLES

LIST OF GRAPHS

1. INTRODUCTION

Monitoring and assessing house price developments has become standard practice in macro-financial surveillance. Housing markets played a key role in sowing the seeds of the 2008 financial crisis. Major housing bubbles were at the heart of the boom-bust dynamics in credit and output in a number of EU countries, including Ireland, Latvia, Spain and the United Kingdom.

Accordingly, the framework for macroeconomic surveillance in the EU was revised in 2011 to include a procedure to prevent and correct macroeconomic imbalances (the Macroeconomic Imbalance Procedure, MIP). One of its aims is to identify potential risks linked to house price developments. Real house price growth is included among the variables of a scoreboard that provides a first screen in MIP surveillance.

This paper establishes methodologies to determine benchmarks for assessing house price developments, including in the MIP context. Such methodologies have been used as part of EU surveillance for several years in MIP Alert Mechanism Reports and in-depth reviews and have been depicted in previous publications (e.g. Cuerpo et al., 2012). The aim of this paper is to provide a detailed explanation of the methodologies used to estimate and identify house price benchmarks and make progress on a number of technical issues that arise in estimating these benchmarks.

Existing empirical literature has developed a number of benchmarks for house prices that are used to determine possible valuation gaps. The benchmarks most commonly used by international agencies monitoring house prices in a multilateral context rely on long-term averages for the *price-to-income ratio*, which give insights into whether house prices are becoming scarcely affordable, and the *price-to-rent ratio*, which allow us to assess whether the price of owning a property is becoming expensive compared with the alternative of renting (Girouard et al, 2006). Alternatively, house price benchmarks are based on predictions from empirical models to estimate macroeconomic drivers of house prices (e.g. Abraham and Hendershott , 1996).

Different benchmarks build on different concepts of ‘house price equilibrium’, i.e. on different requirements for house prices to be considered as sustainable in the absence of sharp corrections. They help shape a detailed assessment and should be considered as complementary tools rather than mutually exclusive alternatives. As a result, this paper takes a comprehensive view and establishes a battery of different benchmarks that allow us to analyse house prices from different angles. In order to combine information from different benchmarks, it also builds synthetic indicators that provide a single measure for the valuation gap.

The paper starts by outlining the methodology for the benchmarks based on the long-term average of the price-to-income and price-to-rent ratios. It describes the dataset used (Eurostat and other sources are used to build sufficiently long time series) and the main features of the benchmarks obtained for EU countries. Compared with standard analyses, the analysis aims to make progress on an issue that could be highly relevant in multi-country house price assessments, and one that is often neglected. The data necessary to build indicators is available in some countries only for a short period of time. This raises the issue of how representative the long-term averages are for the price-to-income and price-to-rent ratios obtained. It also makes it difficult to compare valuation gaps across countries. To address this issue, the paper proposes a backward extension of the available data based on Bayesian updating of the growth rates from the overall available panel.

Benchmarks obtained on the basis of predictions regression-based empirical models are based on a parsimonious specification that reflects a reduced form representation of housing market equilibrium. A cointegration relationship between house prices and a number of selected macroeconomic variables that represent demand and supply side determinants is estimated in both the time series of the individual countries and the overall EU panel.

Finally, the various benchmarks are combined to form a synthetic indicator. In addition to a simple average of the different benchmarks, more sophisticated Bayesian model-averaging techniques are used to make the weight assigned to the different models depend on their capacity to fit the actual data with precision while remaining parsimonious.

The remainder of the paper is organized as follows. Chapter 2 reviews the various methodologies used in the literature to assess house price developments. The Chapters 3 and 4 focus on the analysis of house price ratios and co-integration analysis. Chapter 5 combines the different benchmark to form a synthetic indicator that measures valuation gaps. Chapter 6 contains the concluding remarks.

2. ASSESSING HOUSE PRICE DEVELOPMENTS

Large fluctuations in house prices are a well-documented feature of the business cycle. On the one hand, demand for housing and therefore the level of house prices depend crucially on the availability of credit, which is often pro-cyclical.([1]) On the other, given their importance for collateralised lending, swings in house prices can have major repercussions for credit markets and the banking sector. The housing sector is therefore an important component of the transmission channels between the credit and the business cycle and can act as a propagation mechanism for shocks (e.g. Kiyotaki and Moore, 1997).

The housing sector is not only important for the understanding of economic fluctuations, it can also play a key role in the origin of financial crises. Housing markets can be subject to bubbles, with the increase in house prices becoming disconnected from fundamental drivers of housing demand and supply. This is driven by expectations that are self-fulfilling up to the point in which events occur that lead agents to suddenly revise their expectations and behaviour. The strong auto-correlation in house price changes that is often found is indicative of both very persistent dynamics and the possible presence of bubbles (Case and Schiller, 1989, 2003). The bursting of housing bubbles could be associated with sharp and major price corrections which lead to mortgage distress and deterioration in the quality of banking sector balance sheets. Banking sector bankruptcies are normally followed by deep and long recessions, and the weakening of banks' balance sheets may imply subdued credit growth and very protracted slumps in economic activity (Jorda, Schularick, and Taylor, 2015).

A growing awareness of the relevance of the housing market for economic fluctuations and financial stability has led to increased efforts to monitor housing market developments. This helps assess the sustainability of periods of strong growth in house prices and detect bubbles. To this end, house price benchmarks are increasingly used to assess housing market developments.

The benchmark based on long-term averages in the *price-to-income ratio* provides an indication of whether house price developments are subject to a potential correction as their growth rate exceeds the growth rate in income to such an extent that housing could become unaffordable at some stage. The *price-to-rent ratio* compares house prices to the user-cost of housing. The idea is that, over the long term, and in the absence of pervasive borrowing constraints, the price of houses should equal the present value of the flows of rental income that can be derived from it (e.g. Poterba, 1991). The intuitive nature of these ratios and their wide availability make them useful benchmarks for tracking housing market developments.

However, there are also some caveats to be aware of. First, each of these ratios only takes into account one consistency requirement for house price growth – either affordability or the comparison between owning and renting. Second, the analysis of house price ratios relies critically on assumptions regarding the long-run properties of the related time series. More specifically, if price-to-income or price-to-rent ratios are non-stationary time series, i.e. their mean and variance may change over time, a comparison of their current values to their long-term average may not be indicative of a valuation gap (e.g. Quigley and Raphael, 2004).([2])

The need to document the interplay between various fundamental drivers has resulted in a rich body of empirical literature that also seeks to take into account the various drivers of house price developments by means of multivariate regression analysis – not only income variables, but also cost variables, demographics etc. The prediction based on such regressions is taken as a benchmark for house prices. The difficulty with such an approach is the risk of estimating spurious relationships – a risk that typically arises when time series are non-stationary. As mentioned above, one distinguishing feature of house price data is the strong persistence of house price growth, which implies that house price data in levels is

([1]) Iacoviello (2004) shows the importance of credit constraints for house price dynamics in a dynamic stochastic general equilibrium model.

([2]) Bolt et al. (2014) point out that heterogeneous beliefs held by agents on the housing market may result in non-stationary price-to-rent ratios.

generally non-stationary. Accordingly, early work on house prices determinants often analysed house price changes, in light of their stationarity (e.g. Englund and Ioannides, 1997).

The analysis of house price determinants in levels became standard thanks to the development of cointegration analysis (Engle and Granger, 1987; Johansen, 1988).([3]) Recent work on house price determinants based on cointegration analysis therefore allowed the determination of benchmarks to assess whether house prices are overvalued or undervalued. A survey of this work for advanced countries in summarised in Girouard et al. (2006).([4]) Recent examples of studies that use cointegration analysis to estimate house price benchmarks in the euro area include Annett (2005), Gattini and Hiebert (2010) and Ott (2014).

Multivariate cointegration analysis allows taking a number of determinants into account simultaneously when estimating house price benchmarks. This reduces the risk of omitting relevant factors that could justify variations in the benchmark over time. The obvious limitation of this, and any approach based on linear regression is the assumed stability of the relationship over time. However, theory dictates – and this is supported by the data – that non-linearities in relevant variables and parameter shifts play a significant role in house price developments (e.g. Muellbauer and Murphy, 1997).

([3]) For information on the early applications of cointegration to house price analysis see, e.g., Malpezzi (1999).

([4]) In addition to work on estimating long-term relationships between house prices and their determinants VAR analysis allows the analysis of short term responses to shocks in house prices (e.g. Sutton, 2002; Tsatsaronis and Zhu, 2004).

3. PRICE-TO-INCOME AND PRICE-TO-RENT

House prices are affected by general price inflation, meaning that they do not tend to revert back to previous values. Expressing house prices in relative terms, deflating developments by inflation, corrects only part of this bias. The price-to-income and the price-to-rent ratios are routinely used to gauge the sustainability of house price developments. Index numbers have been calculated for all European countries, which makes it possible to assess long-term developments. However, comparable information on the *level* of these ratios is not generally available for countries in the European Union despite recent efforts (Dujardin et al., 2015).

This chapter provides a description of the indices built for the price-to-income and price-to-rent ratios. It analyses their long-run properties and uses a Bayesian approach to correct the potential bias linked to limited data availability in some countries.

3.1. PRICE-TO-INCOME RATIO

Tracking the price-to-income ratio allows us to compare the developments in house price indices with those in households' nominal per-capita gross disposable income. A sustained rise in the price-to-income ratio signals increasing difficulties for the average household to purchase and afford to own a dwelling. Such pressures can result in a mismatch between the supply and demand of housing and can exert downward pressure on house prices in the long term. Conversely, an increase in per capita disposable income would normally push house prices upwards.([5]) For the above reasons, one would for the price-to-income ratio to revert to its average value over time.

3.1.1. Data and methodology

The house price indices are taken from Eurostat and cover all domestic residential building purchased by households. ([6]) The Eurostat index includes both new and existing housing. The annual data on house prices provided by Eurostat starts at the earliest in 2000. When information on house price growth is available from other sources, the Eurostat time series are extended backwards. To this end, ECB, OECD and BIS data is used. The series for the denominator of the price-to-income ratio are also taken from Eurostat, and consist of the gross disposable income of household and non-profit institutions serving households (NPISH) divided by the total population. AMECO, the European Commission's macroeconomic database is used if Eurostat data is not available. In cases where sector accounts data is missing, which is the case for Malta, the time series is based on the gross national disposable income. The index numbers for the price-to-income series are constructed using 2010 as the base year.

As the series for the price-to-income ratio are index numbers, their level is not comparable across countries. To gauge valuation gaps, the price-to-income index level needs to be compared with a meaningful benchmark, which, following established practice, is chosen to be the long-term average of the ratio. Since there are remarkable discrepancies in the sample length of the price-to-income ratio indices across countries (see Annex 1), constructing the benchmark as an average over the whole available period would create a problem of cross-country comparability of valuation gaps. Mindful of this issue, three alternatives for the compilation of the country-specific average are considered.

- A baseline comparable computation of the average price-to-income ratio is based on the *1995-2015 period*. As the index for this period is available for most EU countries, the resulting average is comparable across countries. The main limitation of this approach is that averages computed over

([5]) Girouard et al (2006) point out that heterogeneity in the individual situations of households means that aggregate disposable income is only a rough measure of the actual income of the smaller, and likely wealthier, group of the population which is active on the real estate market.

([6]) This index may be biased in some countries due to different levels of home-ownership by households. Eurostat data on the rate of home-ownership suggests that cross-country variation is important (see Graph 3.3). However, in a given country, the ratio remains relatively stable over time and the related bias in the price index development is limited.

relatively short time series may not be fully representative. Where available, long series of the price-to-income suggest that over the last 15 years, the value of the ratio has somehow diverged from its long-term average in a number of countries (see Graph 3.1). This suggests that using the 1995-2015 period could lead to an overestimation of the long-term average in some cases.

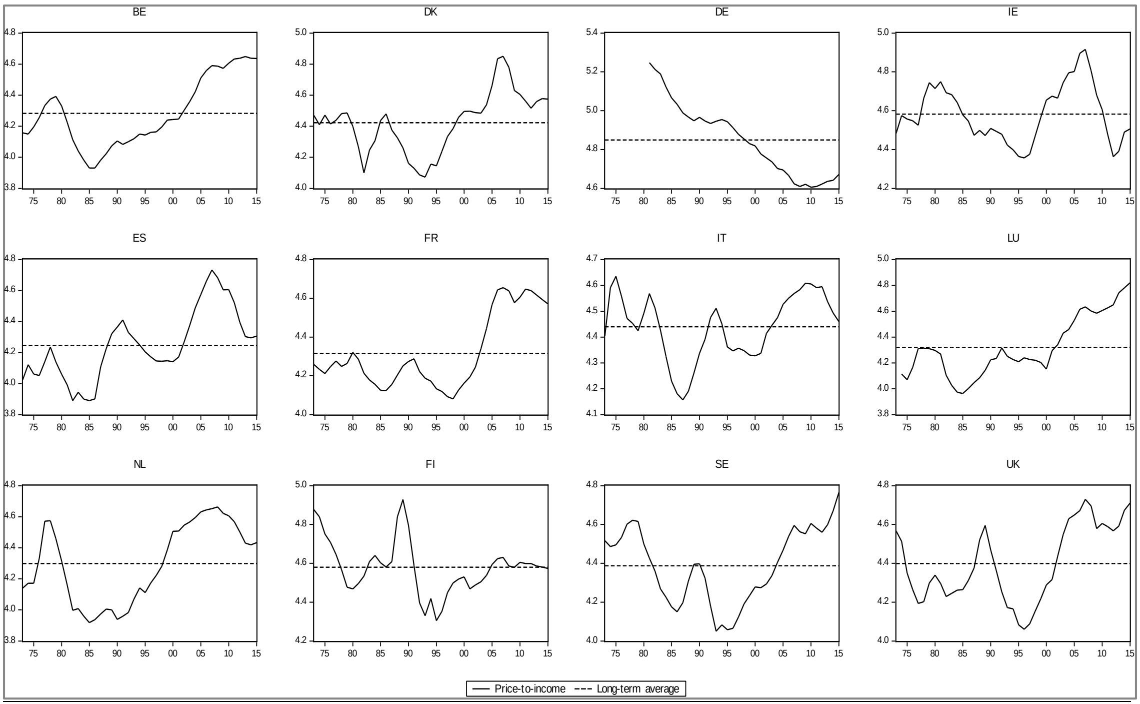
- A second alternative is to use the *full country sample* available to compute the long-term average.

- A third alternative is to estimate the long-term average using information from longer time series available from the panel. Using a Bayesian approach, a comparable adjusted long-term average for the price-to-income ratio can be constructed that uses information related to the entire period 1973-2015. The adjusted long-term average corresponds to a weighted average of (i) the average computed for the actual data for each country; and (ii) the one computed on a reference series over the maximum length of the sample obtained using house price growth rates for the whole sample (see Annex 2). The Bayesian approach allows us to weight the series based on the length and variability of the series that determines the two averages (the shorter the series, and the higher its standard deviation, the lower its weight in computing the adjusted long-term average).

Comparing the price-to-income ratios with their long-term average as a benchmark presupposes that the ratio is a stationary time series. In other words, the price-to-income ratio should not deviate from its mean over the long-term. The augmented Dickey Fuller (ADF) test is used to assess this. Using the whole panel available for EU countries, the ADF test indicates that the price-to-income ratio is stationary (see Annex 1). When the ADF test is run on the available individual time series for each country, the conclusion of stationarity is accepted at the 10% level only in a few cases (Croatia, Finland, Germany, Italy and Poland), although the statistical power of the test may be impaired by the limited data available at country-level.

Looking beyond the issue of stationarity, there are a number of caveats to be aware of when using the price-to-income ratio approach to estimate house price benchmarks. In particular, as households usually become indebted when they purchase a home, changes in the factors that determine the availability of credit (e.g. mortgage term, interest rate, strength of the credit constraints) may result in long-lasting shifts in the price-to-income ratio.

Graph 3.1: **Price-to-income ratio, selected European countries**



Source: European Commission, ECB, OECD, authors' analysis.

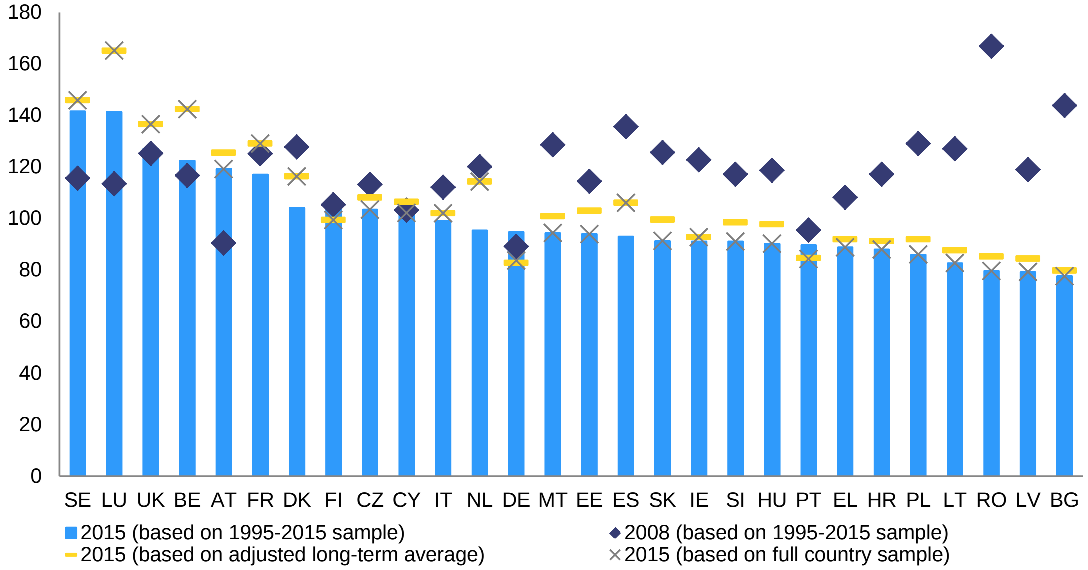
3.1.2. Results

Graph 3.2. displays the deviations between the actual price-to-income ratio and its benchmark. It compares both the average computed over the 1995-2015 sample period and the adjusted long-term average. The comparison refers to data in 2008 and in 2015. The graph shows that, following the outbreak of the financial crisis, the majority of European countries experienced a downward adjustment in the price-to-income ratio. In the majority of countries, the affordability ratio is now close to its long-term average. This is certainly the case in Greece, Ireland, Italy and Spain. In a number of European countries the adjustment in house prices has gone beyond what the affordability ratio would suggest, with the price-to-income ratio particularly low compared to its long-term average in Bulgaria, Latvia, Lithuania and Romania.([7])

In most cases, the assessment of the current valuation gap is robust irrespective of the methodology used to compute the long-term average. Among the countries that have longer time series, Germany and Portugal stand out as having persistently low price-to-income ratios. By contrast some countries, including Belgium, Luxembourg and Sweden, have experienced uninterrupted house price rises, with the affordability ratio now hitting record highs. For those countries, the long-term average based on the adjusted long-term average suggests a valuation gap that is larger than the one based on the 1995-2015 period.

([7]) The data available for these Member States only cover the last house price cycle, thus reducing the robustness of the long-term average

Graph 3.2: **Price-to-income ratio, 100= Long-term average, EU 28**



Annex 2 contains the methodology used to compute the adjusted long-term average.
Source: European Commission, ECB, OECD, author's calculations.

3.2. PRICE-TO-RENT RATIO

As houses are an asset, and in line with an asset pricing approach, the price of dwellings should reflect the present values of the dividends they generate, i.e. their rental yields. Such an approach implies that, for a given cost of capital, households should be indifferent to owning and renting a dwelling. As a consequence, one can expect that large swings in the price-to-rent ratio may at some stage become unsustainable. An increase in the ratio will induce agents to rent rather than buy while a decrease will encourage them to buy instead, which will bring the price-to-rent ratio back in line with its long-term average.

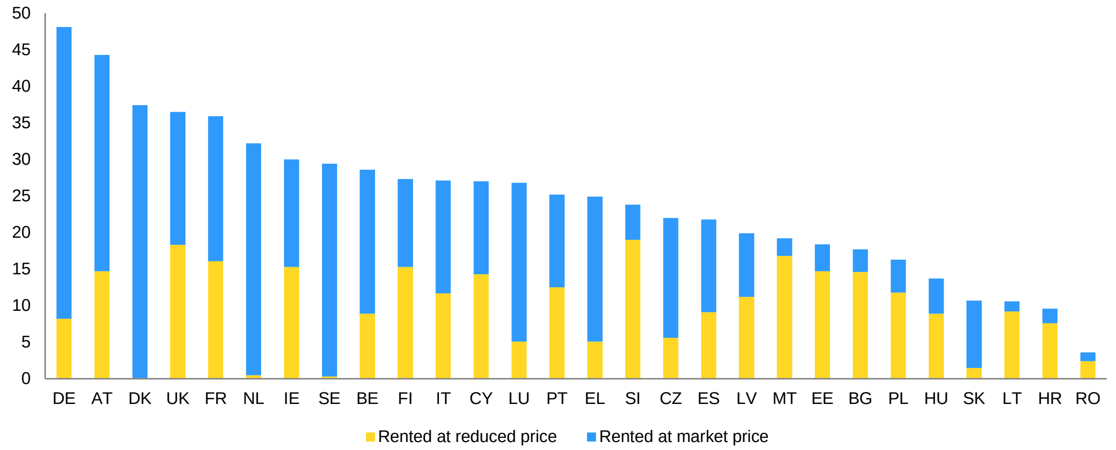
3.2.1. Methodology

House prices data are the same as described in the previous chapter and the rental data used to construct the price-to-rent ratio time series is from Eurostat. More specifically, the "CP041: Actual rentals for housing" item of the Harmonized Index for Consumer Prices (HICP) is used. ([8]) This is the only comparable housing rent index available for all EU countries.

On the computation of the long-term average for the price-to-rent ratio, the same approach as for the price-to-income ratio is followed given that data availability differs across countries (see Annex 1): average over 1995-2015, average over the full sample and adjusted long-term average. As was the case for the price-to-income ratio, statistical tests based on the available time series conclude that the price-to-rent ratio is stationary at panel level. Meanwhile, country-by-country tests reject the existence of a unit root at the 10% level only for Croatia, Cyprus, Poland, Portugal, Romania, Slovakia and Slovenia (see Annex 1).

([8]) In cases where this indicator is not available, the price-to-rent ratio is based on the OECD's Analytical house price indicator which is based on similar metrics and assumptions.

Graph 3.3: **Tenants-occupied housing, % of total dwelling stock, 2015**



Source: Eurostat EU-SILC database

Note that valuation gaps obtained from the price-to-income ratio are subject to a number of caveats. First for the comparison with the long-term average to be meaningful, the price-to-rent ratio series not only need to be stationary. The cost of capital needs also to be broadly stable over time. Indeed, significant fluctuations in the rate used to actualise rent streams affect the choice between renting and owning a property.([9]) Second, there are limitations associated with the available index data. As the housing rent index used for HICP excludes implicit rents on owner-occupied housing, it may provide only a partial view of the overall markets in countries where the share of tenant-occupied housing is low. Also, the HICP-based index includes rents offered below market price (notably on social housing). As a result, the HICP index for rents may not accurately track developments in the rents available to investors and to the households that are in a position to own a property. This is an important aspect as Eurostat EU-SILC data on the occupancy-status of dwellings indicate that, in half of European countries, more than 50% of dwellings are rented below market price (see Graph 3.3).

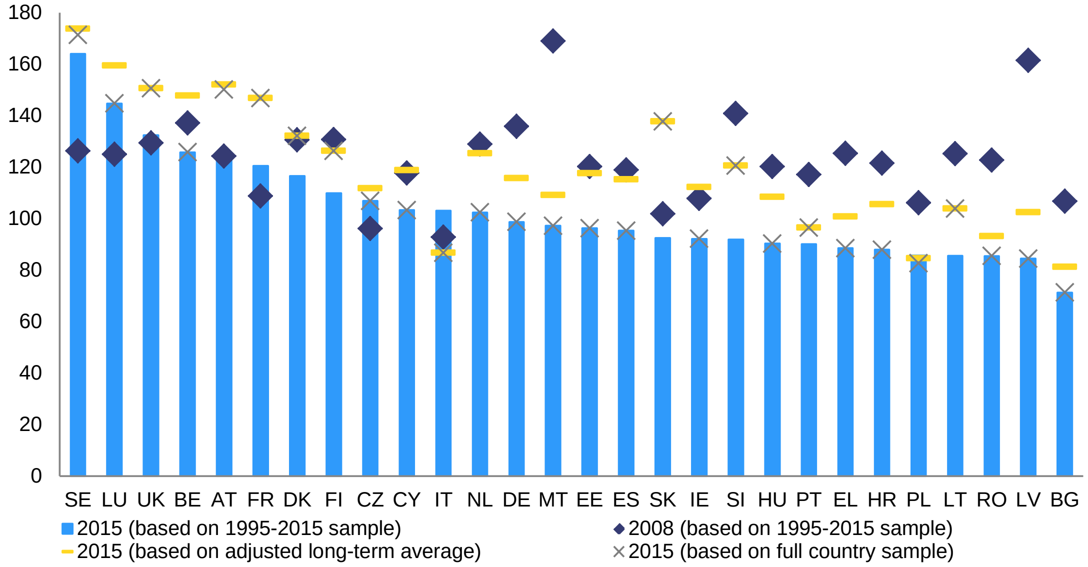
3.2.2. Results

Graph 3.4 compares the values of the price-to-rent ratio for 2008 and 2015 to the long-term average. The results reveal a number of countries with clear signs of overvaluation (Luxemburg, Sweden and the United Kingdom) and some where the data suggests undervaluation (Latvia, Portugal and Romania), which is broadly in line with the results from the affordability ratio. In Ireland, Italy and Spain, the price-to-rent ratio appears to have adjusted, together with the price-to-income ratio, and is in line with the long-term average in 2015.

Comparing the valuation gaps that result from the various estimates of the long-term average shows that, with the exception of Italy and Poland, the gap based on the adjusted average is larger than the one based on the 1995-2015 period although the ranking of countries remains similar.

([9]) Mindful of this issue, Girouard et al. (2006) estimate a valuation gap based on imputed rents that largely depend on the interest rates. Adopting the same methodology, Cuerpos et al. (2012) find that results for European countries are broadly similar to those obtained based on the standard price-to-rent ratio.

Graph 3.4: **Price-to-rent ratio, 100= long-term average, EU 28**



Annex 2 contains the methodology used to compute the adjusted long-term average.
Source: European Commission, ECB, OECD, authors' calculations.

4. BENCHMARKS BASED ON FUNDAMENTAL HOUSE PRICE DRIVERS

This chapter explains house price benchmarks that take into account the simultaneous impact of various fundamental drivers of house prices using an approach that is based on econometric regression. In line with the long-term properties of house price series, a cointegration relationship between house prices in real terms and their determinants is estimated, and the predictions obtained from this relationship are taken as benchmarks.

4.1. METHODOLOGY

The rest of the analysis examines both country-by-country and panel cointegration approaches. A country-specific approach does not mean that the cointegration vector has to be the same across countries, which better reflects country specificities. Such an approach is useful if countries are heterogeneous. However, the fact that the house price time series available are short for some countries may imply low statistical significance and fragile estimates for these countries. This can be addressed by resorting to the cointegration relationship estimation across the whole panel.

4.1.1. Specification

The empirical specification is akin to that used in recent studies on euro area countries (e.g. Gattini and Hiebert (2010)) and is sufficiently parsimonious to allow data to be used that is available over long time periods in a large number of countries. More specifically, the housing market can be represented as follows in accordance with Muellbauer and Murphy (1997):

$$h^d = f(y, POP, \mu, D), \qquad h^s = g(p, POP, S) - \delta H \qquad (4.1)$$

Where h^d and h^s denote, respectively, the demand and the supply of housing *services*, p is the real price of housing, y is real disposable income per capita, *POP* is population; μ is the *real user cost* of housing, δ is the depreciation rate, H is the housing stock, D and S are, respectively, demand and supply shifters. Noting that the user cost μ is a function of the price p and of the interest rate r, the demand and supply equations for house services can be inverted as follows:([10])

$$p = f'(y, POP, r, h, D), \qquad p = g'(h, POP, H, \delta, S) \qquad (4.2)$$

On the basis of system (4.2), a reduced form estimation of the housing market can be obtained using real house prices as a dependent variable and the explanatory variables that appear as drivers of supply, demand, or both. While income and interest rates appear in most reduced form equations, not all existing studies include demographic variables as a separate determinant, and use overall income rather than income per capita. As for the flow of house services h, this is often captured by a measure of the housing stock, assuming that the flow of housing services is proportional to the housing stock. In a number of applications, however, housing investment is used at the place of the housing stock in light of the limited availability of housing stock data for certain countries, the assumption being that housing investment is roughly proportional to the housing stock (the higher the stock, the higher the investment needed to counter depreciation).

With regards to the inclusion of demand and supply shifters, works aimed at providing a good fit of actual data have included several variables aimed at capturing agents' expectations, and features of the mortgage and housing market. As the aim of the analysis is to estimate house prices benchmarks, a balance needs to be struck between two objectives. On the one hand, explanatory variables need to have significant and

([10]) Other factors with an impact on the user cost of housing include the tax system, the average maturity of existing mortgages as well as depreciation and maintenance costs. In practice such information is generally not available in empirical analysis.

robust relationship with house prices. On the other, one should aim to include only fundamental drivers without including explanatory variables that may be subject to the same boom and bust cycles as house prices themselves; mortgage loans are one straightforward example (e.g., Goodhart and Hofmann, 2008). A third requirement is that the data is available for all European countries over a sufficiently long period. ([11])

The specification considered in this paper takes into account the above considerations, and the data restrictions that emerge from the objective of estimating analogous models for all EU counties, which are subject to different degrees of data availability. The specification estimated is as follows:

- **Population (POP)**: Demographic developments have a long-term impact on the housing market as housing demand in the long term is primarily driven by growth in the number of households.([12]) In this respect, population is expected to be positively associated with house prices. However, population is also a variable that is taken into account by urban planners and land developers in taking their decisions. To the extent that the supply of houses is highly sensitive to population changes, the expected impact of population on prices could turn out to be negative. Overall, the sign could a –priori be ambiguous although the majority of studies tend to find a positive relation. Among the recent surveys for the euro area, only Annett (2005) explicitly includes it in its specification and finds no significant impact on house prices.

- **Real per capita disposable income (RYPC)**: The higher the per-capita disposable income of households, the more they can spend to purchase a house. A positive elasticity of real house price to real per-capita disposable income is a sign that housing is a superior good. Indeed, it implies that the demand for housing grows proportionally more than that for other goods, thus leading to a relative increase in house prices with respect to the overall price index. The evidence is overwhelmingly in favour of a positive coefficient for the income variable in house price equations (see, e.g., Girouard et al., 2006, for a survey). More interestingly, a large number of studies find elasticities above unity, implying that house prices not only tend to grow with respect to the price of other goods, but that this increase is more than proportional with income. Among recent work on the euro area, Annett (2005) reports an elasticity of about 0.7 while higher values are found in Gattini and Hiebert (2010) and Ott (2014), which estimate an elasticity of 3.1 and 1.9 respectively.

- **Real housing investment (RHI)**. Housing investment is used as a proxy for the flow of housing services. The alternative of using housing stock is not feasible because of the lack of sufficiently long series on the housing stock for a number of EU countries.([13]) The impact of housing investment by households on house prices is a-priori ambiguous. On the demand side, the first equation in (4.2) suggests that when the availability of house services increases the associated price should fall. On the other hand, in the second equation in (4.2), which is related to housing supply, the price requested by suppliers will be higher when the demand for housing services is high. In particular, high values for housing investment signal demand for new houses, particularly by first-time buyers. In addition, part of the investment by households consists of renovation which can be expected to improve the quality of housing and therefore the price. In existing analyses, the housing stock is generally found to be negatively related to real house prices, suggesting that the demand-side effects are often predominant.

([11]) In particular, the stock of dwelling, which is used in a number of empirical studies is generally not available before 1995 and is only available with a lag.

([12]) Englund and Ioannides (1993) develop a model that takes into account the consumption and investment motives for housing investment. Using an overlapping generation model, they find that house prices are fundamentally linked to demographic factors. Agnello and Schnukecht (2011) point out that due to supply constraints, a rise in the population can have an inflationary impact on the housing market.

([13]) Data on the stock of dwelling is not readily available from national account data. Ott (2014), which restricts its analysis to 8 European countries, uses data on housing stock from the European Mortgage Federation. However, data gaps for recent years hinder the use of such data for surveillance purposes (as of September 2016, data for 2015 was available for only half of EU countries).

- **Real long term interest rates (RLTR).** The lower the affordability for households. In addition, higher interest rates also decrease the present value of future (imputed) rents, which reduces the profit expected by households from investing in a house. All things considered, interest rates can be expected to have a negative impact on house prices. This is indeed the conclusions of most empirical studies, although the magnitude of the estimated impact of interest rates varies considerably depending on the sample and methodology.

In the following analysis, house prices, population, per-capita income and housing investment are used in logarithmic form, so that the estimated coefficients can be interpreted as elasticities.

4.1.2. Data and univariate properties

Not every European country has data on real house prices over a long time period. 11 countries have data series that go back to 1973, while five of them have less than 10 observations. As described in Chapter 3, the nominal house price index is from Eurostat, with data from BIS, OECD and ECB where necessary. Developments in the nominal house price are divided by the inflation in the deflator of private consumption, which is taken from national accounts in Eurostat and is available for all countries with a sufficiently long time history. All explanatory variables are taken from the national accounts recorded in the European Commission's AMECO database.([14]) For most European countries, national account annual data starts from the early 1990's. In particular, data availability constraints suggest using the actual population in national accounts as a proxy for the number of households.([15]) The interest rate considered corresponds to the rate for 10-year government bonds. As is the case for house prices, the interest rate, per-capita disposable income and housing investment are all deflated using the price of private consumption.

The stationarity of the variables is checked both across the whole panel and on a country-by-country basis. For the panel, the existence of a unit root, both in level and in difference, is assessed based on the test developed by Levin, Lin and Chu (2002) – LLC hereafter- and on the augmented Dickey-Fuller Fisher test –ADF hereafter- which allows more heterogeneity across the various cross sections and is thus more general (Im, Pesaran and Shin, 2003; Maddala and Wu, 1999). On a country-by-country basis, a standard augmented Dickey-Fuller test is performed, although the power of this test may be limited for countries with short data history.

([14]) http://ec.europa.eu/economy_finance/db_indicators/ameco/index_en.htm
([15]) While Eurostat compiles data on the size and number of households in European countries, this data is only available from 2005 onwards.

Table 4.1: **Univariate unit root tests for the whole panel**

Variable	Test	Levels				First differences			
		Statistic	Prob.	Cross sections	Obs.	Statistic	Prob.	Cross sections	Obs.
Deflated house prices (RHP)	LLC	-1.6	0.06	21	610	-6.6	0.00	21	602
	ADF	49.0	0.21	21	610	130.6	0.00	21	602
Population (POP)	LLC	3.1	1.00	21	920	-2.9	0.00	21	925
	ADF	14.9	1.00	21	920	131.6	0.00	21	925
Deflated real income per capita (RYPC)	LLC	-2.0	0.02	21	803	-15.9	0.00	21	795
	ADF	16.8	1.00	21	803	309.0	0.00	21	795
Deflated housing investment (RHI)	LLC	-1.6	0.05	20	750	-14.7	0.00	20	746
	ADF	58.6	0.03	20	750	266.5	0.00	20	746
Real long term interest rate (RLTR)	LLC	-3.3	0.00	21	693	-25.8	0.00	21	671
	ADF	79.0	0.00	21	693	495.8	0.00	21	671

The number of lags for the ADF test is selected based on the Schwarz Information Criterion.
Only countries with more than 15 yearly observations for house prices are included in the sample (excluding CY, EE, HU, PL, RO, SI and SK).

At the panel level, the LLC test finds evidence of stationarity at the 10% level for all the variables except population. By contrast, the ADF test appears more selective and finds some evidence of stationarity only for housing investment and interest rates. In first difference, the ADF and the LLC test clearly reject the existence of a unit root for all the variables. All in all, the evidence appears to suggest that the variables are often non-stationary in level but stationary in first differences, i.e., integrated of order 1. Country-by-country analyses also generally conclude that the various variables are integrated of order 1 (see Annex 4 – Table A4.1). On the basis of this evidence, the next steps are to assess whether a cointegration relationship exists and estimate its coefficients.

4.1.3. Cointegration analysis

Cointegration across the whole panel is assessed based on the tests developed by Kao (1999) and by Pedroni (1999 and 2004). The Kao test, whose results are reported in Table 4.2, assumes a homogenous cointegration vector across the panel. The various statistics developed in Pedroni (1999 and 2004) test for cointegration based both on common coefficients for the various cross-section (the so-called within dimension) and on country-specific ones (the so-called between dimension). At panel level, the Kao test concludes that a cointegration relationship can be detected while the detailed results for the Pedroni test appear less conclusive. Running the various Pedroni tests for alternative specifications, using short-term interest rates or dropping some explanatory variables, confirms the use of a complete model using disposable income per capita, population, housing investment and long-term interest rates as explanatory variables.

Cointegration tests are also run on country-specific time series based on the Engel and Granger (1987) approach. Due to the low number of observations for some countries, the results of cointegration tests at country level should be viewed with caution. Accordingly, for the retained specification, the Engle-Granger tests yields mixed results (see Annex 4 – Table A4.2). Evidence of cointegration at the 1% level can be found in Bulgaria, Czech Republic, Cyprus, Germany, Greece, Latvia, Lithuania, Slovakia and Sweden. At the 10% level, cointegration is also found in Denmark, Estonia, Ireland, Italy, Spain, the Netherland and Portugal.

Table 4.2: **Results of the Kao (1999) and Pedroni (1999 and 2004) tests for cointegration**

Alternative hypothesis	Kao (1999) Common cointegration vector	Pedroni (1999 and 2004) Common AR coefs. (within-dimension)				Individual AR coefs. (between-dimension)		
	t-Statistic	Panel v-Statistic	Panel rho-Statistic	Panel PP-Statistic	Panel ADF-Statistic	Group rho-Statistic	Group PP-Statistic	Group ADF-Statistic
Statistics	-4.03	0.12	-0.20	-1.58	-2.72	2.98	-1.51	-3.66
Probability	0.00	0.45	0.42	0.06	0.00	1.00	0.07	0.00

The panel only countries with at least 15 observations on house prices.
Null hypothesis: no cointegration between real house prices and the explanatory variables.

4.2. ESTIMATION RESULTS

4.2.1. Panel estimates

The panel approach relies on the estimation of a single coefficient for the various explanatory variables using data for all countries. The gain obtained in terms of sample size and degrees of freedom needs to be weighed against the possible bias in case of heterogeneous dynamics across countries. Using country fixed-effects to control for time-invariant unobserved country-factors, the model estimated is as follows:

$$RHP_t^i = \alpha^i + b_{pop}.POP_t^i + b_{rypc}.RYPC_t^i + b_{rhi}.RHI_t^i + b_{rltr}.RLTR_t^i + \eta_t^i$$

Where the superscript *i* denotes the country and *t* stands for years. The ordinary least square (OLS) methodology can be used to estimate the coefficients for the cointegration vector, as these are super-consistent if the variables are cointegrated (Stock, 1987). However, OLS estimates tend to be inefficient, and inference cannot be made with estimated standard errors in the context of non-stationary variables. To address these issues alternative estimators have been proposed, notably Dynamic OLS (DOLS, Stock and Watson, 1993) and Fully Modified OLS (FMOLS, Phillips and Hansen, 1990). The coefficients are estimated by means of OLS, DOLS and FMOLS with the number of lags and leads for DOLS based on the Schwarz information criteria. In finite samples, Inder (1993) find that the dynamic OLS has lower bias than alternative approaches. DOLS is thus the preferred estimation approach and results based on FMOLS and OLS are given as benchmarks. Excluding each country from the panel in turn, the difference between the coefficients estimated on the reduced panel and on the full panel provides an indication of the impact of individual countries on the panel results. To limit the heterogeneity in the panel, countries for which the overall distance with the full panel coefficients normalised by the standard deviations for each coefficients is larger than 80%, are removed from the full panel. This procedure leads to remove Sweden, Spain, Ireland and Greece from the estimation panel.

Using this reduced panel, the long-term coefficients are provided in Table 4.3. The signs of the coefficients, which are all significant at the 1% level, are in line with theoretical priors:

- Population is found to have a significant and positive impact on real house prices. This finding is in line with most empirical studies including demographic factors, but in contrast with Annett (2005) which find no significant effect of demographics on house prices.

- The elasticity to disposable income is positive but generally below one, thus being on the low end of those estimated in similar studies.([16]) The relatively low coefficient for income per capita is partly related to the specification. In particular the inclusion of the population variable, which is not always included in other studies, may help explaining the result, as population is found to be positively correlated to real per-capita income controlling for country effects. The absence of demographic variables would therefore result in a positive omitted variable bias for the income coefficient.

- The positive coefficient for housing investment suggests that variation in housing investment are linked to shifts in demand (which push prices and quantities in the same direction) rather than in supply (which result in opposite developments in prices and quantities). This differs from the negative elasticity found in other studies that use housing stock and in Gattini and Hiebert (2010), which uses housing investment to analyse house prices in the euro-area aggregate. This positive sign is confirmed irrespective of the specification used, in particular if population is excluded or if investment by capita is used instead of investment. ([17])

- The coefficient for real interest rates is such that a 1 percentage point increase in the real long-term interest rate is estimated to decrease prices by 1.3 to 1.6%. Such an impact is close to the values estimated by Ott (2014) and Annett (2005) but much lower than that in Gattini and Hiebert (2010).

Table 4.3: **Estimated coefficients for the cointegration vector**

		DOLS	OLS	FMOLS
Total population	Coeff	1.89	1.83	2.01
	Std. Err.	0.28	0.16	0.25
Disposable income	Coeff	0.57	0.80	0.76
	Std. Err.	0.07	0.04	0.06
Housing investment	Coeff	0.39	0.30	0.29
	Std. Err.	0.05	0.03	0.04
Long-term interest rate	Coeff	-0.016	-0.013	-0.013
	Std. Err.	0.004	0.002	0.003
Nb of cross-sections		19	23	23
Nb of observations		492	535	529

Estimated coefficients are all significant at the 1% level.

Results in Table 4.3 show that the various estimators considered provide broadly similar results, although the coefficient for disposable income appears to be significantly lower using DOLS than with the other methodologies. To confirm the validity of the specification used, a full error correction model is estimated, using the variation in real house prices as the dependent variable and the residual from the cointegration relationship and differences in the various determinants as explanatory variables. The results, which are provided in Annex 4 (Table A4.3), confirm that the estimated coefficient for the error-correction term in the short-run relationship is negative and significant. Results for the short-term equation also indicate that the adjustment of house price gaps is slow. A further robustness check was performed to assess the stability of the coefficients over time. DOLS estimates were computed using a fixed-length rolling time-windows. Results indicate that coefficients are rather stable, except the one for population. In particular, comparing samples that include the financial crisis period with those that do not indicates that the strong variability in both house prices and fundamentals since 2007 had an impact on

([16]) Similar results in recent work on euro-area countries are obtained in Annett (2005), while Gattini and Hiebert (2010) and Ott (2014) found estimates above one.

([17]) An alternative pooled OLS model, excluding fixed-effects, actually finds a negative sign for investment. However, tests on the joint significance of fixed-effects confirm that they are not redundant. The country sample and aggregation method used in the various studies may therefore also contribute to the difference in sign.

the robustness of the estimated coefficients. However, the coefficients estimated over the 1970-2015 period remain within one standard deviation away from those estimated over 1970-2005.

Pesaran and Smith (1995) show that, for cointegrated I(1) variables, pooled estimates across a heterogeneous panel yield biased coefficients. Meanwhile, based on out-of-sample forecasting performance, Baltagi et al. (2000) argue that the efficiency gains from pooling can more than offset the potential bias linked to a heterogeneous panel. This suggests that, while a panel approach can yield significant results, it can usefully be complemented by a country-specific approach.

4.2.2. Country-specific approach

Cointegration relationships estimated separately for each country allows to consider dynamics that are specific to that country. The specification tested is as follows:

$$RHP_t^i = \alpha^i + b_{pop}^i.POP_t^i + b_{rypc}^i.RYPC_t^i + b_{rhi}^i.RHI_t^i + b_{rltr}^i.RLTR_t^i + \varepsilon_t^i$$

Because it uses several lags of the dependent variables, DOLS requires longer estimation periods than alternative estimation approaches used for cointegrated variables. Given the substantial data restrictions that apply to some countries, country-specific estimates based on DOLS are not feasible. Following Montalvo (1995), the best alternative is Canonical Cointegration Regression (CCR, Park, 1992) as it exhibits lower bias than FMOLS. Countries with a too limited number of observations are also excluded from the analysis.([18])

The estimated country coefficients are shown in Annex 4 (Table A4.3). For most countries, the coefficients estimated are statistically significant and their sign is in line with what theoretical underpinning would suggest. In accordance with the a-priori ambiguous impact of population on house prices, the coefficient of population appears to be insignificant in a number of cases. In those cases, an alternative specification that excludes population was estimated. The positive sign for the elasticity of house prices to households' investment in dwelling is confirmed and is significant at the 5% level for all but 7 countries.([19]) The estimation of country-specific coefficients makes it possible to compute the mean group estimates, which are the simple averages of the coefficients across the countries in the panel, as suggested by Pesaran and Smith (1995). The results are displayed in Annex 4 (Table A4.4). With the exception of the coefficient for population, for which only a few country estimates are available, the group mean estimator provides results which are close to those of DOLS for the panel.

The country-specific approach makes it possible to take into account the variability of elasticities across countries. However, this comes at the cost of precision and robustness. Accordingly, the coefficients estimated on a country by country basis appear implausible in a number of cases. In addition, as estimates are obtained from samples that differ considerably in length across countries, they are not equally reliable, which implies a comparability issue.

4.2.3. House price benchmarks based on fundamentals

Benchmarks for house prices can be obtained using the prediction from the cointegration relationship. This relationship represents a condition of "equilibrium": divergences from this relationship tend to be corrected automatically, in line with the Granger representation of cointegrated relationships. Benchmarks have been computed based on both country-by-country estimates and panel estimates. Graph 4.1 shows that panel estimates and country-specific estimates are generally similar (notable exceptions being Greece

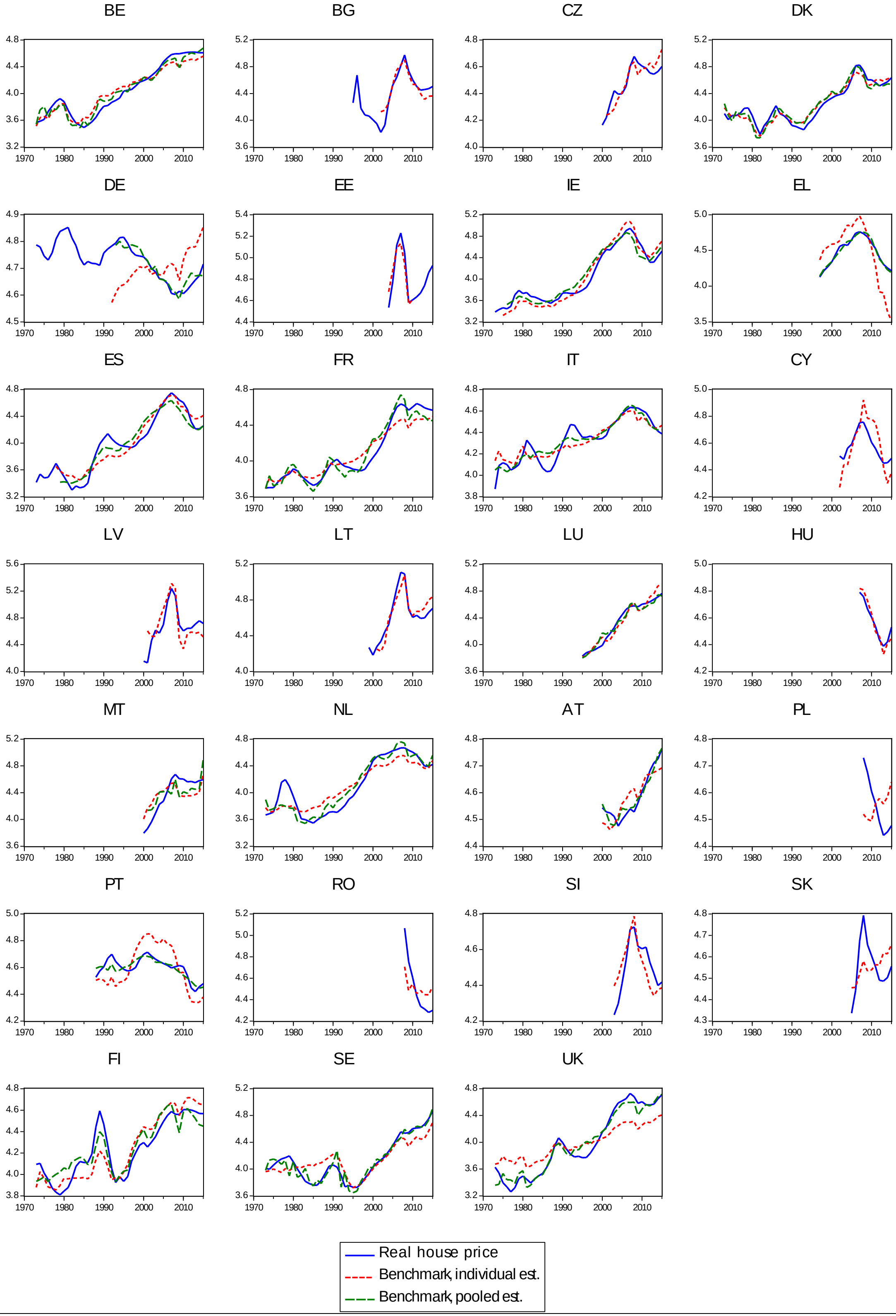
([18]) Only countries with more than 15 observations are considered, meaning that 16 countries are included in the sample. When sufficient data is available, the other estimators have also been used as a benchmark. In a number of cases, the coefficients estimated vary significantly depending on the estimation method adopted, which suggests limited robustness.

([19]) Excluding the post-2008 period for the countries for which sufficient data is available results in lower – and for some countries negative – estimated elasticities. However, shorter data sample also means that results are less robust.

the United Kingdom, Sweden and Finland) and can be used as complementary information to shape a view on valuation gaps.

A number of findings stand out. First, European countries seem to be almost evenly split between those that have a positive gap and others. Based on panel data benchmarks, Greece, the United Kingdom, Sweden, Portugal and Latvia are the countries where prices are the highest when compared to their fundamentals. At the other end of the spectrum, prices in Romania, Ireland, Poland, Spain and Germany are much lower than fundamentals. Second, when focusing on the countries with recent house prices booms, some appear to have corrected their past overvaluation, while in other countries signs of overvaluation are still visible. For example, housing prices in Ireland appear close to fundamentals in 2015, while they were significantly above them in Hungary or Sweden.

Graph 4.1: **Actual and benchmark house prices: individual and panel estimates, index 100 in 2010**



Data necessary to compute fundamental house prices are missing in Estonia and Croatia.

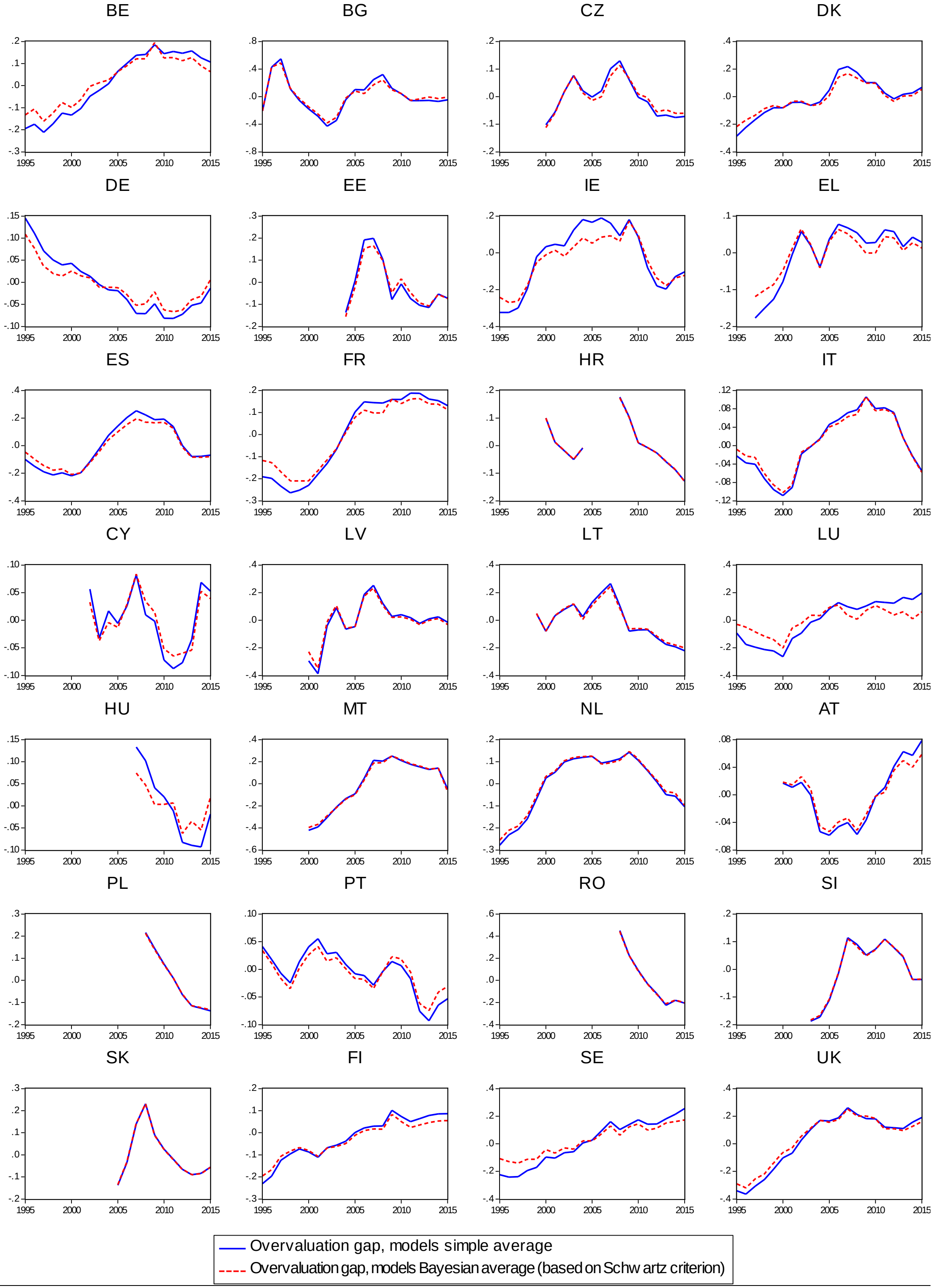
5. COMBINING BENCHMARKS

Three types of benchmarks have been developed: (i) long-term average for the price-to-income ratio; (ii) long-term average for the price-to-rental ratio; (iii) predictions from cointegration relationships between house prices and demand and supply fundamentals. Each of these benchmarks contributes to shape views on valuation gaps bringing insights from a different perspective. As such, the various approaches provide complementary information. It is also to be taken into account that each benchmark relies on simplifying assumptions and has specific limitations. Combining benchmarks would help convey synthesis and smooth out differences among the approaches linked to specific limitations, while keeping in mind that specific information from the alternative approaches need to be retained in making an overall assessment of house price dynamics.

The most straightforward and transparent way to combine the various metrics is to use the *simple average* of the estimated valuation gaps from the various models. The literature on model combinations also suggests that a simple average of the various estimates may be just as accurate as more complex combination methods (see for example Graefe et al., 2014).As an alternative to the simple average, a *Bayesian averaging* approach can be used to give more weight to the benchmarks that appear to be more parsimonious and better suited in tracking the underling house price series with the same amount of information (see Annex 4 for details).

Synthetic valuation gaps obtained from simple averaging are compared with those obtained from Bayesian averaging in Graph 5.1. The graph shows that, results are quite similar in the majority of countries, irrespective of the methodology used to combine estimates. Exceptions include Germany, Hungary and Luxembourg where the Bayesian model-average indicate only a limited overvaluation compared to the one suggested by the simple average. The discrepancy observed in these countries come from the fact that the ratio-based approach, while indicating large adjustment needs, did not track well movement in house prices historically. The Bayesian approach therefore gives a much lower weight to the ratio-based benchmark than to the ones based on the fundamental house price drivers. For Austria, Finland, Portugal and Sweden, the two methodologies also produce markedly different results, although the direction of the overvaluation remains the same. Overvaluation was commonplace in the years leading up to the financial crisis, with clear signs of overvaluation in Ireland, the Netherlands, Spain and the Baltics. After the housing bubble burst, the downward correction put most EU countries into undervaluation territory. The adjustment in house prices happened quickly in the Baltics and in Ireland, with undervaluation already observed in 2010. The correction in Spain and the Netherlands has been more gradual. Belgium, France and the United Kingdom experienced a limited correction despite signs of overvaluation before the crisis. Finally, Sweden and, depending on the metric used, Luxembourg have experienced an increasing degree of overvaluation since 2005.

Graph 5.1: Overvaluation gap based on simple and Bayesian average of the estimates



Long-term average for the price-to-income and price-to-rent ratios are computed over 1995-2015

Graph 5.2 plots real house price growth against the synthetic valuation gap indicator. This provides a snapshot of whether recent trends appear to be correcting estimated valuation gaps. European countries appear to fall into four main categories: ([20])

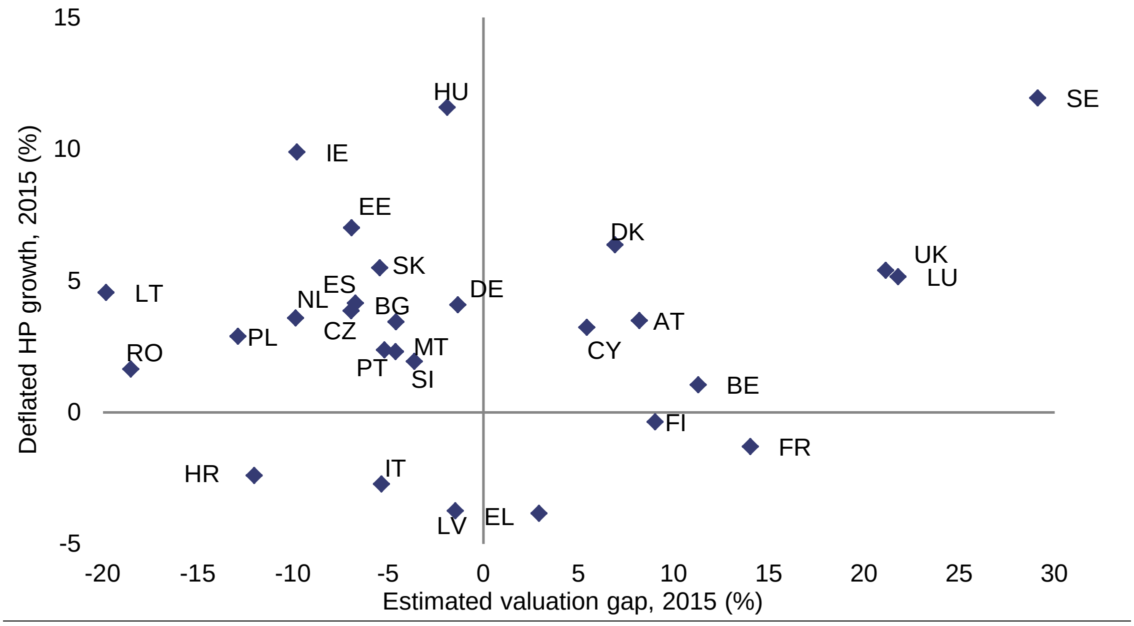
- **Undervalued and still decreasing**: Croatia, Italy and Latvia are the only countries where, in 2015, house prices are falling and were already below the benchmark.

- **Correcting downward**: in a few countries (Greece, Finland, France) the fall in house prices in 2015 appears consistent with the need to correct downward house price levels that appears above the benchmark.

- **Recovery from undervalued levels**: the largest group consists of countries for which real prices started recovering around 2013 and where negative valuation gaps remain. In a number of countries, which includes for example Estonia, Ireland and Spain, the undervaluation is a legacy of the previous house price boom and bust cycle. ([21]) In some of these countries, prices are currently rising rapidly (e.g., Hungary, Ireland).

- **Protracted growth despite overvaluation**: A number of countries have seen a rather limited correction in their house prices since 2008 (e.g., the United Kingdom) or only a minor inflection with positive growth rates (Belgium, Austria, Luxemburg, Sweden). Such a limited adjustment implies persistent valuation gaps which, in Luxemburg, Sweden and the United Kingdom, exceed 20%.

Graph 5.2: **Synthetic valuation gap and real house price increase, 2015, EU 28**



Synthetic valuation gap based on a simple average of the various models, the long-term averages for the price-to-income and price-to-rent ratios computed over 1995-2015.
Source: European Commission, ECB, OECD, authors' analysis

([20]) A number of countries, notably Croatia, Poland and Romania, have less than 15 years of observations for house prices. Valuation metrics for those may have only limited robustness.
([21]) With undervalued and growing house price, Germany also belongs to this group although it follows a very specific cycle driven by the bust in house prices that lasted from 1995 to 2005.

6. CONCLUSION

The assessment of house price developments has become a standard component of macro-financial surveillance. Such an assessment requires the definition of benchmarks to which actual house price data can be compared with a view to judging if ongoing trends are sustainable or if a correction, possibly large and abrupt, is likely at some point in the future. This paper develops a number of benchmarks to analyse house price developments in the EU context. A step forward is made in the attempt to obtain representative and comparable house price series and to develop house price benchmarks that offer different and complementary perspectives, in order to provide a comprehensive overview of house price valuations. An effort is made also in the approach taken to combine alternative valuation gaps, based not only on simple averaging but also on Bayesian averaging techniques.

Various benchmarks to assess house prices hinge on specific requirements for house price developments to be sustainable. This is based either on (i) affordability concerns, (ii) the precondition that the value of property evolves in line with the rental market, or (iii) the fact that the evolution of house prices should reflect that of their demand and supply fundamentals, estimated via cointegration analysis. Price-to-income and price-to-rent ratio indexes are compared to long-term averages. To take into account the need for both cross-country comparability and representativeness (which require sufficiently long time series), long-term averages for price-to-income and price-to-rent ratios are computed alternatively on samples using the same length, on longest available time series and on the basis of Bayesian techniques which use, in addition to country-specific data, information on price dynamics obtained from the whole available panel.

Each approach contributes to a detailed assessment, delivering insights from different angles, and is therefore to be used in a complementary way in the assessment of house price valuation gaps. In addition, each of these benchmarks has caveats and limitations. They therefore need to be interpreted with caution and valuation gaps need to be taken at face value and without an additional interpretation of the evidence in light of country-specific information on the functioning of housing markets.

To provide a synthetic benchmark and smooth out discrepancies linked to the limitations of individual benchmarks, the paper proposes synthetic valuation gaps. These are based on simple averaging and on Bayesian techniques that permit to weight individual models according to their ability to track the data with the same amount of information. Synthetic valuation gaps make it possible to derive a single indicator that summarises the risk of correction on the housing market in the various EU countries. It is therefore an important building block in the assessment of the macroeconomic vulnerabilities in Europe. Based on the synthetic benchmark that is derived, house prices appear to be still recovering in a majority of countries in Europe after the widespread contraction that followed the 2008 global financial crisis. However, the adjustment in house prices has been minor in some countries and growth has recently taken place in countries where prices appear to be overvalued.

REFERENCES

Abraham, J.M. and P.H. Hendershott (1996), Bubbles in metropolitan housing markets, *Journal of Housing Research* 7, pp. 191–207.

Adams, Z. and R. Füss (2010), Macroeconomic determinants of international housing markets, *Journal of Housing Economics* 18, pp. 38-50.

Agnello, L. and L. Schuknecht (2011), Booms and busts in housing markets determinants and implications, *Journal of Housing Economics* 20, pp. 171-190.

Akaike, H. (1973), Information theory and an extension of the maximum likelihood principle, in *Second International Symposium on Information Theory*, Akademiai Kiado.

Annett, A. (2005), House prices and monetary policy in the euro area, in *Euro area policies: Selected issues*, IMF Country report, IMF, Washington D.C..

Burnham, K. P. and D.R. Anderson (2002), *Model selection and multimodel inference: a practical information-theoretic approach*, Springer, New York.

Baltagi, B., J. Griffin and W. Xiong (2000), To pool or not to pool: homogeneous versus heterogeneous estimators applied to cigarette demand, *The Review of Economics and Statistics* 82(1), pp. 117–126.

Bolt, W., M. Demertzis, C. Dijks, M. van der Leij (2011), Complex methods in economics: an example of behavioral heterogeneity in house prices, DNB Working Paper No. 329.

Ca' Zorzi, M., A. Chudik and A. Dieppe (2012), Thousands of models, one story: current account imbalances in the global economy, *Journal of International Money and Finance* 31, pp. 1319-1338.

Case, K.E. and R. J. Shiller (1989), The efficiency of the market for single-family homes, *American Economic Review* 79(1), pp. 125-137.

Case, K.E., and R. J. Shiller (2003), Is there a bubble in the housing market?, *Brookings Papers on Economic Activity*, vol. 34(2), pp. 299-362.

Cuerpo Caballero C., M. Demertzis, L. Fernández Vilaseca and P. Pontuch (2012), Assessing the dynamics of house prices in the euro area, *Quarterly Report on the Euro area* 11(4), European Commission, Brussels.

Dougherty, A., and R. Van Order (1982), Inflation, housing costs, and the consumer price index, *American Economic Review*, 72, pp. 154-164.

Dujardin, M., A. Kelber and A. Lalliard, (2015), Overvaluation in the housing market and returns on residential real estate in the euro area: insights from data in euro per square meter, *Banque de France, Quarterly Selection of Articles* 37(Spring).

Engle, R. and C. Granger (1987), Co-integration and error correction: representation, estimation, and testing, *Econometrica* 55(2), pp. 251-276.

Englund, P. and Y. Ioannides (1993), The dynamics of housing prices: an international perspective, in *Economics in a Changing World, D. Bos, editor*, Volume 3, Chapter 10, pp. 175-197.

Englund, P. and Y. Ioannides (1997) House price dynamics: an international empirical perspective, *Journal of Housing Economics* 6, pp. 119-136.

European Commission (2004), Harmonized Consumer Price Index: a short guide for users, *Methods and Nomenclatures*.

Gattini, L. and P. Hiebert (2010), Forecasting and assessing euro area house prices through the lens of key fundamentals, *ECB Working Papers Series*.

Girouard, N., M. Kennedy M., P. van den Noord P. and C. André (2006), Recent house price developments: the role of fundamentals, *OECD Economics Department Working Papers No. 475*.

Goodhart, Ch. and Hofmann, B. (2008), House prices, money, credit and the macroeconomy, ECB Working Paper Series N°1249.

Graefe, A., H. Küchenhoffb, V. Stierleb and B. Riedlb (2014), Limitations of ensemble Bayesian model averaging for forecasting social science problems, *International Journal of Forecasting*, Forthcoming.

Hansen, B. (2007), Notes and comments: least square model averaging, *Econometrica* 75(4), pp. 1175-1189.

Iacovello, M. (2004), Consumption, house prices, and collateral constraints- a structural econometric analysis, *Journal of Housing Economics* 13, pp. 304-320.

Iacovello, M. (2005), House prices, borrowing constraints, and monetary policy in the business cycle, *American Economic Review* 95(3), pp. 739-764.

Im, K., M. Pesaran and Y. Shin (2003), Testing for unit roots in heterogeneous panels, *Journal of Econometrics* 115(1), pp. 53–74.

Inder, B. (1993), Estimating long-run relationships in economics: A comparison of different approaches, *Journal of Econometrics* 57(1), pp. 53-68.

Johansen, S. (1988), Statistical analysis of cointegration vectors, *Journal of Economic Dynamics and Control*, 12, pp. 231-354.

Jordà, O., M. Schularick, and A. Taylor (2015), Leveraged bubbles, *Journal of Monetary Economics*, 76(S), pp. 1-20.

Kao, C. (1999), Spurious regression and residual based tests for cointegration in panel data, *Journal of Econometrics* 90(1), pp. 1-44.

Kasparova, D. and M. White (2001), The responsiveness of house prices to macroeconomic forces: a cross-country comparison, *European Journal of Housing Policy* 1(3), pp. 385-416.

Kiyotaki, N. and J. Moore (1997), Credit cycles, *The Journal of Political Economy*, Vol. 105(2), pp. 211-248.

Kundan Kishor, N. and H. Marfatia, (2016), The dynamic relationship between housing prices and the macroeconomy: evidence from OECD countries, *Journal of Real Estate Finance and Economics* 54, pp. 237-268.

Leung, C. (2004) Macroeconomics and housing: a review of the literature, *Journal of Housing Economics* 13, pp. 249-267.

Maddala, G.S. and S. Wu (1999), A comparative study of unit root tests with panel data and a new simple test, *Oxford Bulletin of Economics and Statistics* 61(S1), pp. 631-652.

Malpezzi, S. (1999), A Simple Error Correction Model of House Prices, *Journal of Housing Economics* 8, pp. 27–62.

Montalvo, J. (1995), Comparing cointegrating regression estimators: some additional Monte Carlo results, *Economics Letters* 48, pp. 229-234.

Muellbauer, J. and A. Murphy (1997), Booms and busts in the UK housing market, *Economic Journal* 107, pp. 1701-1727.

Ortalo-Magné, F. and S. Rady (1999), Boom in, bust out: young households and the housing price cycle, *European Economic Review* 43, pp. 755-766.

Ott, H. (2014), Will euro area house prices sharply decrease?, *Economic Modelling* 42, pp. 116-127.

Park, J. (2002), Canonical cointegration regressions, *Econometrica* 60(1), pp. 119-143.

Pedroni, P. (1999), Critical values for cointegration tests in heterogeneous panels with multiple regressors, *Oxford Bulletin of Economics and Statistics* 61(S1), pp. 653-670.

Pedroni, P. (2004), Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis, *Econometric Theory* 20(3), pp. 597-625.

Pesaran, H., Shin Y. and R. Smith (1999), Pooled mean group estimation of dynamic heterogeneous panels, *Journal of the American Statistical Association* 94(446), pp. 621-634.

Phillips, P.C.B. and B. Hansen (1990), Statistical inference in instrumental variables regressions with I(1) processes, *Review of Economic Studies*, 57, pp. 99-125

Poterba, J. (1991), House price dynamics: the role of tax policy and demography, *Brookings Paper on Economic Activity* 2, pp. 143-203.

Quigley, J. and S. Raphael (2004), Is housing unaffordable? Why isn’t it more affordable?, *Journal of Economic Perspectives*, Vol. 18, No. 1., pp. 191-2014.

Raftery, A. E., D. Madigan and J. Hoeting (1997), Bayesian model averaging for regression models, *Journal of the American Statistical Association* 92 (437), pp. 179-191.

Sala-i-Martin, X., G. Doppelhofer and R. Miller (2000), Determinants of long-term growth: a Bayesian averaging of classical estimates approach, NBER Working Paper No. 7750.

Schwarz, G. (1978), Estimating the dimension of a model, *Annals of Statistics* 6(2), pp. 461-464.

Stock, J. and M. Watson (1993), A simple estimator of cointegrating vectors in higher order integrated systems, *Econometrica* 61(4), pp. 783-820.

Stock, J. (1987), Asymptotic properties of least square estimators of cointegrated vectors, *Econometrica* 55(5), pp. 1035-1056.

Sutton, G. (2002), Explaining changes in house prices, *BIS Quarterly Review – September 2002*, pp. 46-55.

Terrones, M. and C. Otrok (2004), The global house price boom, *World Economic Outlook,* September, pp. 71–89.

Tsatsaronis and Zhu (2004), What drives housing price dynamics: cross-country evidence, *BIS quarterly review – March 2004*, pp. 65-78*.*

Zentrum fur Europäische Wirtschaftsforschung (ZEW) (2011), Housing markets and intra-euro area macroeconomic imbalances: identifying policy instruments, *mimeo*.

ANNEX 1

Descriptive statistics for the price-to-income and price-to-rent ratios

Table A1.1: **Price-to-income ratio - descriptive statistics (2010=100)**

Country	Number of observations	Average	Standard deviation	Probability of a unit root*
AT	16	101	8.9	94.0%
BE	43	74.2	17	55.7%
BG	21	103.1	25.3	20.5%
CY	14	103.9	4.4	13.2%
CZ	16	96.1	6.4	40.1%
DE	35	130	25.4	8.8%
DK	43	84.8	16.5	22.2%
EE	12	121.5	26.8	20.3%
EL	19	94.8	8.9	27.2%
ES	43	71.6	16.8	25.9%
FI	43	98.4	14.1	0.2%
FR	43	76.3	15.5	48.3%
HR	13	101.4	9.8	4.3%
HU	9	93	13.1	19.1%
IE	43	98.9	14.9	14.5%
IT	43	85.4	10.4	1.3%
LT	17	118.1	21.5	48.1%
LU	42	77.2	19	99.8%
LV	16	120.3	20.7	92.0%
MT	16	84.7	17.9	14.9%
NL	43	76	19.1	29.8%
PL	8	94.5	14.6	0.3%
PT	28	115.3	15.8	67.1%
RO	8	90.9	28.1	22.1%
SE	43	81.9	15.5	70.9%
SI	13	94.8	10.1	12.1%
SK	11	100.3	11.7	35.1%
UK	43	82.2	16.8	35.8%
Panel	**744**			**0.2%**

* Null hypothesis under the augmented Dickey-Fuller test. The p-value for the panel corresponds to the ADF-Fischer Chi-square statistic.

Table A1.2: **Price-to-rent ratio - descriptive statistics (2010=100)**

Country	Number of observations	Average	Standard deviation	Probability of a unit root*
AT	16	101.2	4.4	78.2%
BE	39	69.7	20.6	71.7%
BG	19	99.9	39.9	39.1%
CY	14	100.9	8.5	3.7%
CZ	16	107.6	14.4	28.7%
DE	43	131.1	24.8	49.1%
DK	43	79.8	17.9	32.1%
EE	12	86.6	10.6	22.4%
EL	19	95.3	14.3	28.4%
ES	43	66.2	25.0	26.6%
FI	43	70.5	19.5	82.4%
FR	43	73.1	17.4	52.4%
HR	8	100.2	11.1	8.8%
HU	9	100.2	14.8	26.1%
IE	43	71.3	35.8	41.1%
IT	43	86.2	13.1	13.2%
LT	17	106.1	20.0	48.9%
LU	20	83.4	22.9	76.9%
LV	16	101.1	27.4	50.2%
MT	16	83.1	22.5	27.5%
NL	43	76.4	21.9	13.4%
PL	8	96.1	10.7	3.7%
PT	28	103.3	11.3	3.6%
RO	8	95.1	24.7	0.7%
SE	36	74.3	20.6	97.6%
SI	13	91.8	12.2	8.1%
SK	11	99.9	12.6	4.9%
UK	43	73.4	19.1	69.8%
Panel	**712**			**0.1%**

* Null hypothesis under the augmented Dickey-Fuller test. The p-value for the panel corresponds to the ADF-Fischer Chi-square statistic.

ANNEX 2

Adjusting long-term ratios

The price-to-income and price-to-rent ratios can be considered to follow normal distributions around their long-term average. However, given the few data points available for a number of countries, averaging across the available sample may yield a biased estimate of the long-term average.

One way to address this issue is to use information from the overall panel to extend backward the available series. In a Bayesian inference setting, this amounts to estimating the posterior sample mean of a series based on actual data and on a set of priors about its distribution. Let *X* be the variable of interest, which for country *i*, is available from time *t1* to *t*. If *Xi* is normally distributed with mean *mi* (unknown) and standard deviation *si* then the sample average of *Xi* also follows a normal distribution:

$$m_{X^i} = \sum_{t_1}^{t} \frac{X_u^i}{(t - t_1 + 1)} \sim N(m_i, \frac{s_i}{\sqrt{t - t_1 + 1}})$$

The posterior probability of *mi* based on the available data is provided by:

$$p(m_i | m_{X^i}) = \frac{f(m_{X^i} | m_i).p(m_i)}{\int f(m_{X^i} | m_i).p(m_i) dm_i}$$

Where $f(m_{X^i} | m_i)$ *is* the probability density of the observed sample average given *mi*. An intuitive prior distribution for *mi* can be derived from the sample mean of series combining country and panel data. To this end, a long "reference" series can be constructed using the average growth rate across all countries in the panel and rebasing the series to ensure that, for years where data is available, the reference series and the country series have the same mean. Denoting this series by X^{ref}, its starting year by *t0*, a prior distribution of *mi* can be expressed based on the sample mean and sample standard error of X^{ref}:

$$p(m_i) = N(m_{X^{ref}}, \frac{s_{X^{ref}}}{\sqrt{t - t_0 + 1}})$$

The *posterior* probability density of *mi* is then proportional to:

$$p(m_i | m_{X^i}) \propto \exp[-\frac{1}{2\, s^2 / (t - t_1 + 1)} (m_{X^i} - m_i)^2 - \frac{1}{2\, {s_{X^{ref}}}^2 / (t - t_0 + 1)} (m_{X^{ref}} - m_i)^2$$

The posterior distribution of *mi* is therefore also a normal distribution whose mean is given by:

$$m_i^{post} = \frac{\frac{t - t_1 + 1}{s^2} m_{X^i} + \frac{t - t_0 + 1}{{s_{X^{ref}}}^2} m_{X^{ref}}}{\frac{t - t_1 + 1}{s^2} + \frac{t - t_0 + 1}{{s_{X^{ref}}}^2}}$$

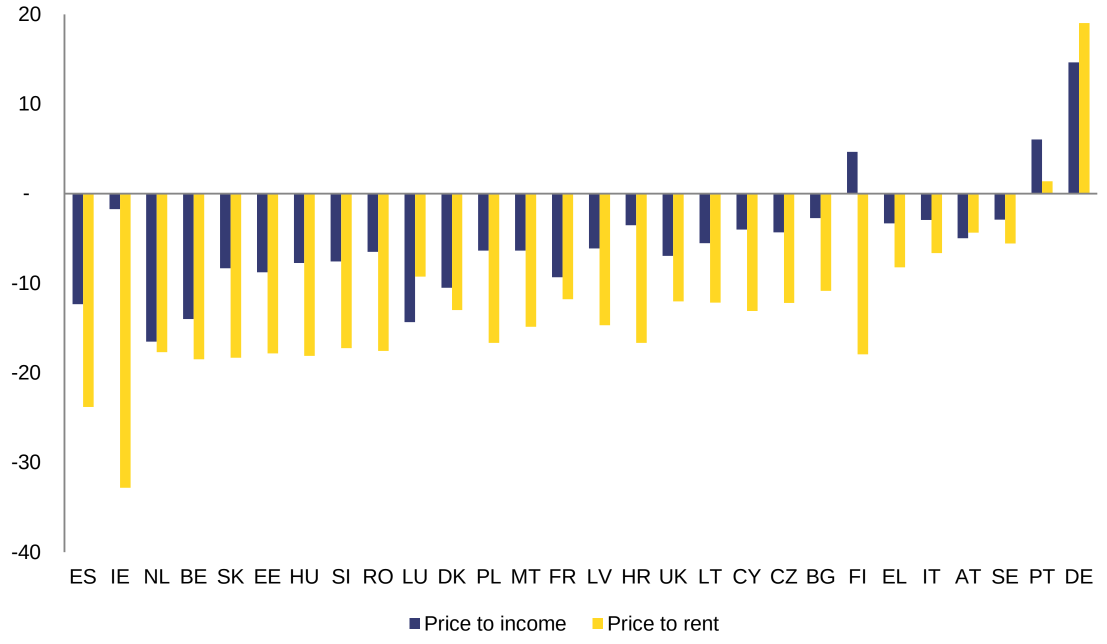
The posterior estimate of the long-term average for country *i* is therefore equal to the weighted average of: (i) the sample average based on individual country data; (ii) the sample average obtained from the reference series. The weights applied take into account both the variability and the number of observations. It should be noted that, by construction, as the number of available observations for the individual country increases (i.e. as t1 approaches t0), the posterior estimation of the means comes closer to the average of the available observations.

The last step necessary to compute the posterior long-term average is to take an estimate of *si*, the "true" standard error of the distribution of *X*i. A natural possibility in that respect is to take the sample standard deviation for *Xi*, which is based on the available observations over t1 to t. However, as data for some countries is mostly available close to crisis episodes, it is likely that this could lead to an overestimation of the variance of the overall series. ([22]) An alternative is therefore to adjust the sample standard deviation based on the reference series over the same period:

$$s = s_{X^{ref}} \frac{s_{X^i}}{[s_{X^{ref}}]_{over\ [t_1,t]}}$$

As can be seen from Graph A2.1 below, the gap between the observed and the posterior long term average can be significant, in particular in countries where the number of observation is limited and where post-1995 developments have diverged significantly from the past.

Graph A2.1: **Adjustment of the mean linked to priors, price-to-rent and price-to-income ratios**



Difference between the 1995-2015 average and the adjusted average. By construction, in countries with a complete data sample, the adjustment is equal to the difference between the 1995-2015 average and the full sample average.

([22]) Statistical tests on the reference series show that its variance is significantly different when assessed over 1995-2015 or over the full sample.

ANNEX 3
Combining benchmarks: a Bayesian approach

A3.1. MODEL AVERAGING: CRITERIA

Confronted with the multiplicity of models that can be used to assess developments in one specific indicator, the econometric literature has developed two types of approaches: model selection and model averaging. Model selection relies on the definition of a loss function to compare the performance of a large diversity of models. Model averaging seeks to use the information contained in the various models to come up with a synthetic, more performing, indicator.

In its seminal article, Akaike (1973) introduces an information criterion that measures the loss of information linked to the use of one particular model to estimate the data generating process. The Akaike information criterion (AIC) is defined as:

$$AIC = \frac{-2.\ln(L) + 2k}{n}$$

Where L is the maximum likelihood of the model studied, k the number of parameters estimated in the model and n the number of observations. The best model is the one that minimises the AIC statistics, i.e. the one that has the largest likelihood while using the smallest number of variables, which therefore reduces the risk of over-fitting. A number of variations on the AIC have been introduced for model selection.([23]) The Bayesian Information Criterion (BIC), defined by Schwarz (1978) has been used as an alternative to the AIC, the difference being that it assigns greater weight to parsimonious specifications.([24]) The AIC and the BIC are routinely used for model selection (see for example Ca' Zorzi et al. (2012)).

As an alternative to model selection, *model averaging* uses a weighted average of the estimates provided by the various models to derive a synthetic estimator. Bayesian model averaging, introduced in Raftery et al. (1997), combines models using as weight the conditional probability that each competing model is the 'true model' based on the data. To this end, the AIC and the BIC are commonly used to derive a weighted average model called respectively smoothed AIC and smoothed BIC. ([25]) The observation obtained from the average model Y based on the combination of observations *Yi* obtained from model *Mi* using the information criteria *IC* is therefore provided by:

$$Y = \sum_i Y_i \times \frac{\mathrm{e}^{-0.5.\mathrm{IC}(M_i)}}{\sum_j e^{-0.5.IC(M_j)}}$$

A3.2. APPLYING MODEL AVERAGING TO HOUSE PRICES BENCHMARKS

Valuation gaps obtained from the four house price benchmarks can be combined on the basis of both the AIC and the BIC as alternative information criteria. Benchmarks based on cointegration are evaluated both in their country-by country formulation and when estimated across the whole panel. Results for the information criteria of the different benchmarks are provided in Table A3.1. It appears that benchmarks based on cointegration analysis perform better than benchmarks based on price ratios in terms of information criteria (both based on the AIC and on the BIC). In addition, panel estimates somehow perform less well than estimates based on country-specific cointegration analysis, which are able to track

([23]) In particular, for small-sized sample, Burnham and Anderson (2002) propose to use a corrected AIC
([24]) Using the same symbols as before, the BIC is defined as BIC=[-2.ln(L)+k.ln(n)]/n
([25]) Hansen (2007) suggests that in cases where the number of observations is small, less than 50, the smoothed BIC estimator performs better than the smoothed AIC while the latter provides better estimates for large numbers of observations.

country-specific dynamics more closely. Price-to-income ratios perform considerably better than price-to-rent ratios. ([26])

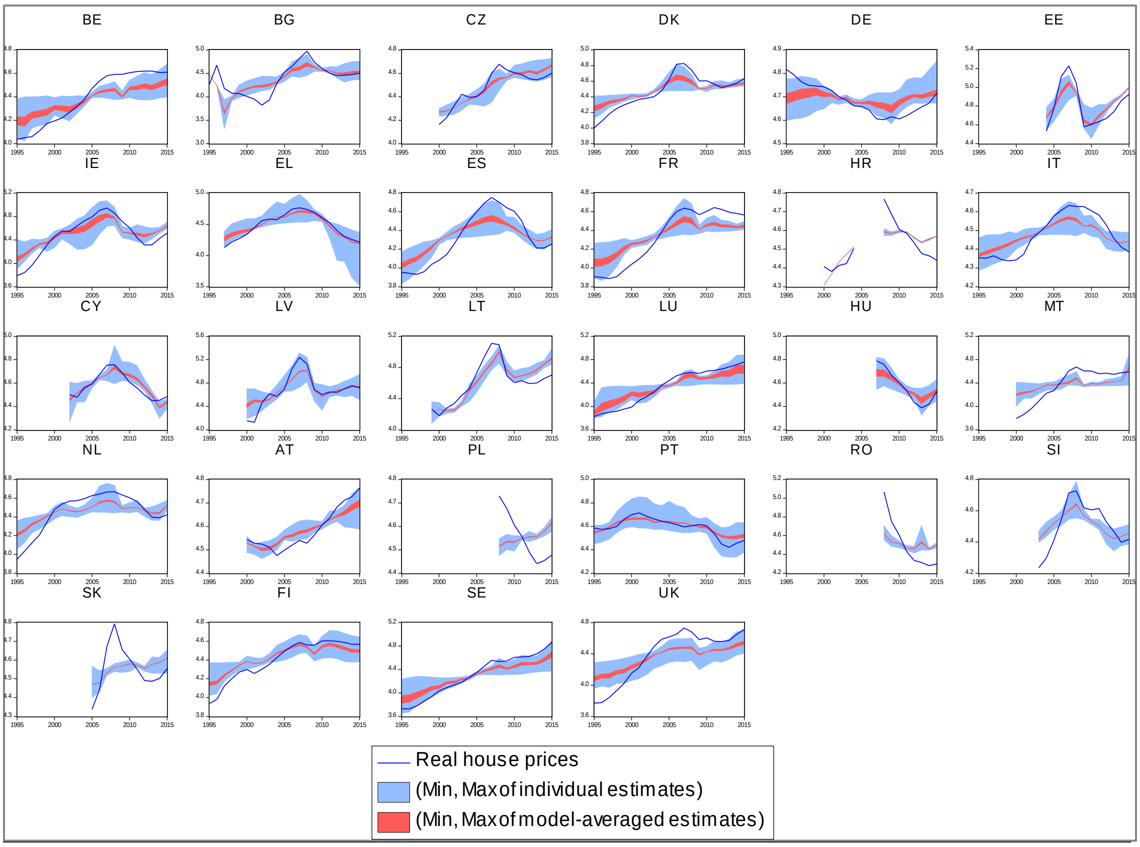
Table A3.1: **AIC and BIC for the various models**

	Estimated - Panel	Estimated - Country	Price-to-income	Price-to-rent
AIC	-0.91	-1.54	-0.66	-0.14
BIC	-0.70	-0.98	-0.41	0.11
Number of cross sections	24	16	28	28
Number of parameters	31	71	28	28

To compute a benchmark at country-level, the BIC is computed for each country for the various models. The resulting weights are shown in Annex 4 – Table A4.5. To reflect the uncertainty related to the actual model to be used to assess house price fundamentals, Graph A3.1 shows the interval of possible fundamental prices as provided by the four different methodologies. It also provides the narrower range of possible fundamental prices derived from model averaging using the smoothed-AIC, the smoothed-BIC as well as the more "naïve" simple average of the various methodologies.([27]) While the various benchmarks give conflicting results in some cases on the sign of the valuation gap, this is never the case for model averages, irrespective of the weighting applied.

([26]) Comparison between the information criteria for the various models needs to take into account the fact that they are estimated on different samples. Table A3.1 provides the AIC and BIC based on the largest sample available for each model. A pair-wise comparison of models based on their common sample provides similar results.
([27]) The weight for the two econometric approaches based on fundamentals is divided by two to reflect the similarities in these methodologies.

Graph A3.1: **Actual and estimated house prices (in logarithm)**



Individual estimates include, where available, benchmarks based on: price-to-income, price-to-rent, fundamentals for the panel and country data. Model-averaged estimates are based on a simple average, a smoothed AIC and a smoothed BIC.

ANNEX 4

Statistical tables

Table A4.1: **Country-level unit-root tests (augmented Dickey-Fuller tests)**

	RHP			POP			RYPC			RHI			RLTR		
	Level	1st diff.	Obs.	Level	1st diff.	Obs.	Level	1st diff.	Obs.	Level	1st diff.	Obs.	Level	1st diff.	Obs.
BE	0.71	0.13	43	1.00	0.46	46	0.07	0.02	46	0.28	0.00	46	0.47	0.00	46
BG	0.50	0.00	21	0.97	0.16	46	0.94	0.00	21	0.36	0.17	18	0.08	0.02	14
CZ	0.34	0.04	16	0.71	0.06	46	0.60	0.16	24	0.45	0.00	21	0.17	0.00	15
DK	0.61	0.00	43	1.00	0.43	46	0.60	0.00	46	0.14	0.00	46	0.78	0.00	46
DE	0.23	0.04	43	0.64	0.25	46	0.96	0.00	25	0.38	0.03	25	0.92	0.00	24
EE	0.05	0.09	12	0.73	0.15	46	0.60	0.04	23	0.64	0.02	21	0.32	0.02	13
IE	0.64	0.07	43	0.91	0.35	46	0.90	0.01	46	0.25	0.04	41	0.14	0.00	45
EL	0.20	0.58	19	0.10	0.24	46	0.20	0.00	46	1.00	0.00	46	0.43	0.00	40
ES	0.59	0.00	43	0.88	0.07	46	0.88	0.00	46	0.37	0.05	46	0.01	0.00	38
FR	0.81	0.03	43	0.98	0.01	46	0.27	0.00	46	0.19	0.00	46	0.35	0.00	46
HR	0.02	0.83	13	0.84	0.20	46	0.40	0.12	21				0.25	0.04	10
IT	0.26	0.01	43	0.90	0.19	46	0.10	0.01	46	0.22	0.00	46	0.36	0.00	46
CY	0.11	0.47	14	0.79	0.00	46	0.23	0.00	21	0.02	0.42	21	0.30	0.00	19
LV	0.03	0.03	16	0.85	0.46	46	0.51	0.12	21	0.13	0.04	21	0.15	0.02	15
LT	0.11	0.17	17	0.34	0.72	46	0.63	0.05	21	0.88	0.03	21	0.08	0.00	15
LU	0.79	0.19	21	1.00	0.33	46	0.35	0.00	46	0.07	0.00	46	0.01	0.00	43
HU	0.11	0.97	9	0.87	0.08	46	0.60	0.07	21	0.66	0.06	21	0.27	0.00	17
MT	0.09	0.38	16	1.00	0.00	46	1.00	0.02	21	0.31	0.30	16	0.09	0.00	16
NL	0.41	0.11	43	0.45	0.20	46	0.66	0.00	46	0.07	0.02	46	0.27	0.00	46
AT	1.00	0.19	16	1.00	0.04	46	0.00	0.00	46	0.27	0.00	40	0.47	0.00	46
PL	0.27	0.89	8	0.01	0.76	46	0.50	0.05	25	0.42	0.01	21	0.02	0.00	17
PT	0.10	0.01	28	0.83	0.00	46	0.74	0.00	46	0.89	0.00	46	0.01	0.00	31
RO	0.00	0.27	8	0.11	0.43	46	0.84	0.14	26	0.03	0.00	21	0.00	0.00	10
SI	0.09	0.47	13	0.01	0.31	46	0.19	0.03	26	0.20	0.08	26	0.35	0.01	14
SK	0.03	0.06	11	0.00	0.71	46	0.43	0.03	22	0.06	0.10	23	0.03	0.00	16
FI	0.61	0.00	43	0.79	0.00	46	0.46	0.01	46	0.09	0.00	46	0.35	0.00	46
SE	0.90	0.11	43	1.00	0.54	46	0.89	0.00	46	0.23	0.01	45	0.53	0.00	46
UK	0.79	0.03	43	0.99	0.67	46	0.52	0.00	46	0.01	0.00	46	0.08	0.00	46

The probability reported is the one associated with the null hypothesis that the time series has a unit root

Table A4.2: **Results of the country-specific tests for cointegration (Engle and Granger, 1987)**

	Engle-Granger tau-statistic		Engle-Granger z-statistic	
	Value	**Prob.**	**Value**	**Prob.**
BE	-2.81	0.70	-14.50	0.65
BG	-3.49	0.46	-27.60	0.00
CZ	-3.69	0.39	-34.82	0.00
DK	-4.84	0.04	-29.00	0.05
DE	-2.52	0.82	-45.23	0.00
EE	-7.43	0.04	-10.63	1.00
IE	-4.94	0.04	331.62	1.00
EL	-4.17	0.21	-37.13	0.00
ES	-4.64	0.07	50.60	1.00
FR	-4.10	0.17	39.30	1.00
IT	-4.08	0.17	-29.04	0.05
CY	-3.21	0.57	-27.20	0.00
LV	-4.52	0.17	-50.94	0.00
LT	-3.09	0.62	-23.98	0.00
LU	-2.44	0.84	-9.39	0.86
HU	-3.01	0.69	-10.04	0.19
MT	-1.65	0.98	-4.97	0.99
NL	-4.25	0.13	-32.81	0.02
AT	-3.44	0.47	-27.59	0.76
PL	-2.44	0.87	-7.33	0.96
PT	-3.45	0.42	-25.45	0.05
RO	-2.56	0.83	-7.15	0.42
SI	-4.74	0.15	-69.93	1.00
SK	-4.82	0.15	-15.88	0.00
FI	-2.11	0.93	-7.06	0.96
SE	-5.81	0.00	-37.71	0.00
UK	-3.58	0.34	-14.68	0.63

The probability reported is the one associated with the null hypothesis that there is no cointegration between the variables

Table A4.3: **Estimated coefficients for the error correction model (OLS)**

Variables	Coefficients	Standard errors	p-values
Error correction term - 1 lag	-0.10	0.02	0.00
D(POP)	1.70	0.61	0.00
D(RHI)	0.17	0.02	0.00
D(RYPC)	0.97	0.08	0.00
D(RLTR)	0.00	0.00	0.00
D(RYPC) - 1 lag	0.29	0.07	0.00
Nb of cross sections			27
Nb of observations			649
Adjusted R^2			0.54

Number of lags for the explanatory variables (in difference) selected based on significance at the 10% level. Estimated specification includes country-fixed effects.

Table A4.4: **Estimated country-specific coefficients (Canonical Cointegration Regression - Park, 1992)**

	POP		RYPC		RHI		RLTR		Nb. Obs.
	Coef.	p values	Coef.	p values	Coef.	p values	Coef.	p values	
BE	2.9	0.00	0.38	0.09	0.43	0.00	-0.036	0.09	43
DK			0.90	0.00	0.57	0.00	0.000	0.00	43
DE			-0.64	0.00	0.49	0.00	-0.014	0.00	23
IE			0.94	0.00	0.20	0.01	-0.010	0.00	40
EL	8.9	0.00	0.80	0.07	0.05	0.03	-0.004	0.07	19
ES			1.13	0.01	0.39	0.14	0.012	0.01	37
FR			0.84	0.00	1.86	0.00	-0.007	0.00	43
IT	2.1	0.04	0.41	0.02	0.73	0.00	0.002	0.02	43
LU	1.4	0.01	1.71	0.00	0.16	0.23	0.024	0.00	21
MT			1.06	0.03	0.20	0.08	-0.089	0.03	15
NL			1.37	0.00	0.58	0.00	-0.042	0.00	43
AT	5.6	0.00	-1.00	0.01	0.82	0.00	-0.004	0.01	16
PT			0.18	0.04	0.20	0.00	0.002	0.04	28
FI			0.34	0.07	0.89	0.00	0.009	0.07	43
SE	2.8	0.03	0.59	0.03	0.17	0.01	-0.071	0.03	43
UK	2.5	0.19	1.24	0.00	0.59	0.04	-0.025	0.00	43
Group Mean	**3.7**		**0.64**		**0.52**		**-0.016**		**543**

Table A4.5: **Model weights based on the Bayesian information criterion**

	Individual country model	Panel estimate	Price-to-income ratio	Price-to-rent ratio
BE	0.34	0.33	0.18	0.15
BG		0.52	0.29	0.19
CZ		0.39	0.40	0.21
DK	0.31	0.36	0.17	0.15
DE	0.51	0.12	0.14	0.23
EE			0.38	0.62
IE	0.30	0.33	0.24	0.13
EL	0.54	0.07	0.23	0.16
ES	0.30	0.30	0.22	0.19
FR	0.37	0.34	0.16	0.14
HR			0.58	0.42
IT	0.27	0.26	0.23	0.24
CY		0.17	0.54	0.28
LV		0.34	0.42	0.25
LT		0.48	0.27	0.26
LU	0.37	0.37	0.15	0.11
HU		0.57	0.21	0.21
MT	0.25	0.29	0.27	0.19
NL	0.28	0.25	0.26	0.22
AT	0.36	0.23	0.14	0.28
PL		0.29	0.30	0.41
PT	0.40	0.16	0.23	0.21
RO		0.37	0.28	0.35
SI		0.36	0.36	0.28
SK		0.32	0.36	0.32
FI	0.25	0.23	0.36	0.16
SE	0.38	0.28	0.21	0.13
UK	0.41	0.20	0.22	0.17

Table A4.6: **Valuation gaps based on the various approaches (in pps. compared to 2015 prices)**

	Individual country model	Panel estimate	Price-to-income ratio		Price-to-rent ratio	
			Standard	*Adjusted*	Standard	*Adjusted*
BE	-6.7	5.4	22.5	*42.4*	23.9	*52.0*
BG		15.1	-22.4	*-20.2*	-2.8	*9.0*
CZ		-12.0	3.5	*8.1*	-11.5	*0.8*
DK	10.4	0.2	4.1	*16.3*	9.9	*26.3*
DE	4.4	-12.8	-5.2	*-17.3*	3.1	*-13.4*
EE			-6.0	*3.0*	-7.8	*12.1*
IE	-9.1	-17.1	-8.9	*-7.3*	-7.5	*37.7*
EL	2.8	100.8	-11.2	*-8.1*	-14.6	*-6.9*
ES	-0.8	-14.5	-7.0	*6.1*	-8.1	*20.6*
FR	12.0	7.3	17.1	*29.1*	16.5	*32.1*
HR			-12.0	*-8.8*	-12.1	*5.5*
IT	-3.8	-7.5	-0.9	*2.1*	-9.9	*-3.5*
CY		11.1	2.2	*6.5*	3.3	*18.8*
LV		22.3	-20.7	*-15.6*	-1.3	*15.7*
LT		-12.5	-17.3	*-12.4*	-28.7	*-18.8*
LU	3.6	-11.5	41.4	*65.0*	44.7	*59.4*
HU		8.7	-9.8	*-2.2*	-3.8	*17.5*
MT	-25.8	-7.4	-5.6	*0.8*	25.7	*47.7*
NL	-12.5	-5.4	-4.5	*14.4*	-14.5	*3.9*
AT	-0.2	7.3	19.2	*25.4*	6.8	*11.7*
PL		-15.0	-14.0	*-8.1*	-9.7	*8.4*
PT	2.6	10.5	-10.3	*-15.4*	-14.3	*-15.4*
RO		-19.6	-20.3	*-14.8*	-15.6	*2.4*
SI		3.1	-8.9	*-1.5*	-4.7	*15.1*
SK		-9.5	-8.8	*-0.5*	2.4	*25.3*
FI	12.5	-7.7	4.0	*-0.7*	20.4	*46.7*
SE	-3.5	19.1	41.6	*45.9*	64.0	*73.7*
UK	-0.2	35.8	27.1	*36.6*	32.4	*50.6*

EUROPEAN ECONOMY DISCUSSION PAPERS

European Economy Discussion Papers can be accessed and downloaded free of charge from the following address:
https://ec.europa.eu/info/publications/economic-and-financial-affairs-publications_en?field_eurovoc_taxonomy_target_id_selective=All&field_core_nal_countries_tid_selective=All&field_core_date_published_value[value][year]=All&field_core_tags_tid_i18n=22617

Titles published before July 2015 under the Economic Papers series can be accessed and downloaded free of charge from:
http://ec.europa.eu/economy_finance/publications/economic_paper/index_en.htm

Alternatively, hard copies may be ordered via the "Print-on-demand" service offered by the EU Bookshop: http://bookshop.europa.eu.

HOW TO OBTAIN EU PUBLICATIONS

Free publications:

- one copy:
  via EU Bookshop (http://bookshop.europa.eu);

- more than one copy or posters/maps:
  - from the European Union's representations (http://ec.europa.eu/represent_en.htm);
  - from the delegations in non-EU countries (https://eeas.europa.eu/headquarters/headquarters-homepage/area/geo_en);
  - by contacting the Europe Direct service (http://europa.eu/europedirect/index_en.htm) or calling 00 800 6 7 8 9 10 11 (freephone number from anywhere in the EU) (*).

  (*) The information given is free, as are most calls (though some operators, phone boxes or hotels may charge you).

Priced publications:

- via EU Bookshop (http://bookshop.europa.eu).

KC-BD-17-048-EN-N

Publications Office

ISBN 978-92-79-64887-8