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An alternative method for identifying booms and busts in the euro area housing market

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AN ALTERNATIVE METHOD FOR IDENTIFYING BOOMS AND BUSTS IN THE EURO AREA HOUSING MARKET

Dieter Gerdesmeier, Andreja Lenarčič
and Barbara Roffia



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Abstract

The main aim of this paper is to apply a method based on fundamentals — which has already been applied in the stock market analysis — to detect boom/bust in the housing market, with a focus on the euro area. In this context, an underlying model is developed and tested. It turns out that the user cost rate, a demographic variable, the unemployment rate, disposable income (or disposable income per capita), the debt-to-income ratio and, finally, the housing stock are fundamental variables which significantly explain house price developments. Booms and busts are then selected as episodes when the house price index deviates excessively from the levels which would be implied by these economic fundamentals. In addition, a cross-check of the boom/bust episodes based on this method and other statistical and fundamental ones is carried out in order to substantiate the results obtained. Finally, money and credit aggregates are included in the specifications and are found to be useful in explaining boom/busts cycles in house prices.

Keywords: house prices, booms, busts, quantile regressions, monetary and credit aggregates

JEL-classification: E37, E44, E51

Non-technical summary

During the past decades, asset markets have played an increasingly important role in many economies, and large swings in asset prices have become a relevant issue for policy-makers, thus bringing new attention to the linkages between monetary policy and asset markets. Monetary policy has been cited as both a possible cause of asset price booms and a tool for defusing those booms before they can cause macroeconomic instability. Consequently, economists and policymakers have focused on how monetary policy might cause an asset price boom or turn a boom caused by real phenomena, such as an increase in aggregate productivity growth, into a “bubble”, which may burst unexpectedly, thus rendering damage to the economy.

The novelty of this study lies in the application of the methodology used in Machado and Sousa (2006) to house prices developments, by means of selecting underlying fundamental variables and applying the quantile regression approach to detect booms and busts. Our main results are as follows.

First, house price developments are significantly explained by the user cost rate (with a negative coefficient), a demographic variable (working population or labour force) which affects the house prices positively, the unemployment rate (with a negative sign), disposable income (or disposable income per capita) with a positive coefficient, the debt-to-income ratio (with a negative effect) and, finally, the housing stock and the housing stock per capita (with a positive sign). In terms of R^2 statistics, all quantile regressions equations give satisfactory results, being fully in line with those reported in the literature.

Second, the effects of the fundamental variables on house prices are found to vary in some cases across quantiles. In particular, the demographic variables, the unemployment rate, the disposable income and the debt-to-income ratio mostly affect the upper part of the conditional distribution of house prices. This leads to the conclusion that conventional linear methods do not always fully summarize the existing disparities and that there is benefit in cross-checking the former results by means of quantile regressions.

Third, the additional information on the distribution in house prices is used as an alternative method to identify booms and busts in this type of asset prices class. Using the estimated coefficients, we calculate fitted values for specific quantiles of the conditional distribution and plot them against the developments in real house prices. If house prices move into the highest (lowest) quantile, this can be dubbed as a boom (bust) period. The performance of the model in detecting booms and busts is also assessed vis-à-vis other, statistical and fundamental methods which have been used in the literature for selecting such episodes. A comparison across these methods suggests that the booms and busts based on the quantile methods are broadly consistent with the episodes resulting from the other methods.

Fourth, the growth rates of money and credit aggregates enter significantly into the quantile regressions and seem to have additional explanatory power in detecting house price misalignments.

Overall, the quantile approach provides a supplementary useful tool which can help to detect misalignments in the housing market.

1 Introduction

Over the past decades, asset markets have played a growing role in macroeconomic dynamics. Policy-makers have become increasingly aware of the fact that sizeable changes and significant periodic corrections in asset prices may lead to financial and, ultimately, macroeconomic instability. For example, rapidly rising asset prices are often associated with an easing in credit conditions, increased spending on account of wealth increases and relaxation of credit constraints and, ultimately, inflationary pressures. The bursting of an asset price bubble, however, could imply significant financial losses by institutions and investors, and a sharp drop in aggregate demand, leading to deflationary risks via both direct wealth effects and instability in the financial sector. A zero lower bound on nominal interest rates, as well as heightened uncertainty with respect to the monetary transmission mechanism in times of turmoil, could then make it more difficult for central banks to maintain price stability. The developments in asset price indices and the interaction between asset prices and monetary developments is, therefore, worth close attention.

In principle, the analysis and the monitoring of developments in asset prices for policy purposes rest on three basic steps. The first step is to define and identify asset price boom and bust periods. The second step aims at finding indicator variables that can predict these periods. Finally, the third step consists in using the historical relationship between the indicator variables and the boom/bust periods to derive a likelihood of asset price boom/busts in real time. In this paper, we focus on checking the robustness of the various methods that can be used in the first step by applying them to the housing market.

Identifying and quantifying asset price misalignments has always represented an extremely difficult task, in particular from an ex-ante point of view. This observation is supported by the heterogeneity of studies based on different criteria, each involving some degree of arbitrariness, and the different results found in the recent literature on this topic. Generally speaking, the methods that have been applied in order to select periods of asset price booms and busts can be divided into two broad categories. The first category contains purely statistical methods which identify particularly strong or weak asset price developments, while the second category consists of model-based analysis of the fundamental drivers of the developments in asset price indices. In either case, significant deviations from some norm, defined by historical experience in the first and the underlying model in the second case, would be considered booms or busts.

A few examples of statistical methodologies used include Bordo and Jeanne (2002) define a bust as a period in which the three-year moving average of the growth rate of asset prices is smaller than a specific threshold. They define the threshold as the average growth rate less a multiple (1.3) of the standard deviation of the growth rates. In other studies applying a similar criterion, the threshold is defined either by choosing a different multiple of the standard deviation (e.g. Gerdesmeier et al., 2010)

or it is fixed at a constant value (e.g. IMF, 2009). The duration of asset price misalignments is also sometimes taken into account, whereby excessive developments in asset prices are labeled as imbalances if they last for a protracted period, for instance if they deviate from their threshold for a certain number of consecutive quarters. All these criteria can be applied symmetrically to booms by considering the periods when the index overshoots a pre-defined threshold. The studies above also differ in terms of whether the boom/bust detection method is applied to the individual asset market price indices, such as stock and housing markets, or to a composite asset price index.

Apart from the statistical approaches, another way to detect whether the asset prices are undervalued or overvalued is to compare the individual market indices with the levels which would be implied by economic fundamentals. One of the methods which can be used for this purpose is the so-called “quantile” regression approach applied on a reduced form model of the relation between the asset prices and the underlying fundamentals. This methodology for constructing indicators of misalignments in individual asset markets is based on the hypothesis that asset prices have a long-run relation with some macroeconomic fundamentals. When asset prices are close to the levels implied by such long-run relation, they can be considered “fair” or at a “normal” level, while any deviation from such a value would mean an emergence of misalignment. Booms and busts are then defined as periods when these misalignments are larger than a certain threshold. In principle confidence bounds of the model-based estimates of the long-run relationship between a price index and its fundamentals could serve as such a threshold. However, as the developments in the asset price indices are fairly non-linear, the use of quantile regressions is warranted. Machado and Sousa (2006) were the first to apply this approach to boom/bust identification in the case of the stock price index.

The novelties of the present paper are threefold. First, the quantile regression approach for detecting booms and busts is applied to the housing market. . This, *inter alia*, requires the development of a plausible model of fundamental factors in the house price index.¹ Second, we proceed by comparing the performance of the quantile method with that of a number of alternative, statistical methods. Third, in the context of the quantile regression approach, we analyze the impact of money and credit developments on the boom/bust cycles in the housing market.

The paper is structured as follows. Section 2 briefly describes the methodology of quantile regressions, their main advantages and reviews the papers using the quantile regressions in the context of asset and housing prices. Section 3 reviews the literature on modeling the developments in the housing markets. Section 4 contains the description of the data set, the selection and construction of the variables that are used in the estimations, and their properties. It also presents some simple reduced-form housing models estimated by dynamic OLS and discusses the estimates of the preferred specifications. Section 5 contains the results obtained by means of the quantile regression approach and

¹ Kennedy and Andersen (1994) study developments in house prices and discuss the fundamental developments (based on simple models of house price dynamics) and speculative bubbles. Fundamentals and house price bubbles are also analysed in McCarthy and Peach (2002).

the identified boom and bust periods for the euro area. In Section 6, we compare the boom and bust periods identified by the means of quantile regression techniques with the results based on statistical methods. Section 7 investigates the role for money and credit developments in such framework. Section 8 concludes.

2 The quantile regression framework and selected empirical evidence

Linear regression is a very popular statistical tool for quantifying the relationship between a predictor variable and a response variable. In particular, this method estimates the mean value of the response variable for given levels of predictor variables. As an example, suppose one is interested in the relationship between house prices and their fundamentals. The linear regression model then estimates how, on average, the fundamentals affect house prices. However, such methodology cannot answer another important question, which is whether the disposable income or other fundamental variables influence the house prices differently at a higher quantile of the distribution than on average. The latter question is clearly of relevance in the context of our study since house price boom/busts are well-known to be highly non-linear events. Against this background, a more comprehensive picture can be provided by the use of quantile regression techniques. Originally developed by Koenker and Bassett (1978), the quantile regression models the relationship between a set of predictor variables and specific percentiles (or quantiles) of the response variable. For instance, if one looks at the 50th percentile, a median regression is obtained, i.e. the changes in the median house prices as a function of the predictors. Similar regressions can be run for other quantiles. The size of the regression coefficients then quantifies the effect that the predictor variables have on a specified quantile of the response variable.

To formalise these considerations in a more technical way, consider a linear regression model of the following form:²

$$(1) \quad Y_t = X_t' \beta + \varepsilon_t$$

where X_t is a $[k \times 1]$ vector of regressors and β is the vector of coefficients. Moreover, $\beta_k = \frac{d E(Y_t | X_t)}{d X_t^{(k)}}$ where $X_t^{(k)}$ is the k^{th} element of the vector X_t and β_k is the corresponding coefficient. The coefficient β_k tells how the mean of Y_t shifts following a unit change in the k^{th} conditioning variable $X_t^{(k)}$.

² See Cecchetti and Li (2008).

More generally, quantile regressions seek to model the conditional quantile functions, in which the quantiles of the conditional distribution of the dependent variable are expressed as functions of observed covariates. The main advantage of quantile regressions is that potentially different solutions at distinct quantiles may be interpreted as differences in the response of the dependent variable to changes in the regressors at various points of the conditional distribution of the dependent variable.

The quantile estimator solves the following optimization problem:

$$(2) \quad \min_{\beta} \sum_{t=1}^T \sigma_{\tau}(y_t - x_t' \beta)$$

where y_t is the vector of the dependent variable, x_t is a matrix of independent regressors, β is the estimated vector of parameters and $\sigma_{\tau}(\cdot)$ is the absolute value function that yields the τ^{th} sample quantile as its solution. In general, the linear model for the τ^{th} quantile ($0 < \tau < 1$) solves:

$$(3) \quad \min_{\beta} \frac{1}{T} \left\{ \sum_{t: y_t \geq x_t' \beta} \tau |y_t - x_t' \beta| + \sum_{t: y_t < x_t' \beta} (1 - \tau) |y_t - x_t' \beta| \right\}$$

The resulting minimisation problem can be solved using linear programming methods. The coefficient for a regressor j can be interpreted as the marginal change in the τ^{th} conditional quantile of y due to a marginal change in j .³ As one keeps increasing τ from zero to one, one can trace the entire conditional distribution of the dependent variable. In the particular case of this paper, the quantile regression allows us to trace the entire asset price distribution, conditional on the set of regressors, reflecting the set of fundamental variables.

The use of quantile regressions has a number of additional benefits. The median regression can be more efficient than mean regression estimators in the presence of heteroskedasticity. Quantile regressions are also robust with regard to outliers in the dependent variable. The latter is due to the fact that the quantile regression objective function is a weighted sum of absolute deviations, which gives a more robust measure of location. Finally, when the error term is non-normal, quantile regression estimators may be more efficient than least squares estimators.

In recent years, the quantile methodology has been increasingly used in several fields in empirical economics, among other also in the studies of the stock and house markets. For instance, Machado and Sousa (2006) use this approach for identifying booms and busts in the stock markets. In essence, they estimate the distribution of prices conditional on a set of macroeconomic determinants of

³ Standard errors and confidence limits for the quantile regression coefficient estimates can be obtained with asymptotic and bootstrapping methods. Both methods provide robust results with the bootstrapping method often being seen as more practical (see Greene, 2003).

asset prices, such as GDP and the real interest rate, using both parametric and nonparametric quantile regression approach. Based on the estimated fitted values for the quantiles, they identify the booms and busts in the stock market.

Cecchetti and Li (2008) use quantile vector autoregressions to measure the impact of housing and stock price booms and busts on particular quantiles of the distribution of GDP growth and inflation. In their study, the asset price boom and bust periods are defined as substantial deviations of (real) house and (real) stock prices from their respective trend. Using panels of 17 and 27 countries they find that the impact of housing and equity booms on growth and inflation differs considerably across quantiles.

Xiao (2010) advocates the use of the quantile regression methodology for the analysis of the relationship between stock prices and market fundamentals by relying on a time-varying cointegration framework subject to shocks. Other papers applying quantile regression methodology for the analysis of stock prices are, for instance, Allen et al. (2009), Barnes and Hughes (2008) and Saastamoinen (2008).

Several studies use quantile regressions specifically for the analysis of the housing market. Zietz et al. (2008) use quantile regressions to determine the valuation of the housing characteristics across a given house price distribution in a hedonic house pricing model. Similarly, McMillen (2008) estimates a quantile regression in the framework of a hedonic house pricing model to decompose changes in the distribution of house prices into the portion induced by the changes in the distribution of the explanatory variables and the portion caused by changes in the quantile regression coefficients. He finds that nearly the entire change in the distribution of house prices can be explained by changes in the coefficients rather than by changes in the distribution of the explanatory variables. Also related to the housing market, Liao and Wang (2010) combine quantile regression and spatial econometric modelling to examine how implicit prices of housing characteristics may vary across the conditional distribution of house prices.

3 Selected literature on modelling house prices

The quantile regression approach to identifying booms and busts implicitly rests on the assumption that there exists an underlying model for the variable to be explained. For example, Machado and Sousa (2006) use standard asset pricing theory to model the fundamental developments in stock prices. In the same vein, other authors, such as, Kennedy and Andersen (1994) and McCarthy and Peach (2004) have used asset pricing theory also for the valuation of house prices. It seems, however, that for modelling house prices the structural approach - based on demand and supply equations - is preferred in the literature.⁴

⁴ For an overview of early studies, see Fair (1972). Other early studies modelling housing market include Alberts (1962), Kearl (1979) and Poterba (1984).

Despite the consensus to use the structural demand and supply approach to model house prices, the literature appears to be quite heterogeneous in many other respects. First, the models used differ in terms of the exact specification of the dependent variable as well as in terms of the explanatory variables included. Second, some papers focus only on the demand equation, which is due to the fact that the supply is seen as being relatively static in the short run and sometimes even in the long run (see, for instance, Kennedy and Andersen, 1994). In addition, while several papers model the demand and supply side of the housing market separately, a number of studies simply include supply and demand determinants in a single equation framework. Finally, some studies focus on the fundamental long-run developments and use the instrumental variable estimation techniques, whereas others analyse also the short-run dynamics by estimating an error correction model (see, e.g., Antipa and Lecat, 2009).

In the case of the present analysis, our interest consists in developing a simple linear model which specifies a long-run relation between housing prices and some fundamental variables and which can — in a subsequent step — serve as a basis for applying the quantile regression approach. In what follows, we thus present a subset of models which represent a long-run relationship between housing prices and various demand and supply determinants suggested by the literature.

Kennedy and Andersen (1994) use house price index normalized by income as the dependent variable in their demand-based empirical model. The explanatory variables in their housing demand equation are represented by the household real disposable income, the unemployment rate, the user cost of housing, a time trend as a proxy for existing stock of dwellings, the share of the 15 to 64-year-old cohort over total population, the lagged household debt-to-income ratio and an autoregressive term. The user cost of housing is calculated following Poterba (1984) as the mortgage interest cost after adjusting for inflation and the tax treatment of the mortgage interest. In the case where the user cost of housing turns out to be insignificant, the authors also use the real or nominal mortgage rate as a proxy for it.

Other studies identify the most important fundamentals of house prices using a theoretical model that captures separately the supply and demand forces central to the determination of the house price equilibrium. DiPasquale and Wheaton (1994) for instance develop a structural specification of the single family housing market, where on the demand side the price is explained by rents, stock of houses per household, permanent income of households (proxied by personal consumption), the expected home-ownership rate and the user cost of housing. In this context, the latter was calculated using both rational and backward looking expectations of house price appreciation. The authors also add a term capturing the short-run price adjustments. On the supply side of the model, investment in housing is explained by house prices, the existing stock of houses, short-term construction financing, construction costs and land prices. In a comparable study, Kaufmann and Mühleisen (2003) develop a model where the supply side is explained by construction cost, the housing stock and home ownership levels, the last two being later replaced by the time trend and average household size. The demand side determinants include real disposable income, the real mortgage rate, the unemployment rate, financial

wealth and age structure of the population. They estimate the equations jointly using the 3SLS procedure.

McCarthy and Peach (2002) develop a structural housing model, in which the supply and demand relations are estimated separately in an error correction framework. In their model, the demand price depends on permanent income of households (proxied by consumption of non-durables and services), on the user cost of holding the residential property and on the existing stock of houses. On the supply side, the price is determined by the investment rate and construction costs.⁵ Similarly, using the data for the French and Spanish housing market, Antipa and Lecat (2009) estimate the long-term demand and supply equations in the first step and respective error correction models to capture the short-term dynamics in the second step. In the long-term demand equation, they regress house prices on existing housing stock, households' permanent income and the user cost of housing. The latter variable is computed using data on the price of housing per square meter in real terms, the average income tax, the real long term interest rate (real yield on 10-year government bonds), the depreciation rate for residential structures and expected capital gains from owning residential property (proxied by average house price inflation over the last four quarters). In some specifications the number of households and the unemployment rate to the explanatory variables are also added. Since the housing stock is not predetermined in this regression, the authors use construction costs and the long-term interest rate as instruments in a two stage least squares procedure. On the supply side, the residential investment is modelled as being dependent on the real house prices, the construction costs, and number of housing permits and starts. The existing house prices used in the supply equation are supposed to be in close relation to the new dwellings prices due to the possibilities of arbitrage.

In another study, Klyuev (2008) assumes that housing supply is affected by real construction costs and the average household size, while the demand side is represented by changes in the real disposable income per capita, the unemployment rate and the real interest rate on mortgages. The quantity and price variables are the number of sales and the median sale price for an existing home, on a yearly basis. In addition to OLS estimates of these demand and supply equations, Kluyev also estimates an error correction model on quarterly US data, where the real house price index, the real interest rate and real rents are assumed to form a cointegrating relationship.

Several papers use the demand and supply variables in a reduced-form model. Kasparova and White (2001), for instance, start from separate demand and supply equations but then proceed by constructing a single equation reduced-form model, where the developments of house prices depend on real GDP, real mortgage rate, population and previous period housing stock. Due to data limitations, the long-run model is further reduced to include only the GDP, the real mortgage rate as the demand side variables and as a supply side variable, the housing permits. The resulting model is then estimated

⁵ In their 2004 study, McCarthy and Peach use an updated version of this model to assess the evidence of the existence of a house price bubble that could potentially burst in the first half of the 2000s. In this context, they use some indicators of house under-/over-valuation, such as the home-price-to-income ratio and implicit-rent-to-price ratio.

in an error correction framework for four European countries. Also using a sample of some European countries, Ganoulis and Giuliadori (2010) build a model for real house prices that includes real disposable income per capita, the real mortgage rate, the real stock of mortgage debt per capita, total population older than 24 years, construction cost index, residential housing stock and the real stock market index as an approximation of financial wealth.⁶

In another study that represents an interesting starting point for our analysis, Gattini and Hiebert (2010) estimate a vector error correction model of housing prices using euro area quarterly data in order to form forecasts for house prices and to identify the permanent and transitory component in their dynamics. The variables included in their reduced form model are: real housing prices, real housing investment, real disposable income per capita and a mixed maturity measure of the real interest rate.

Finally, Tsatsaronis and Zhu (2004) in their study of housing market employ a structural VAR instead of an error-correction model. Factors influencing the long-run demand for housing include the growth in household disposable income, the shifts in the relative size of older and younger generations, the properties of the tax system and the average level of the interest rate. At the same time, the supply side is affected by the availability and the price of land and the costs of construction and improvement of the quality of dwellings.

4 Model selection and the data

The crucial step in applying the quantile method for boom/bust detection is to choose a simple model that captures the relation between the asset prices and underlying fundamentals reasonably well. The model used in this study can be summarised in the following general form:

$$(4) \quad \text{Asset Prices} = \beta_1 + \beta_2 \cdot (\text{Fundamentals}),$$

where “Asset Prices” represents the (log of) the house prices and “Fundamentals” denote a vector of fundamental determinants of the market. The latter are selected following the literature reviewed in Section 3 and include the main driving forces as suggested by the literature, in particular some measure of income, a demographic factor and a measure of user cost. In addition, we base our choice of variables on the data availability and their time series properties.

Since we are trying to model the long-run equilibrium in the housing market in a simple reduced-form equation, we test for the existence of a single cointegrating relationship among the non-stationary variables in the model.⁷ In the next step, we then estimate this selection of models with dynamic OLS, using a number of leads and lags as suggested by the standard Schwartz and Hannan-Quinn Criteria. Our choice is motivated by a number of studies criticizing the robustness and efficiency of the long-run

⁶ See also Goodhart and Hofmann (2008).

⁷ See Philips and Loretan (1991).

estimates derived on the basis of the standard cointegration approaches à la Johansen (1995). It is for this reason that a number of alternative approaches have been suggested, among them the autoregressive distributed lag (ARDL, see Pesaran and Shin, 1995, and Pesaran et al., 2001), the Fully Modified Ordinary Least Squares (FMOLS, see Philips and Hansen, 1990) and the dynamic OLS (DOLS, Saikkonen, 1992 and Stock and Watson, 1993). The latter involves augmenting the cointegrating regression with leads and lags of the changes in the right-hand variables, so that asymptotically more efficient estimates may be obtained. It would not only yield consistent estimates, but also remove potential simultaneity issues from the long-run relationship.

Finally, we narrow down the set of specifications on the basis of their performance, by considering the statistical significance as well as the meaningfulness of the sign of estimated coefficients.

4.1 *The dataset*

We consider a number of variables that represent fundamental determinants of house prices (PH) as suggested by the literature. The data availability for the euro area limits the selection to the following list of potential regressors: disposable income (DISPI), disposable income per capita (DISPIPC), the user cost rate (UCR), the unemployment rate (UR), the housing stock (HS), the housing stock per capita (HSPC), the number of households (NHH), the share of the 15 to 64-year olds in total population (WAPOP), the share of the labour force in total population (LFPOP) and the debt-to-income ratio (D2I)⁸. Some of the variables can only be included interchangeably. For instance, we use either disposable income or disposable income per capita, housing stock or housing stock per capita and either a number of households or the share of working age population or labour force in population.

The data for the euro area are quarterly and the sample period runs from 1983 Q1 to 2011 Q4. All the variables are in real terms and where needed, we use the private consumption deflator to transform the nominal values into real ones. The house prices, GDP, household disposable income and the private consumption deflator are seasonally adjusted. All per capita variables are obtained by dividing the variable in question with total population. Except for the interest rates (long-term interest rate and mortgage rate), the unemployment rate, the user cost rate, house price inflation and the household debt-to-income ratio, all the variables are measured in logarithms. For some of the variables, only the annual data are available and in those cases we interpolate the series using the cubic-spline method to transform the data into the quarterly frequency. Such interpolations were necessary for the following variables: the housing stock, the number of households and the population between 15 and 64 years. The sources of the series are the Eurostat and the European Central Bank databases. More

⁸ Due to the data limitations for the euro area, we could not include two variables affecting the supply side that are often used in the literature: the number of housing permits and the construction costs.

details about the data and their sources are listed in Annex 1, which also contains details about the construction of the series that were not readily available, for instance, the debt to income ratio.

Another variable needed to be constructed is the cost of using the housing services (UCR). Like most of the literature, we refer to the definition of this cost as outlined in Poterba (1984, 1992), where a one-period user cost of housing is defined as a sum of depreciation, repair or maintenance costs, after-tax mortgage interest payments and property taxes (which together form the opportunity cost of housing equity) less the capital gain from holding the residential structure. Poterba (1992) considers also a risk premium for housing investments. The subsequent literature uses variants of this approach, omitting one or several determinants of the cost that are believed to be relatively stable over time, namely the repair and maintenance costs, property taxes and the depreciation rate.⁹ The papers also differ in whether the user cost is expressed in terms of the price of residential unit or as the percentage rate (and, therefore, called “user cost rate”). We use the latter format and consider several versions of the user cost, all based on the following expression:

$$(5) \quad ucr_t = i_t(1 - \tau_t) + \delta_t - E_t(\pi_{t+1})$$

where ucr_t denotes the user cost rate, i_t the long-term interest rate or the mortgage rate, τ_t the average income tax rate, δ_t the depreciation of the residential capital and $E_t(\pi_{t+1})$ the expected future nominal capital gains from owning a residential property. We proxy the latter with either a four-quarter average of house price inflation or a four-quarter average of inflation derived from the private final consumption deflator. Given that we do not have data on the depreciation of the residential capital for the euro area, we assume that it is constant¹⁰ and leave it out as it would only shift the level of the user cost rate, while not affecting its dynamics. In addition, due to the heterogeneity of the tax treatment of mortgage payments across euro area, we also omit the average income tax rate from the user cost rate calculation. Our approximate calculations of average income tax rate show that it is fairly stable over the period of interest (moving slowly between 11% and 15%).

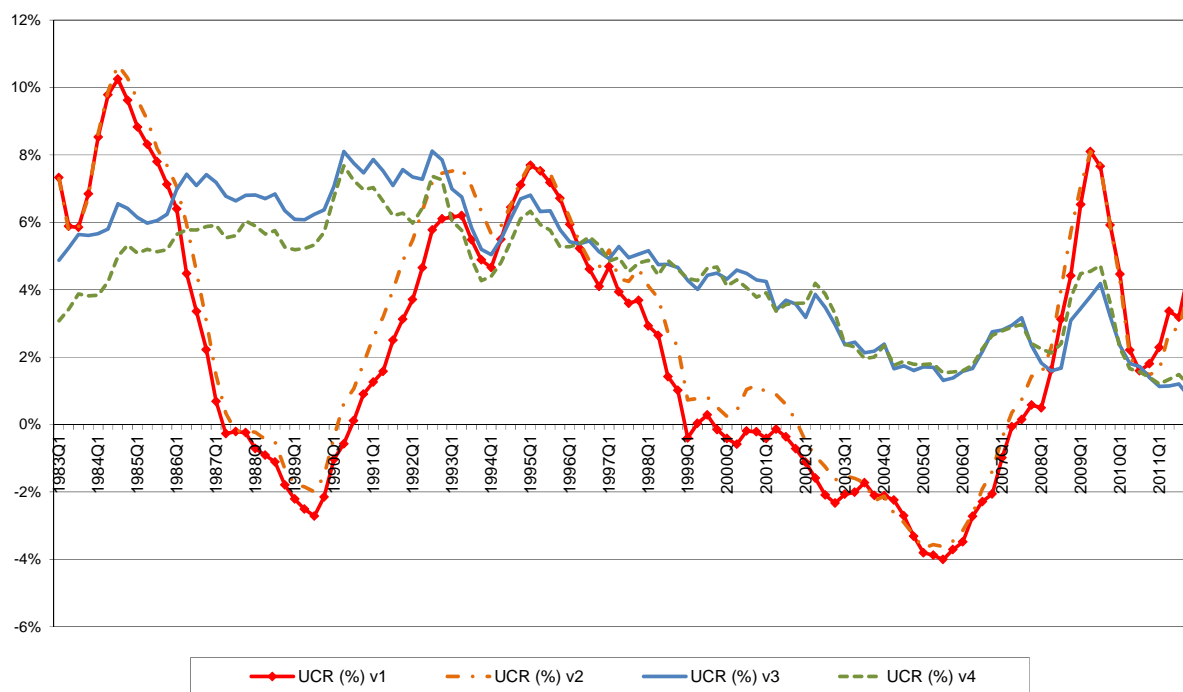
In **Chart 1** we plot four versions of the user cost rate, which differ in terms of what measures of the interest rate and of the expected capital gains are used. The figure shows that the choice of the interest rate affects the user cost rate only slightly (comparing the red line **v1** based on the long-term interest rates and dotted pink **v2** which has been constructed using the mortgage rate). Conversely, the choice of different proxies for the expected future capital gains changes the dynamics of the user cost rate considerably. In particular, the dynamics are very different when house price inflation (lines **v1** and **v2**) is used, compared to the user cost rate calculated using the consumer price inflation (see blue

⁹ See DiPasquale and Wheaton (1994), Kennedy and Andersen (1994), McCarthy and Peach (2004), Lecat and Mésonnier (2005) and Antipa and Lecat (2009).

¹⁰ In ECB (2006), the depreciation rate of residential construction for the period 1981-2005 is estimated to be around 2% per year and fairly constant over the period.

line **v3**) and the private final consumption inflation (green dashed line **v4**). In addition, the latter two user cost rates show very similar dynamics.

Chart 1 Variants of the user cost rate for the euro area



Source: Own calculations.

4.2 Unit root tests and testing for cointegration

The candidate variables for fundamental determinants of housing prices were tested for stationarity using three unit-root tests: the Augmented Dickey-Fuller test (ADF), the Phillips-Perron test (PP) and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS). The null hypothesis in ADF and PP tests is that the series has a unit root, while the KPSS test is based on the null hypothesis of stationarity. The results are presented in **Table 7** in **Annex 2**. Most of the variables seem to be integrated of order one, since the tests cannot reject the null hypothesis of unit root in levels, but reject it for the same variables in first differences (second column of **Table 7**). The few exceptions for which at least two of the conducted tests point toward stationarity in levels are the unemployment rate (UR), the share of working age population in total population (WAPOP) and two versions of the user cost rate (**v3** and **v4** of the UCR). The number of households (NHH) is the only variable that is integrated of order two according to our tests and we therefore exclude it from our consideration.

Based on these results, we proceed by analysing the number of cointegrating relationships among the nonstationary dependent and explanatory variables, using the Johansen cointegration test and we

retain only the models where a single cointegrating relationship is found (see **Table 8** in Annex 3).¹¹ More precisely, the models used include the main three determinants of house prices (i.e. the user cost rate, the demographic variable and the disposable income), but differ in terms of what measures for these variables are used, and which additional explanatory variables from the list in Section 4.1 are included.

4.3 *Results from the DOLS estimations and selection of the best models*

Once the set of single-equation models with one cointegrating relationship is determined, we then narrow down this selection based on the results of dynamic OLS regressions. More precisely, we drop all the specifications in which the sign of some coefficients is different from what the economic theory would indicate. For instance, it would be plausible to find a positive coefficient for disposable income since a higher disposable income should affect the demand for houses and, in light of the relatively fixed supply of housing stock in the short run, also increase the prices.

Table 1 and **Table 2** show the DOLS results for the best selected specifications. More precisely, in **Table 1**, we present the results of models where the working age population is employed to represent the demographic explanatory variable, while **Table 2** contains the results of the best specifications with the labour force in total population as demographic variable. All the specifications include the version *v4* of the user cost rate.^{12, 13}

In the selected specifications in **Table 1**, the signs and magnitude of the coefficients remain quite stable over different specifications. Also, almost all the variables enter the regression with the expected sign and turn out to be significant. As regards the coefficient of housing stock and housing stock per capita, one would expect it to be negative, in principle, given that a higher existing housing stock can be interpreted as higher supply which would lead to lower house prices, everything else equal. However, given the fact that the housing stock is measured in terms of its value and thus includes a price component, a positive sign could also be plausible with a predominantly demand-driven phenomenon, i.e. if agents expect prices to follow an upward spiral this could trigger a self-fulfilling prophecy.

¹¹ The stationary variables, such as WAPOP and UR, are treated as variables exogenous to the cointegrating relation in the model.

¹² Among the other three versions, version *v3* led to very similar results, while this does not hold for the other two versions *v1* and *v2*, which deliver unsatisfactory results in terms of coefficients signs. It is also worth noting that in both tables, for space reasons, we omit the coefficients of the lags and leads of cointegrating variables.

¹³ For the sake of consistency, we use only combinations of variables that are either all specified in absolute or in per capita terms.

Table 1: DOLS regression results for house prices in the euro area – working age population

Dependent variable: real house prices			
Explanatory variables	1	2	3
User cost rate	-1.156*** 0.294	-1.216*** 0.305	-1.097*** 0.279
Working population	3.150* 1.727	3.695** 1.780	6.207** 1.846
Disposable income per capita	0.597** 0.263		0.073 0.289
Disposable income		0.463* 0.273	
Housing stock per capita	0.835*** 0.142		1.101*** 0.154
Housing stock		0.668*** 0.169	
Unemployment rate			-1.785*** 0.504
Constant	9.594*** 2.098	-15.41*** 1.019	5.264** 2.329
No. of leads and lags	2	2	2
No. of observations	111	111	111
R²	0.98	0.96	0.98

Notes: Standard errors are reported below the respective coefficients and are heteroskedasticity-consistent. ***, ** and * indicate significance at the 1%, 5% and 10% significance levels.

In terms of significance, only one variable fails to have a significant effect in all the specifications, namely disposable income per capita in specification 3. This could be due to collinearity issues, i.e. the inclusion of unemployment rate that also affects disposable income and consequently demand for housing. Other variables affect house prices significantly and with coefficients of the expected sign. The user cost rate (UCR) affects the house prices negatively, as lower costs increase demand and thus prices. Positive demographic developments and more disposable income instead affect the demand and prices in a positive way. The magnitude of the coefficients for the latter two explanatory variables is slightly sensitive to the inclusion of additional explanatory variables, such as unemployment rate. Finally, the unemployment rate affects the house prices negatively, which is in line with the expectations that demand would be lower at higher rates of unemployment.

When considering the specifications with the share of labour force to total population as demographic variable (see **Table 2**), the best ones yield similar results in terms of sign and significance. The housing price index is affected negatively by the user cost rate and the unemployment rate, while it is affected positively by the demographic variable and disposable income or disposable income per

capita. In most cases, the demographic variable turns out to be insignificant. Other models with additional explanatory variables or excluding the share of labour force to total population gave insignificant results or were characterized by more than one cointegrating relationship and were thus discarded. Finally, specifications 7 and 8 that include the debt-to-income ratio of the households as an explanatory variable yield interesting results. In specification 7, the coefficient is not significant, while in specification 8 it is negative and significant, which is consistent with the idea that higher debt means that the households are more credit constrained and are consequently able to demand less housing.

Table 2: DOLS regression results for house prices in the euro area – share of labour force to total population

Dependent variable: real house prices					
Explanatory variables	4	5	6	7	8
User cost rate	-0.646*** 0.189	-0.634*** 0.176	-0.616*** 0.196	-0.645*** 0.203	-0.820*** 0.196
Labour force in total population	3.084 1.886	2.766* 1.613	2.691 1.999	2.476 2.025	2.129 1.637
Disposable income per capita	1.514*** 0.369		1.583*** 0.387	1.511*** 0.376	
Disposable income		1.143*** 0.228			1.515*** 0.280
Unemployment rate			-0.268 0.440		
Debt-to-income ratio				0.001 0.001	-0.002** 0.001
Constant	11.61*** 4.119	-13.86*** 1.713	11.61*** 4.119	11.83*** 4.189	-17.44*** 2.338
No. of leads and lags	1	1	1	1	1
No. of observations	113	113	113	113	113
R²	0.97	0.97	0.97	0.97	0.97

Notes: Standard errors are reported below the respective coefficients and are heteroskedasticity-consistent. ***, ** and * indicate significance at the 1%, 5% and 10% significance levels.

5 Quantile regression results and identifying boom/bust episodes

After having selected the best models which explain house prices in terms of their main fundamentals, we further analyse these relationships by means of quantile regressions. Our aim is to better quantify the relationship between the set of the predictor variables and specific quantiles of the response variable. Based on the values of predictors and the estimated regression coefficients, fitted values are derived for the quantiles of interest, smoothed by the HP-filter (with $\lambda=1600$) and used for

identifying the periods of booms and busts in the house price dynamics.¹⁴ More precisely, booms/busts are represented by longer-lasting deviations from equilibrium, with observations falling outside the [20,80] interval (for busts and booms, respectively). In addition to the estimates for this set of percentiles, we report the results for the median. **Table 3** reports the results of quantile regressions related to our best specifications using working age population as demographic factor, while **Table 4** contains the results for the best specifications with the share of labour force in total population.¹⁵

Table 3: Quantile regression results for house prices in the euro area – working age population (a)

Explanatory variables	Dependent variable: real house prices								
	1			2			3		
	0.20	0.50	0.80	0.20	0.50	0.80	0.20	0.50	0.80
User cost rate	-1.09** 0.43	-1.22*** 0.32	-1.18*** 0.34	-0.95** 0.38	-1.3*** 0.35	-0.99*** 0.36	-0.94*** 0.26	-1.17*** 0.34	-1.3*** 0.28
Working population	2.89 3.43	5.02** 2.1	4.75*** 1.57	2.44 3.42	5.63** 2.29	4.19** 1.63	3.48 2.13	7.1*** 2.42	9.07*** 2.04
Disposable income				0.34 0.4	-0.12 0.26	1.27** 0.57			
Disposable income per capita	0.26 0.39	0.1 0.27	1.21** 0.52				0.24 0.32	-0.17 0.36	-0.32 0.54
Housing stock per capita	1.06*** 0.21	1.13*** 0.15	0.52** 0.25				1.07*** 0.17	1.25*** 0.19	1.28*** 0.27
Housing stock				0.79*** 0.25	1.04*** 0.16	0.18 0.33			
Unemployment rate							-0.69 0.57	-1.82** 0.78	-3.28*** 0.87
Constant	8.54** 3.95	6.34*** 2.12	11.41*** 2.96	-14.7*** 1.25	-14.77*** 1.63	-18.83*** 2.49	8.17*** 2.72	3.72 2.41	1.5 2.94
No. of leads and lags	2	2	2	2	2	2	2	2	2
Pseudo-R ²	0.88	0.85	0.87	0.88	0.85	0.86	0.89	0.86	0.88
Wald slope equality test		0.000			0.000			0.000	

Notes: Standard errors are reported below the respective coefficients. ***, ** and * indicate significance at the 1%, 5% and 10% significance levels. The Wald slope equality test (a test of the coefficients being identical across the quantile values) is based on a Chi-Sq. distribution, p-values are shown for this test.

The coefficients should be interpreted as follows. For instance, in the first specification, one percent increase in real housing stock per capita raises real house prices by 1.06 percent at the 20th percentile of the conditional distribution and by 0.52 percent at the 80th percentile. Generally speaking, we find that the results are broadly consistent with the earlier DOLS results in qualitative terms. There are, however, some differences in the coefficients across quantiles. This feature is also statistically

¹⁴ We follow the approach used by Machado and Sousa (2006), pp. 13-14. Note also, that results presented do not significantly differ from the ones based on alternative filtering techniques, such as the asymmetric Christiano-Fitzgerald filter.

¹⁵ As in previous tables, the coefficients pertaining to the additional lags and leads are not reported for the sake of brevity.

confirmed by the Wald tests, reported in the **Table 3** and **Table 4**, that reject the null hypothesis of equality of slope coefficients in all the specifications.

When focusing on the specifications with the working age population as demographic variable presented in **Table 3**, we can observe the following regularities. The coefficient estimates for the user cost rate tend to be fairly similar across the reported quantiles of the (conditional) distribution of house prices. The coefficient for the working population is mostly insignificant at the lowest reported quantile but tends to become larger and significant at higher quantiles. This suggests that the demographic factor mostly affects the upper part of the conditional distribution of house prices. In other words, there is more upward pressure from the demographic factor on the house prices when they are in the upper part of their distribution. Similarly, the effect of the unemployment rate in specification 3 is negative across the quantiles and it becomes significant only in the highest two reported quantiles. This suggests that higher unemployment curbs the prices in the periods when they are relatively high, i.e. in the higher quantiles, but does not have a significant effect on the lower levels of house price distribution. Another interesting result arises in relation to the coefficients of disposable income and disposable income per capita. The effect of disposable income seems to have a significant positive effect only in the highest reported quantile of the distribution, indicating that the average effect (resulting from DOLS-estimations) does not properly pick up the fundamental relation. As could be expected, disposable income has a positive impact on house prices. Finally, housing stock and housing stock per capita seem to have a fairly similar effect on the house prices at different quantiles. The sign of the related coefficients remains the same across the distribution and specifications, while there are only some changes in the size of the coefficients, and in case of specification 2, significance of the coefficient related to the 80th percentile.

Turning to the specifications with labour force, we can observe the following. In almost all specifications, the disposable income and the disposable income per capita have a significant positive effect on all reported quantiles of the house price distribution (see **Table 4**). The labour force enters significantly at least for some quantiles in most of the specifications and whenever significant, it has a positive effect on house prices. The effect of the user cost rate is significant and negative, with a slightly lower coefficient in the lowest quantile. Interestingly, the unemployment rate (in specification 6) gives mixed results as it affects the upper part of the distribution negatively, while having a positive effect on lower quantiles of the house price distribution. The effect of the debt-to-income ratio is negative and significant in the higher quantiles in specification 8 and negative and insignificant in all quantiles in specification 7.

In terms of R^2 statistics, all quantile regressions equations give satisfactory results, being fully in line with those reported in the literature. Given these results, we conclude that the conventional DOLS method does not always fully summarize the existing disparities and that there is benefit in cross-checking the results by means of quantile regression.

Table 4: Quantile regression results for house prices in the euro area – share of labour force to total population

series to total population

Dependent variable: real house prices

Explanatory variables	4			5			6			7			8		
	0.20	0.50	0.80	0.20	0.50	0.80	0.20	0.50	0.80	0.20	0.50	0.80	0.20	0.50	0.80
User cost rate	-0.69** 0.31	-0.8*** 0.25	-0.65** 0.25	-0.38* 0.21	-0.83*** 0.24	-0.52** 0.2	-0.6*** 0.2	-0.61*** 0.22	-0.69*** 0.26	-0.2 0.29	-0.78** 0.31	-0.92*** 0.19	-0.47* 0.26	-0.92*** 0.26	-0.95*** 0.18
Labour force in total population	4.38 3.9	0.63 1.62	4.07 2.93	-1.97 1.58	1.47 1.56	6.69*** 1.91	5.33*** 1.93	-0.34 1.8	-1.03 2.77	-2.88 2.24	0.38 1.87	2.06 2.6	-0.54 1.5	1.55 1.64	4.93** 2.29
Disposable income				1.78*** 0.22	1.33*** 0.22	0.61** 0.29							1.69*** 0.23	1.69*** 0.24	1.55*** 0.31
Disposable income per capita	1.21 0.73	2.02*** 0.31	1.37** 0.61				1.03*** 0.37	2.21*** 0.36	2.37*** 0.56	2.21*** 0.35	2.12*** 0.33	2.09*** 0.44			
Housing stock per capita															
Housing stock															
Unemployment rate							1.93*** 0.00	-0.81 0.00	-1.56*** 0.00						
Debt-to-income ratio										0.002 0.001	-0.0002 0.001	-0.001 0.001	-0.001 0.001	-0.002** 0.001	-0.004** 0.002
Constant	8.28 8.24	17.19*** 3.51	9.95 6.74	-18.52*** 1.69	-15.31*** 1.68	-9.95*** 2.24	6.14 4.15	19.43*** 4.01	21.23*** 6.23	20.31*** 3.88	18.19*** 3.56	17.32*** 4.85	20.31*** 3.88	18.19*** 3.56	17.32*** 4.85
No. of leads and lags	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Pseudo-R2	0.84	0.83	0.83	0.86	0.83	0.83	0.85	0.83	0.84	0.85	0.83	0.84	0.86	0.84	0.85
Wald slope equality test	0.000			0.000			0.000			0.000			0.000		

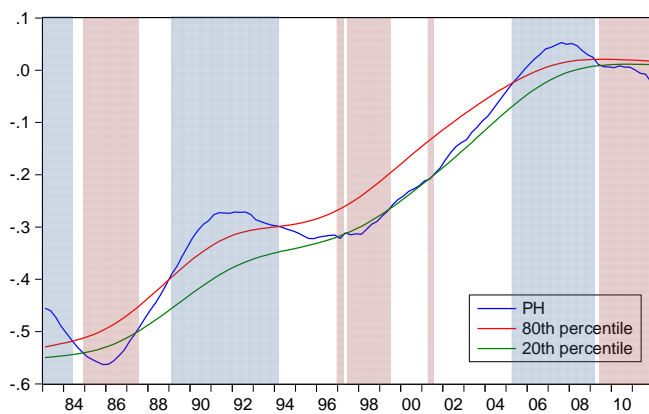
Notes: Standard errors are reported below the respective coefficients. ***, ** and * indicate significance at the 1%, 5% and 10% significance levels. The Wald slope equality test (a test of the coefficients being identical across the quantile values) is based on a Chi-Sq. distribution, p-values are shown for this test.

5.1 Identifying boom/bust episodes with quantile regression

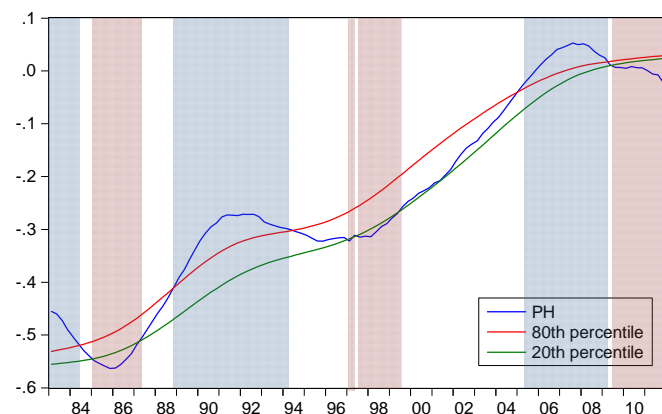
The additional information provided about the distribution in house prices can be used as an alternative method to identify booms and busts in this type of asset prices. Using the estimated coefficients, we calculate fitted values for specific quantiles of the conditional distribution and plot them against the developments in real house prices. If house prices move into the highest (lowest) quantile, this can be dubbed as a boom (bust) period (see **Chart 2**). For instance, according to this line of reasoning, the specification 1 that is illustrated in graphical terms in **Chart 2** (corresponding to the first equation in **Table 3**) would detect a boom in 1983-1984, 1989-1993 and in the most recent period around 2005-2008. A bust instead would be detected in the years 1985-1987, 1997-1999 and in the last part of the sample from 2009 onwards. These results can be considered as ‘core years’ of booms and busts, especially in the first half of the sample, and are also broadly confirmed by the other specifications. This notwithstanding, when looking at the years from 1995 onwards, half of the specifications used would point towards a longer-lasting bust period from the mid-1990 till early 2000, whereas for the same specifications, the bust at the end of the sample would only be detected in 2011. The quantile method, therefore, seems to represent a very useful tool for cross-checking the results of other more statistically-oriented methods for identifying booms and bust periods. The boom and bust periods for the selected models are presented in Annex 4 (see **Table 9**).

Chart 2 Example of booms and busts in euro area house prices using the quantile methodology

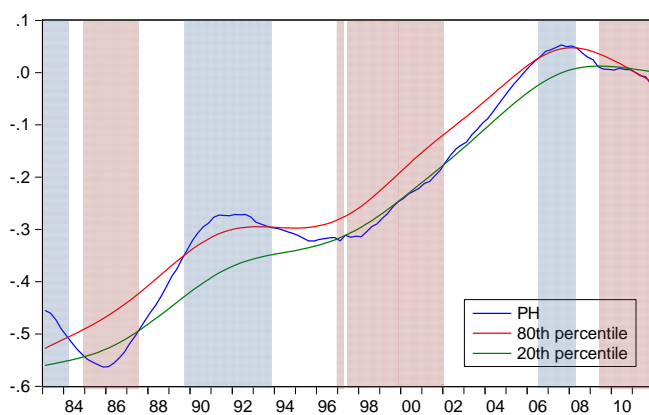
Specification 1



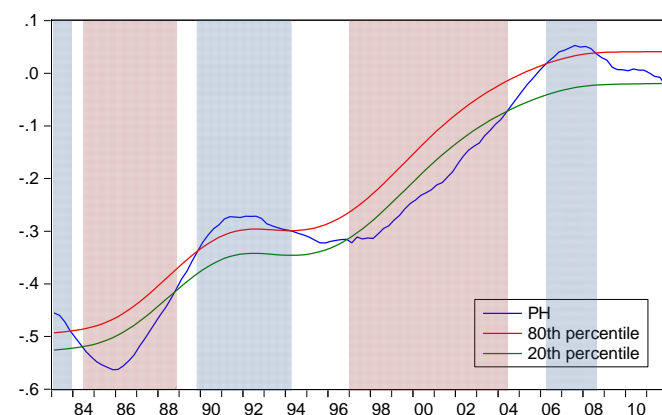
Specification 2



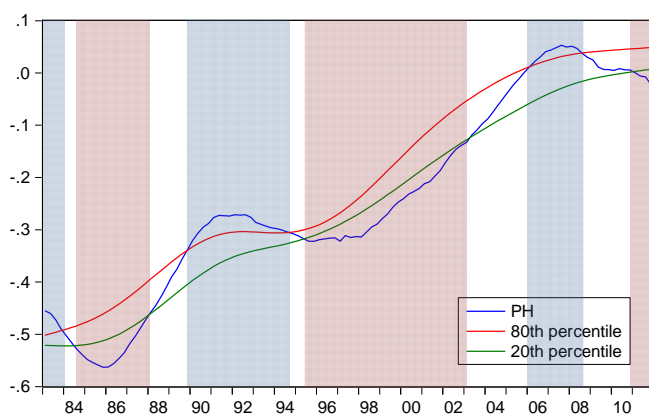
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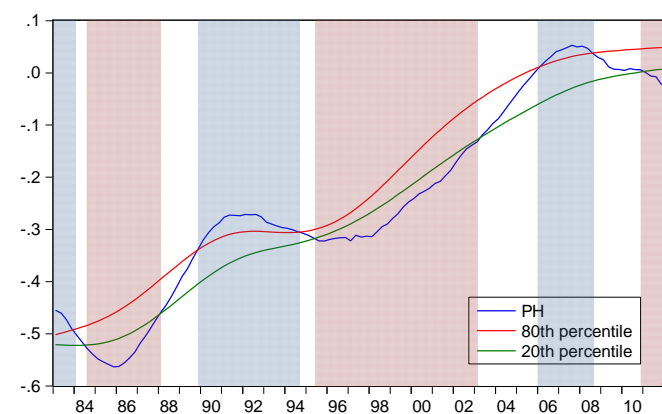
Specification 4

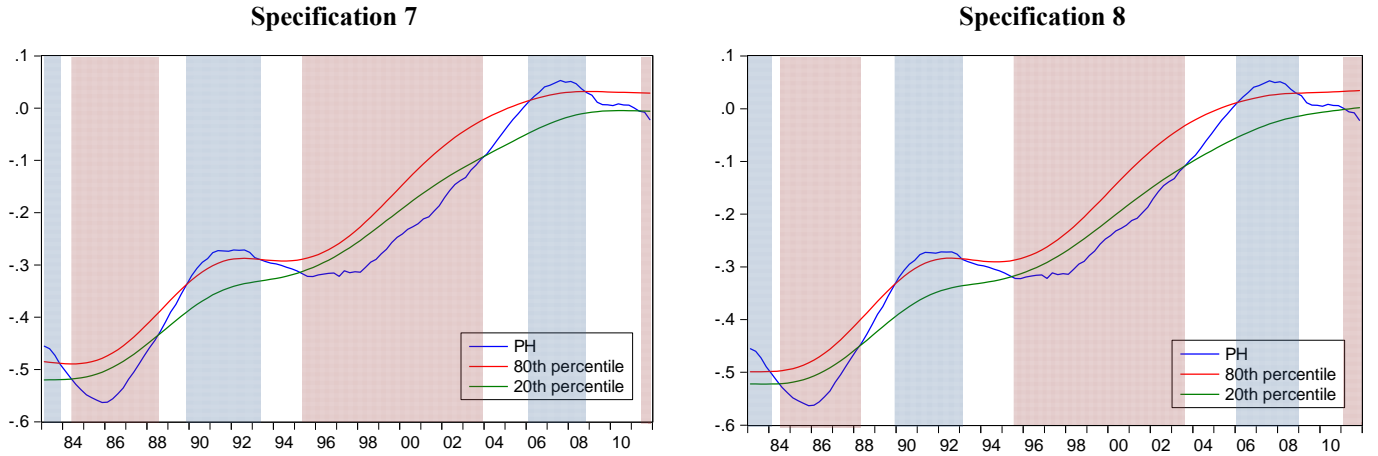


Specification 5



Specification 6





Source: Own calculations.

Notes: Referring to the specifications in **Table 3**. Real house prices (denoted as PH in the charts) are reported together with the [20,80] percentile interval of the distribution. Blue-shaded areas denote boom periods, while red-shaded areas represent bust periods.

6 A comparison of methods for identifying boom and bust periods in the housing market

In the literature, there is a variety of methodologies for identifying asset price booms and/or busts, some of which being more of a “statistical” nature and others (such as the quantile methodology) being more of a “fundamental” nature. In this section we compare the results (for the housing market) from the quantile regressions described above with those stemming out of three statistical methods which have been widely used in the literature. In particular, the methodologies which are adopted for the comparative analysis in this section identify booms and busts in the housing price markets in the following ways:

a) a boom (bust) is defined as a period in which the 3-year moving average of the annual growth rate of the index of house prices is bigger (smaller) than the average growth rate plus (minus) 1.3 times its standard deviation (see Bordo and Jeanne, 2002);

b) a boom is defined as a period in which the house price gap (i.e. the gap between the actual house price index and its trend calculated using the Christiano-Fitzgerald filter) is above its mean plus a factor of $\gamma = 1.75$ times its standard deviation, whereby both the mean and the standard deviation are calculated over a rolling period of 60 quarters (see Gerdesmeier, Reimers and Roffia, 2011).¹⁶ A bust event instead is defined as a situation in which — at the end of the rolling period of $r = 12$ quarters — the house price index has declined below its mean minus a factor of $\delta = 1.5$ times the standard deviation in the period from 1 to $(t + r)$ with respect to its maximum reached in the same period (see Gerdesmeier, Reimers and Roffia, 2010);

¹⁶ See Borio and Drehmann (2009). The criterion applied to derive a boom episode is different from the one applied for detecting bust episodes, as the cumulated increase in the indicator over the boom periods is usually much slower and smoother than the corresponding decrease in times of busts.

c) a boom (bust) is a period when the 4-quarter trailing moving average of the annual growth rate of the real house price index rises (falls) above (below) its mean plus (minus) 1.3 times its standard deviation (modified from 5% in the original paper by the IMF (2009) due to heterogeneity among euro area countries);

d) and, the quantile regression technique adopted in the previous section, where booms/busts are represented by longer-lasting deviations from equilibrium, with observations falling outside the [20,80] interval (for booms and busts, respectively), using the best model specification illustrated in the previous section in **Table 3** and **Table 4**. The results of the comparative exercise for house prices across the four methodologies are reported in **Table 5**.¹⁷

Taken together, the following observations are worth noting. First, the two periods when booms are detected by most of the methods are those related to the early 1990s and mid-2000s. As regards the 1980s, while the quantile model detects a boom in 1983, two other methods point to a boom in the late 1980s. Second, with regard to busts, the two periods selected by most methods are those in the mid-1980s and around 2008-2010. In particular, the last episode related to the recent financial crisis represents a typical episode, whereby a bust occurred in the aftermath of the boom and is characterised by a more synchronised house price developments across euro area countries, while previous episodes experienced a large dispersion across euro area countries in general. Overall, this comparative analysis suggests that a comprehensive approach which takes into account both statistical and more fundamental methods for boom/bust identification is warranted.

Table 5: House price booms/busts in the euro area using selected statistical and fundamental methods

BOOMS				BUSTS			
Gerdemeier-Lenarcic-Roffia (2012)	IMF (2009)	Gerdemeier-Reimers-Roffia (2009)	Bordo and Jeanne (2002)	Gerdemeier-Lenarcic-Roffia (2012)	IMF (2009)	Gerdemeier-Reimers-Roffia (2009)	Bordo and Jeanne (2002)
Quantile methodology (> 80th percentile)	4 qtr. M.A. of the y-o-y growth rate > mean + 1.3*stdev	house price gap > mean + 1.75*stdev (calculated over 60 qtrs)	3-year M.A. of the y-o-y growth rate > mean + 1.3*stdev	Quantile methodology (< 20th percentile)	4 qtr. M.A. of the y-o-y growth rate < mean - 1.3*stdev	Q-o-q growth rate < mean - 1.5*stdev (within 3 yrs)	3-year M.A. of the y-o-y growth rate < mean - 1.3*stdev
1983					1982-1983	1981-1982	
	1987-1988	1986-1988		1985-1987	1985		1984-1986
1990-1993	1989-1991		1990-1992	1997-1999			
				2000-2003			
2005-2008		2005	2005-2007	2009-2010	2009	2008-2009	
				2011		2011-2012	

Note: The results of the quantile methodology shown refer to the episodes selected by the two best specifications presented in **Table 3** and **Table 4** (namely equations 1 and 6).

¹⁷ For this comparative analysis, the quantile regressions were run to cover a sample up to 2009 in order to include the most recent bust into the data. Due to missing observations in 2009 for two variables, the respective forecasts were taken into account. Overall, the quantile regressions were found to be robust to this sample expansion.

Finally, some remarks should be made regarding this comparative analysis and, especially, on the results obtained with the three statistical methods. First, it is possible that, by construction, the statistical methods encounter some difficulties in detecting the boom and/or bust at the beginning of the sample due to a “starting-point” problem. Second, the statistical methods used in the analysis do not imply a certain duration of the boom/bust periods as a criterion for their identification, which may be reflected by the fact that some episodes consist only in one quarter of over/undershooting of the housing prices. Finally, as regards the quantile methodology, it detects the misalignments with some delay which could be due to the fact that the standard deviation also adapts to slow increases/decreases and thus only sharp and abrupt changes easily cross the boundaries.

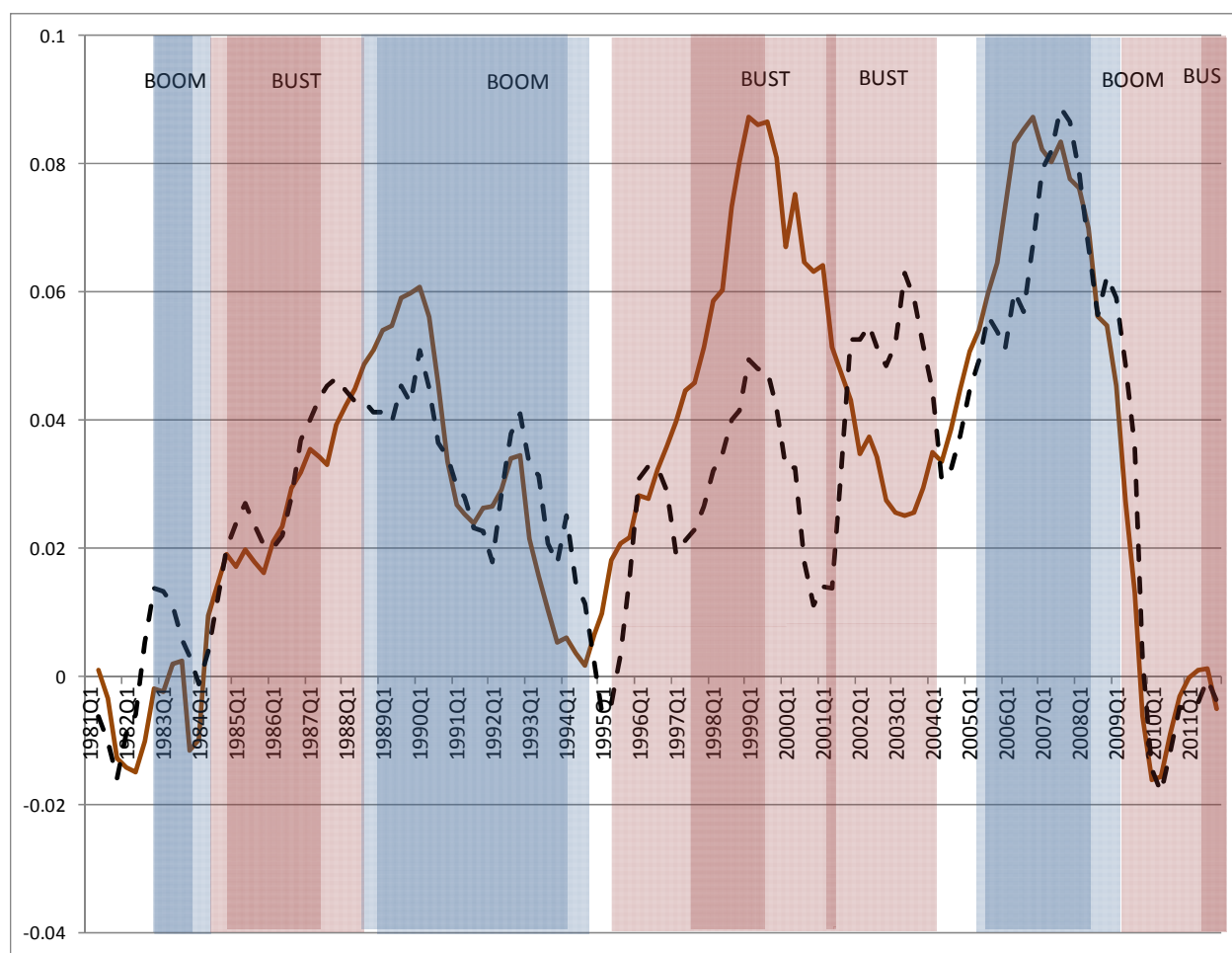
7 Money, credit and boom/bust cycles

In addition to the identification of booms and busts, for policy purposes it is also important to find predictors that can anticipate these episodes. For this purpose, following Machado and Sousa (2006), we provide a visual inspection of the behaviour of money and credit growth prior to the boom and bust periods in stock prices. The results from their study suggest that, while the link between real money growth and stock prices is generally weak, by contrast asset price booms seem to occur at times of rising credit growth or at times when loan growth is close to its peak following prolonged periods of accelerating real credit. We, therefore, carry out the same exercise for house prices booms and busts, by looking at the developments of real money and credit growth prior and during the busts.¹⁸ In **Chart 3**, we plot the two monetary indicators measured as growth rates, along with the boom and bust periods obtained by merging the results of Specifications 1 and 6 from the previous section. The source of the money and credit data is reported in Annex 1, while the results of the unit root tests for these variables (as well as for the money and credit growth rate gaps) are included in Annex 5.¹⁹

¹⁸ See Borio and Lowe (2002, 2004), Adalid and Detken (2007) and Alessi and Detken (2009) for some evidence of the importance of money and credit as indicators for asset price misalignments.

¹⁹ The gaps are calculated using the Hodrick-Prescott filter (using $\lambda=1600$).

Chart 3: Boom/bust cycles and monetary indicators (growth rates) (quarterly frequency)



Sources: Own estimations.

Note: Boom periods are determined using models 1 and 6, and are denoted in red (booms) and blue (busts).

Starting with the money indicator, the evidence seems to be mixed, when considering boom periods. While at the beginning of the 1980s and in mid-2000, the growth of monetary indicator was positive during the boom, on the occasion of the boom at the beginning of the 1990s the developments in money growth seem to be less clear-cut. A similar situation also applies to credit. In addition, as regards busts, in all episodes we observe either a subdued or a declining money and credit growth preceding the busts, while during the busts the behavior of the indicators varied. For instance, when looking at the last bust episode, the declining growth in money and credit was leading or coinciding with the bust depending on which of the two models is considered.²⁰ Interestingly, the behavior of money and credit in the last boom/bust cycle seems to be perfectly in line with the empirical regularities. Overall, the results from our exercise on house prices and from Machado and Sousa (2006) on stock prices are together consistent with what Gerdesmeier, Reimers and Roffia (2010) find for a

²⁰ Similar conclusions can be reached when plotting money and credit growth rate gaps vis-à-vis boom and bust episodes.

composite asset price indicator, which takes into account developments in both housing and stock markets, whereby credit aggregates help to predict asset price misalignments.

Nevertheless, it can be argued that this visual inspection is not sufficient and that empirical analysis of these preliminary results would be warranted. For this reason, we re-estimate all the different quantile specifications whereby we include credit and money indicators shown in **Chart 3**, in order to analyse whether they have a significant role in explaining the emergence of booms and busts in house prices. We re-estimate the specifications with up to 8 lags of money and credit indicators, specified either in growth or growth gap terms. Following the well-known general-to-specific methodology, the insignificant lags are then deleted in a stepwise procedure. In Annex 5 (see **Table 11**), we briefly summarize the results. The following patterns emerge. First, it seems that the credit and money growth are more relevant for explaining house prices, compared to the money and credit growth gaps. Second, in most specifications, money and credit significantly explain house prices in contemporaneous terms and with 4 and 8 lags.

Focusing on our preferred quantile specifications (specifications 1 and 6 in **Table 3** and **Table 4**) we analyse these results further. The estimated coefficients of these specifications including money and credit growth and gaps are shown in **Table 6**. The estimation of these augmented specifications is carried out in two steps. In the first step, we include up to 8 lags of a selected measure of money and credit dynamics, while in the second step we re-estimate the models including only the lags of the money and credit variables that were significant in the first step. The specifications where money and credit failed to enter the regression significantly are not reported. It turns out that money and credit aggregates enter significantly into the quantile regressions and seem to have additional explanatory power in detecting house price misalignments, especially when measured in growth terms.²¹ Money growth appears to affect house prices positively contemporaneously and with a lag of eight quarters, while credit has significant negative effects on house prices contemporaneously and with 8 lags and positive effects with 4 lags. Therefore, it seems that developments in money and credit variables tend to show leading properties, with credit being subject to more sign variability. Another issue is worth mentioning, in particular, money and credit may at times be highly collinear, albeit not perfectly. This, of course needs to be taken into account, when judging significance.

²¹ We also run the estimations using the growth gap measures of money and credit, but the additional variables turned out to be insignificant.

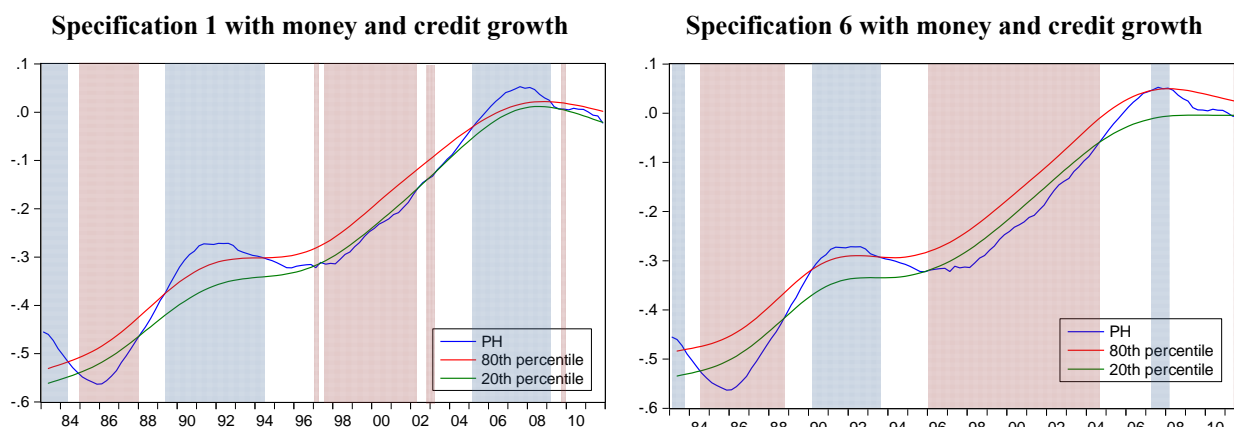
Table 6: The role of money and credit in house price booms and busts in the euro area – measure: credit and money growth

Dependent variable: real house prices										
Explanatory variables	Specification 1					Specification 6				
	0.10	0.20	0.50	0.80	0.90	0.10	0.20	0.50	0.80	0.90
User cost rate	-1.25*** 0.24	-1.36*** 0.26	-1.5*** 0.28	-1.47*** 0.29	-1.41*** 0.29	-0.45 0.29	-0.24 0.36	-0.32 0.22	-0.47* 0.26	-0.54* 0.4
Working population	2.69 1.86	4.22*** 1.4	5.26*** 1.79	5.3*** 1.35	5.21*** 1.22					
Labour force in total pop.						0.86 1.93	1.32 2.61	-3.33 1.91	0.07 2.73	5.49 5.08
Disposable income										
Disposable income p.c.	0.45* 0.25	0.33 0.25	0.57 0.36	0.79 0.6	1.06** 0.49	2.002*** 0.39	1.98*** 0.52	2.81*** 0.36	2.17*** 0.55	0.97 1.06
Housing stock p.c.	0.89*** 0.16	0.94*** 0.17	0.76*** 0.22	0.64** 0.26	0.55** 0.23					
Housing stock										
Unemployment rate						-0.15 1.4	-1.24 1.93	-2.88*** 0.85	-1.65* 0.91	0.04 1.26
Credit growth (t)						-0.19 0.19	-0.41* 0.24	-0.42* 0.22	-0.6 0.45	-0.52 0.44
Credit growth (t-4)						0.2 0.25	0.43 0.3	0.22 0.36	1.25** 0.6	1.55*** 0.57
Credit growth (t-8)						-1.15** 0.45	-1.57*** 0.51	-1.49*** 0.34	-2.38*** 0.6	-1.82** 0.73
M3 growth (t)	0.58*** 0.16	0.57*** 0.2	0.61** 0.25	0.24 0.29	-0.01 0.19					
M3 growth (t-8)	0.39 0.32	0.48 0.38	0.83** 0.35	0.73*** 0.27	0.59** 0.23	0.86*** 0.32	0.87** 0.35	1.42*** 0.25	1.4*** 0.24	1.03** 0.49
Constant	8.97*** 2.25	7.32*** 1.81	7.27*** 2.26	8.27** 3.43	10.06*** 2.8	16.92*** 4.43	16.6*** 5.91	26.27*** 4.04	19*** 6.1	5.73 11.64
No. of leads and lags	2	2	2	2	2	1	1	1	1	1
Pseudo-R ²	0.91	0.90	0.87	0.88	0.88	0.89	0.89	0.87	0.87	0.86
Wald slope equality test			0.000					0.029		

Notes: Standard errors are reported below the respective coefficients. ***, ** and * indicate significance at the 1%, 5% and 10% significance levels. The Wald slope equality test (a test of the coefficients being identical across the quantile values) is based on a Chi-Sq. distribution, p-values are shown for this test.

Finally, we also use these last two models to derive the boom and bust episodes (see **Chart 4**) and find that the episodes are quite robust vis-à-vis the original specifications without money and credit. It turns out that the boom and bust episodes are mostly shorter if money and credit growth are included as explanatory variables in the model. There is only one exception, namely the bust in the late 1990s in the plot pertaining to specification 1 (see **Chart 4**). In that case the bust period, as detected with the model that included money growth, lasted longer compared to the original model without money and credit variables. This would imply that in this period house prices were lower than what would be suggested given the growth of money.

Chart 4: Example of booms and busts in euro area house prices using the quantile methodology and with money and credit



8 Conclusions

It is a well-known fact that asset markets have been playing an increasingly important role in many economies, and the large swings in asset prices have become a relevant issue for policy-makers. Monetary policy has been cited as both a possible cause of asset price booms and a tool for defusing those booms before they can cause macroeconomic instability. Consequently, economists and policy-makers have focused on how monetary policy might cause an asset price boom or turn a boom caused by real phenomena into a “bubble”, which may burst unexpectedly rendering damage to the economy.

This paper adds to the literature in many respects. First, the quantile regression approach advocated by Machado and Sousa (2006) is applied to the housing market to detect booms and busts. This, *inter alia*, requires the development of a model for the house price index. Second, when developing and estimating such a model, the following fundamental variables are found to explain house price developments: demographic variables, the unemployment rate, the disposable income, the housing stock, the debt-to-income ratio and a user cost measure. Third, in many cases, these effects seem to be non-linear, as they vary across specific quantiles. Fourth, the additional information provided on the distribution in house prices can be used as an alternative method to identify booms and busts in this type of asset prices class. Fifth, the outcome of the identification of boom/bust episodes based on these quantile regressions seems to be in line with other statistical and fundamental methods usually used for this purpose, and thus can be regarded as complementary tool for identifying those episodes. Finally, money and credit developments are found to have an additional explanatory power in the context of boom/bust cycles in the housing market.

While the results are overall encouraging, a number of issues are worth of further investigation. In particular, promising results related to the money and credit developments would warrant a deeper analysis. For instance, the apparent high collinearity among these measures would ask for a more detailed investigation of different regimes. Similarly, it is not clear, why annual growth rates

significantly affect house prices, whereas other indicators, such as for instance, gap measures seem to be performing less well. This is, however, left for further research.

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Annex 1. Data sources

Variable	Description	Source
House price	Residential property prices, new and existing dwellings, in good & poor condition, based on aggregating euro area country residential property prices, using GDP weights at PPP exchange rates.	Residential Property Price Index Statistics, ECB, own calculations
Housing stock	Net capital stock, housing, for EA17 (fixed composition), current prices, annual data, interpolated with cubic spline to the quarterly frequency. Neither seasonally nor working day adjusted.	ESA 95, ECB calculations
Disposable income	Disposable income (of the total economy).	ECB, own calculations
Nominal GDP	Gross domestic product at market price (ESA 95), current prices. Based on aggregating euro area country nominal GDP using the irrevocable fixed exchange rates.	ESA 95, own calculations
Mortgage rate	Lending for house purchase excluding revolving loans and overdrafts, convenience and extended credit card debt, total maturity, new business coverage, euro, to the households and non-profit institutions serving households sector. Credit and other institutions (MFI except MMFs and central banks) reporting sector; annualised agreed rate (AAR) / Narrowly defined effective rate (NDER), euro area (changing composition).	ECB, own calculations
Long term interest rate	10-year government bond yield, based on aggregating euro area country 10-year government bond yields (or their closest substitutes) using GDP weights at PPP exchange rates.	BIS, ECB, ECB calculations, IMF
Number of households	Number of households, interpolated from the annual data using the cubic spline. Annual data obtained by summing the country series for EA17 (without Malta). Some of the series needed to be extrapolated for early years.	ECB Structural Housing Indicators Statistics
Total population	Total population, EA17, on 1 January, annual data interpolated to quarterly frequency (cubic spline).	Eurostat
Population from 15 to 64 years	EA17 - Population from 15 to 64 years (in 1000), annual data, interpolated to the quarterly frequency (cubic spline).	Eurostat - AMECO
Share of 15-64 year olds in total population	Constructed using the data on population and population between 15 and 64 years.	
Labour force	Labour Force in EA17 (fixed composition). Seasonally adjusted, but not working day adjusted.	ECB-AWM
Unemployment rate	Unemployment as percentage of labour force in EA17 (fixed composition), seasonally adjusted, but not working day adjusted.	ECB-AWM
Household liabilities	Closing balance sheet of households and non-profit institutions serving households in EA17 (fixed composition) - All financial assets and liabilities: credit, total. Current prices - Millions of Euro, neither seasonally nor working day adjusted. Before 1999q1 the series is extrapolated based on the series of the MFI loans growth.	Eurostat - Quarterly Euro Area Accounts

Variable	Description	Source
Household debt to income ratio	Constructed as a ratio of household liabilities over disposable income.	
HICP	Harmonised Index of Consumer Prices (HICP) – overall index. Before January 1992 national Consumer Price Indices (CPIs, excluding owner occupied housing, except for Spain). Overall index for EA17 countries.	ECB, ECB calculations, Eurostat
GDP deflator	GDP Deflator for EA17 countries, seasonally adjusted, 2005=100.	ECB-AWM
Private final consumption deflator	Final private consumption deflator, households and NPISH's, in EA16 (fixed composition). Computed using growth rates from the AWM for the period till 1994q4 and the actual data from 1995q1 on.	ESA 95, ECB-AWM
User cost of capital (%) v4a	Constructed using the data on average income tax, house price inflation and long-term interest rate.	
User cost of capital (%) v11	Constructed using the data on average income tax, house price inflation and mortgage interest rate.	
User cost of capital (%) v12a	Constructed using the data on average income tax, inflation and mortgage interest rate.	
User cost of capital (%) v13a	Constructed using the data on average income tax, personal consumption inflation and mortgage interest rate.	
M3	Harmonised broad monetary aggregate (M3) “adjusted” stock, based on aggregating euro area country harmonised M3 series using the irrevocable fixed exchange rates. Adjusted after October 1997 for the effect of reclassifications, other revaluations, exchange rate variations and the euro area enlargements.	ECB, ECB calculations
Credit	Loans to the private sector (adjusted after October 1997 for the effect of reclassifications, other revaluations, exchange rate variations and the euro area enlargements), total maturity, all currencies combined. Based on aggregating euro area country harmonised loans series using the irrevocable fixed exchange rates.	ECB, ECB calculations

Annex 2

Table 7: The unit root tests for the main variables

Variable	Level (test with constant)	First difference
PH (sa)	-, -, KPSS	PP**, <i>adf</i>
UR	-, ADF*, KPSS	PP***, ADF***
NHH	-, -, -	-, -
WAPOP	PP***, -, KPSS	PP***, ADF***
LFPOP	-, -, -	PP***, ADF***
D2I	-, -, -	PP***, ADF**
DISPI	-, -, -	PP***, ADF**
HS	-, -, -	PP**, ADF**
DISPIPC	-, -, -	PP***, ADF***
HSPC	-, -, -	PP**, ADF***
UCR (v1)	-, -, KPSS	PP***, ADF***
UCR (v2)	-, -, KPSS	PP***, ADF***
UCR (v3)	PP***, ADF***, kpss	PP***, ADF***
UCR (v4)	PP***, ADF***, kpss	PP***, ADF***

Notes: Sample runs from 1983 Q1 to 2011Q4. PP and ADF stand for Phillips-Perron test and Augmented Dickey-Fuller test, where the null of unit root is rejected, at 10%(*), 5%(**) and 1%(***) significance level. In the Kwiatkowski-Phillips-Schmidt-Shin test, the null hypothesis is stationarity, so KPSS denotes instances where the stationarity could not be rejected (at 10% level). ‘-’ means that the unit root could not be rejected (in the case of PP and ADF test) or (in the case of KPSS test) that stationarity was rejected (at 10% level or more strictly).

Annex 3

Table 8: Cointegration tests results for house prices in the euro area

COINTEGRATION TESTS (Trace Test/Max. Eigenvalue Test)							
Specifi cation	Cointegrating vector	External*	Suggested lags		HQ	2 lags in levels	3 lag in levels
			AIC	SC		1 lag	2 lags
1	ph, dispipc, hspc	ucr, wapop	3	2	3	0/1	1
2	ph, dispi,hs	ucr, wapop	3	2	3	0/1	1
3	ph, dispipc, hspc	ucr, wapop,ur	3	2	3	0	1
4	ph, dispipc, lfpop	ucr	3	2	3	1	2
5	ph, dispi, lfpop	ucr	3	2	3	1	2
6	ph, dispipc, lfpop	ucr,ur	3	2	3	1	2
7	ph, dispipc, lfpop, d2i	ucr	12	2	3	1	2
8	ph, dispi, lfpop, d2i	ucr	12	2	3	3/1	2

Notes: “ph” denotes real house prices, “dspci” denotes disposable income (while “dspipc” is the respective per capita measure), “hs” is housing stock (while “hspc” is the respective per capita measure), “d2i” denotes debt-to-income ratio, “lfpop” is the labour force, “ucr” is the user cost rate, “ur” denotes the unemployment rate and “wapop” is the working population. In all the models, the variables which are stationary are added as “external” regressors and are not included in the cointegrating vector. Tests reported include a constant in the cointegrating relationship and assume no trend in the data. The cells marked in yellow denote the relevant lag length selected by the HQ and SC criteria.

Annex 4

Table 9: Boom-bust periods based on quantile regressions for house prices in the euro area

obs	1	2	3	4	5	6	7	8
1983	+	+	+	+	+	+	+	+
1984	+	+	+	+	+	+	+	+
1985	+	+	+	+	+	+	+	+
1986	+	+	+	+	+	+	+	+
1987	+	+	+	+	+	+	+	+
1988	+	+	+	+	+	+	+	+
1989	+	+	+	+	+	+	+	+
1990	+	+	+	+	+	+	+	+
1991	+	+	+	+	+	+	+	+
1992	+	+	+	+	+	+	+	+
1993	+	+	+	+	+	+	+	+
1994	+	+	+	+	+	+	+	+
1995	+	+	+	+	+	+	+	+
1996	+	+	+	+	+	+	+	+
1997	+	+	+	+	+	+	+	+
1998	+	+	+	+	+	+	+	+
1999	+	+	+	+	+	+	+	+
2000	+	+	+	+	+	+	+	+
2001	+	+	+	+	+	+	+	+
2002	+	+	+	+	+	+	+	+
2003	+	+	+	+	+	+	+	+
2004	+	+	+	+	+	+	+	+
2005	+	+	+	+	+	+	+	+
2006	+	+	+	+	+	+	+	+
2007	+	+	+	+	+	+	+	+
2008	+	+	+	+	+	+	+	+
2009	+	+	+	+	+	+	+	+
2010	+	+	+	+	+	+	+	+
2011	+	+	+	+	+	+	+	+

Note: the yellow area denotes booms, while the blue area represents busts.

Annex 5

Table 10: The unit root tests for the money and credit variables

Variable	Level (test with constant)	First difference
M3 to GDP ratio	-, -, -	PP***, ADF***
Credit to GDP ratio	-, -, -	PP***, ADF***
Credit growth	-, ADF*, KPSS	PP***, ADF***
M3 growth	-, ADF*, KPSS	PP***, ADF***
Credit growth gap	PP**, ADF***, KPSS	PP***, ADF***
M3 growth gap	PP**, ADF***, KPSS	PP***, ADF***

Notes: Credit and M3 growth gaps are calculated using Hodrick-Prescott filter (using $\lambda=1600$). All variables are in real terms, deflated by private consumption deflator for comparativeness reasons. Sample runs from 1983Q1 to 2011Q4. PP and ADF stand for Phillips-Perron test and Augmented Dickey-Fuller test, where the null of unit root is rejected, at 10%(*), 5%(**) and 1%(***) significance level. In the Kwiatkowski-Phillips-Schmidt-Shin test, the null hypothesis is stationarity, so KPSS denotes instances where the stationarity could not be rejected (at 10% level). ‘-’ means that the unit root could not be rejected (in the case of PP and ADF test) or (in the case of KPSS test) that stationarity was rejected (at 10% level or more strictly).

Table 11: Significant lags of money and credit variables in the models

Significant lags in models including 0 to 8 lags of:						
Model	Credit and M3 growth		Credit and M3 growth gap		Only credit growth	Only M3 growth
	Credit	M3	Credit	M3		
1	-	0	-	-	8	0,8
2	-	0,1	-	1	8	0
3	0,8	-	-	-	-	0
4	0,3,4,8	1,2,3,7,8	4,8	4,5,8	-	0,8
5	0,4,8	0,4,8	8	4	-	0,4,8
6	0,4,8	8	-	4	-	0,8
7	0,8	4,8	8	-	8	-
8	8	0,4,8	8	-	3,8	0,8

Notes: Credit and M3 growth gaps are calculated using Hodrick-Prescott filter (using $\lambda=1600$). All variables are in real terms, deflated by private consumption deflator for comparativeness reasons. Sample runs from 1983 Q1 to 2011Q 4. In versions of models where we included only credit growth gap and M3 growth gap separately, none of the lags of these variables had a significant coefficient and is thus not reported.