Eyes Wide Shut?

The U.S. House Price Bubble through the Lens of Statistical Process Control

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Abstract

While most economists agree that the recent worldwide financial crises evolved as a consequence of the US house price bubble, the related literature yet failed to deliver a consensus on the question when exactly the bubble started developing. The estimates in the literature range in between 1997 and 2002, while applications of market-based-procedures deliver even later dates. In this paper we employ the methods of statistical process control (SPC) to date the likely beginning of the bubble. The results support the view that the bubble on the US house market already emerged as early as 1996. We also show that SPC in general might be a useful tool in constructing early warning systems for asset price bubbles.

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1 Introduction

Throughout the last years, the world was hit by a deep financial crisis. Financial institutions around the globe have collapsed or been bought out. Often banks could be rescued only because governments came up with huge rescue packages. The most severe crisis since the Great Depression also affected the real economy and contributed to the most acute recession of the post-war period.

As soon as the crisis became obvious, a bulk of economic literature evolved studying the likely causes of the crisis. According to the prevailing view the global crisis originated in the U.S. house market.[1] The dramatic growth of mortgage lending in the risky subprime sector contributed to strongly rising house prices.[2] Most studies argue that the U.S. house market was subject to a huge price bubble which finally bursted and then triggered the worldwide financial crisis. Such a bubble can hardly be distinguished from a change in expectations about fundamentals which later on turns out to be wrong. The literature has yet failed to deliver powerful tests allowing to distinguish between bubbles and misguided expectations. Although the question whether the developments in the U.S. house market should be qualified as a speculative bubble or rather as a consequence of misguided expectations therefore remains unresolved, both cases have in common that the actual prices deviate from their fundamental values. While somewhat imprecise, we use the term bubble in the remainder of this paper to describe a situation in which the actual prices systematically exceed their fundamental values. In this sense it is uncontroversial that the U.S. house market experienced a huge bubble before the

[1] See, e.g., Demyanyk and van Hemert (2011) or Mishkin (2011).

[2] Some authors go even further and argue that the global financial crisis is the logical consequence of a series of sequential events. Based on a general equilibrium model Caballero, Farhi and Gourinchas (2008) argue the DotCom bubble in the 1990s, the asset bubbles over 2005-2006, the subprime crisis in 2007 and the commodity bubbles of 2008 to be closely related. Phillips and Yu (2011) recently presented empirical evidence in favor of this line of argument.

worldwide financial crises evolved.

Economists have been accused for both their failure to predict the upcoming crisis and for underestimating its consequences (Colander et al. (2009)). In fact, only a few economists such as Nouriel Roubini and Robert Shiller sent early warnings on the upcoming financial turmoil. A number of methods have been developed to identify unjustified price developments in house markets. However, these methods are mostly backward-looking.[3] While they are thus potentially useful in dating a crisis from an ex-post perspective they are less useful in constructing early warning systems. Interestingly enough, the existing studies and methods have also delivered quite heterogenous answers on the question when exactly the U.S. house price bubble originated (see, e.g., Hagerty (2009)). While some authors date back the origin of the bubble to 1997/1998, others argue the crisis started in 2001/2002 or even later.

Against this background further research on detecting bubbles in financial markets and constructing early warning systems seems to be necessary. In this paper we employ methods of Statistical Quality Control (SQC) for this purpose. For decades Statistical Process Control (SPC), the related sub-field of SQC, has routinely been used to monitor manufacturing processes. Somewhat surprisingly, only a few attempts were yet undertaken to apply this method to economic data.[4] SPC is the application of statistical methods to the monitoring and control of a process to ensure that it doesn't not change its properties unnoticedly. For this purpose, SPC typically uses control charts. A control chart is a specific kind of run chart allowing to differentiate between natural and excess variability of a process. Control charts can be seen as part of an objective and disciplined approach of statistical surveillance of a process. SPC can be used to detect change points in time series

[3]We briefly review these methods in Section 2.

[4]See, e.g., Theodossiou (1993), Yashchin et al. (1997) or Blondell et al. (2002).

of any kind and thus can be highly useful in dating the beginning of bubbles in financial markets. Moreover, SPC methods have the advantage to be applicable under real-time conditions. They are thus a natural candidate for constructing early warning systems.

We illustrate the usefulness of SPC at the example of the U.S. house market. In order to do so, we apply SPC to U.S. data under quasi real-time conditions. After estimating a vector autoregressive model (VAR) of the U.S. economy for a base period we generate a time series of house price forecasts for the monitoring period via a recursive procedure. We argue that these forecasts are indicating the fundamentally justified value of house prices. By comparing the forecasts to the realizations we yield a time series of house price forecast errors, which are thus a measure of mispricing. We then monitor this time series using two different control charts (EWMA, CUSUM). Employing the usually applied parametrization of these control charts we study whether and when the control charts generate alarms, thereby indicating that the underlying process generating the forecast errors has changed. Based on occurring alarms we proceed by estimating the likely change point of the process. We interpret the estimated change point as the most likely beginning of the upcoming house price bubble in the U.S. house market.

Both employed control charts deliver quite similar results. Depending on the exact parametrization, the EWMA control chart identifies the period between September 1996 and April 1997 as the most likely starting point of the house price bubble. The CUSUM control chart implies a change point in between November 1996 and June 1998. In line with Shiller (2007) and parts of the literature our empirical results thus indicate that in fact the U.S. house price bubble emerged already in the late 1990s. Moreover, our results indicate that SPC might be a useful method not only in ex-post timing of bubbles in financial markets but also a suitable tool to design early warning systems of upcoming financial market turmoil.

The paper is organized as follows: the second section gives a brief review of early warning systems of asset price bubbles, already considered in the literature. The third section delivers an introduction to SPC and the considered control charts. Section 4 explains the estimation approach and the employed data. Section 5 delivers an overview on the results of previous studies concerned with dating the U.S. house price bubble and presents results from an application of conventional dating techniques to our dataset. The 5th section also delivers the results for the SPC technique and compares the results to the earlier findings. Section 6 summarizes the main results and concludes.

2 Identification of Asset Price Bubbles

In order to be able to identify asset price bubbles, the fundamental part of asset prices has to be separated from speculative components. However, neither is the fundamental value of an asset price easy to calculate nor is the speculative element easy to measure. In the course of time, a considerable literature on bubble identification and the construction of early warning systems of asset market bubbles evolved. Roughly, this literature can be classified into three groups: Indicator-based procedures, market-orientated analyses and econometric approaches (see Gurkaynak (2008), Mikhed and Zemcik (2009)). We discuss these methods briefly in the following, thereby focussing on the identification of house price bubbles.

Indicator-based identification schemes monitor a set of variables that are assumed to be closely linked to the asset prices being studied. Typically, these variables are monetary and credit aggregates. Whenever they develop in an "abnormal" or "conspicuous" way this is taken as a signal of an upcoming bubble.

An indicator which is often employed in the context of house prices is the price-earnings-ratio (P/E-ratio). It is defined as the current price at which a house sells divided by the current rent that could be earned if the house was rented (see Leamer (2002), Feldman (2003), Case and Shiller (2003) or Himmelberg, Mayer and Sinai (2005)). According to the theory of asset pricing, the price of a house is related to current and future rents as well as to the interest rate. Thus, house price changes should be in line with rent changes given constant interest rates and the P/E-ratio should be constant over time in the abscence of a bubble. If house prices are too high compared to current rents over a long period, this might be interpreted as a sign of an existing house price bubble. Various empirical studies find the ratio of aggregate bank lending and income ("credit-to-income ratio") or the ratio of house prices to income ("price-to-income ratio") to serve as reliable early-warning indicators of financial imbalances in both stock markets and real estate markets (see Borio and Lowe (2002), Case and Shiller (2003), ECB (2005) or Alessi and Detken (2009)). However, two shortcomings of monetary and credit aggregates as indicators of asset price bubles are well-known. First, they do not feature any component that accounts for financial risk premia. Second, high growth rates of aggregate bank lending are not always followed by asset price booms (see Bernanke (2002)).

Market-based identification schemes directly monitor developments of asset prices. Such schemes identify asset price bubbles as excessive deviations of a particular asset price from its long-term trend (see Borio and Lowe (2002), Detken and Smets (2004), Hülsewig and Wollmershäuser (2006), Adalid and Detken (2007) or Alessi and Detken (2009)). In order to define what is "excessive" the papers typically use pre-defined threshold levels. The main drawback of market-based identification schemes is that the thresholds obviously lack any economical or methodological foundation. In consequence, empirical studies using such schemes have yielded quite heterogeneous results with respect to the number and timing of bubbles in financial markets. One might also argue that concentrating on pure asset price developments is problematic whenever the macroeconomic environment plays a decisive role for their explanation. Unusual behavior of asset prices does not always imply that an asset price bubble is evolving since the observed asset price development could well be the result of macroeconomic fundamentals.

Econometric studies try to overcome the problems of the market-based approach. In the early 1980s the literature began establishing various econometric tests in order to decide whether observed asset prices are fundamentally justified (see Shiller (1981), LeRoy and Porter (1981), West (1987), Flood, Hodrick, Kaplan (1994) or Gurkaynak (2005)). Especially cointegration tests have been in use to test for the existence of a stable long-term relationship between asset prices and other variables considered as fundamentals (see Campbell and Shiller (1987), Diba and Grossmann (1988), Meen (2002) or Gallin (2003, 2004)). If such a relationship exists, market prices do not systematically deviate from their fundamentally justified values. Evans (1991) criticized traditional unit root and cointegration tests for their lack of power in the wake of periodically collapsing asset price bubbles. His critique triggered renewed interest in the development of new tests for asset price bubbles. One such test, based on cointegration techniques, has been developed by Taylor and Peel (1998). Their test is applicable to the case of periodically collapsing asset price bubbles (see also Pierdzioch (2010)). A yet different class of econometric tests based on Markov switching models has been explored by Funke et al. (1994) and Schaller and van Norden (2002), among others. Other researchers use advanced state-spaces models for bubble identification (Wu (1995, 1997), Bhar and Hamori (2005), Kizys and Pierdzioch (2009), to name just a few).

Although the briefly reviewed methods clearly have their virtues in detecting speculative bubbles, they mainly focus on ex-post identification of asset-price bubbles. In consequence, they are less useful in constructing efficient early-warning systems of speculative asset bubbles. While recursive estimation may remedy this shortcoming to some extent (for an application of recursive methods to the study of stock markets in times of financial crises, see Hartmann, Kempa and Pierdzioch (2008)), SPC methods seem to be natural candidates to solve the real-time problem (see Knoth (2002, 2006), Andersson (2002), Blondell et al. (2002), Zeileis et al. (2005)). While the classical structural break methodology within econometrics relies more or less exclusively on power measures that are less useful in real-time monitoring schemes, the SPC framework and its set of performance measures allows appropriate evaluation and tuning of the considered alarming schemes.

3 Statistical Process Control

Most of the econometric literature concerned with estimating and monitoring changes in time series employs the traditional methods of structural change. These methods have in common that they are based on functional central limit theorems. While this is unproblematic whenever long time series are to be studied, these methods are less suitable when the time series are comparatively short, as it is often the case in economics. Moreover, the traditional methods of detecting structural changes in time series can detect change points only retrospectively since numerous observations before and after the ocurring change are necessary.

The sequential methods of Statistical Process Control (SPC) avoid many of the drawbacks of the traditional methods. Within the SPC framework parametric models dominate. For a given distribution model — mostly the omnipresent normal distribution – the related procedures are constructed. Due to the rather simple and easy-to-implement setup of SPC algorithms, accurate solutions can be derived numerically. Moreover, at least some optimality properties of control charts have already been proven.[5] The favourable properties of control charts make them an ideal candidate of detecting changes of time series' properties under real-time conditions.[6] As at least one scheme, the CUSUM control chart, comes with a built-in change point estimator. The CUSUM chart can therefore also be used to date structural breaks in time series. For the EWMA control chart, the change point can also be estimated in a reasonable way.

Originally, SPC methods were used to maintain or even to improve the quality of manufactured goods. Nowadays, these techniques are applied to any area within a company such as manufacturing, process development, engineering design, finance and accounting, distribution and logistics. However, the main field of application is still the control of production processes in order to detect anomalies in quality performance early. In econometrics, SPC has yet been used only very rarely.[7]

The primary tools of SPC, control charts, plot sample averages or other suitable statistics of quality measurement against time. Every control chart has one or two (upper and lower) control limits which are determined from statistical considerations. While traditional methods of detecting structural breaks employ measures of testing theory such as size, power or error probabilities,[8] the limit values of control charts are based on the expected time to signal measures. The most popular measure is the Average Run Length (ARL), i.e., the time until a signal occurs for an undisturbed process. A process is judged to be out-of-control whenever the uti-

[5] See Moustakides (1986).

[6] Note that in Mathematical Statistics (Sequential Analysis) the term "change point detection" is usual while in Biostatistics the term "surveillance" is used.

[7] See Zeileis et al. (2005).

[8] All SPC procedures are power 1 algorithms so that the econometric approach would not help in identifying reasonable procedures.

lized statistic exceeds the alarm thresholds, thereby indicating that the monitored process has changed significantly in one (or more) of its properties, e.g., a shift in the mean, variance or any other distributional parameter. Given this "alarm", the surveillant then investigates the likely sources of the observed changes.[9]

For our purposes we consider three different control charts: the classical Shewhart chart, the Exponentially Weighted Moving Average chart (EWMA) and the Cumulative Sum chart (CUSUM).[10]

3.1 Shewhart Chart

Among the most simple control charts is the Shewhart chart.[11] To illustrate its operation, assume a stream of empirical residuals ε_t which are independent and normally distributed with mean 0 and variance σ^2. The Shewhart chart uses only the most recent residual to determine the control chart's stopping time. Its stopping time L is defined as

$$L_{\text{Shewhart}} = \inf \left\{ t \in \mathbb{N} : |\varepsilon_t| > c_s \sigma \right\}.$$

The Shewhart chart thus sends an alarm whenever the latest residual exceeds the control limits $\pm c_s \sigma$, which are expressed in units of the standard deviation of the stream of residuals σ. In order to be able to use the Shewhart chart, the so-called critical value c_s has to be specified. Obviously, the choice of the control limits is closely related to type I and type II errors, which might occur when using the control chart. Widening the limits decreases the risk of type I errors, however this comes at the price of an increasing risk of type II errors (and vice versa). A possible

[9] In production processes the sources for the occurred changes will be removed whenever possible, see e.g. Montgomery (2013).

[10] For an overview and a comparison of these control charts see Montgomery (2013).

[11] See Shewhart (1926).

and often employed way of specifying the appropriate control limits is to utilize the concept of average run length. For the case of the Shewhart control chart, the average run length is directly related to the probability p that any residual exceeds the control limits

$$ARL = \frac{1}{p}\,,$$

because L_{Shewhart} follows a geometric distribution. The knowledge of the distribution of ε then allows us calculating the control limit c_s for an ARL value predefined for the undisturbed process. While the Shewhart chart is easy to implement, it does not allow identifying the most likely point in time when the underlying process got out of control. Since we aim at dating the likely begin of house price bubbles, the Shewhart chart is of limited use for our purposes. Moreover, it is pretty slow in detecting small and medium changes, as we will illustrate later.

3.2 Exponentially Weighted Moving Average Chart (EWMA)

In contrast to the simple Shewhart chart, the EWMA control chart uses more than just the most recent empirical residual to monitor the underlying process.[12] The EWMA control chart monitors the series $\{Z_t\}$ with

$$Z_0 = z_0 = 0\,,$$
$$Z_t = (1-\lambda)Z_{t-1} + \lambda\varepsilon_t\,,\ t = 1, 2, \ldots$$

Thus, the EWMA chart employs all available residuals, although with decreasing weights. The memory of the EWMA chart crucially depends on the parameter $\lambda \in (0, 1]$. Values of λ close to zero lead to long memories of Z_t and vice versa.

[12]The EWMA chart was introduced by Roberts (1959) and is intensively discussed in Lucas and Saccucci (1990).

In general, the parameter λ is chosen to most rapidly detect a certain shift of magnitude μ in the residuals' mean. However, there is no formal rule how λ should be chosen for given values of μ. Based on approximations, some useful design rules are provided in Srivastava and Wu (1997). The related literature[13] recommends to use of $\lambda = 0.05$, $\lambda = 0.10$ or $\lambda = 0.20$.

The EWMA chart gives an out-of-control signal if the current value of Z_t exceeds the following limit:

$$L_{\text{EWMA}} = \inf \left\{ t \in \mathbb{N} : |Z_t| > c_E \sqrt{\frac{\lambda}{2-\lambda}} \sigma \right\} .$$

The normalizing term resembles the asymptotic standard deviation of Z_t ($t \to \infty$). In order to calculate the critical value c_E of the EWMA chart, again the ARL criterion can be employed. However, the calculation of the ARL for given λ and c_E is much more complicated. The task of determining c_E for a predefined ARL is, consequently, performed by applying further numerical techniques (secant rule). In what follows, the R package spc is used for calculating the ARL and c_E.[14]

Different from the Shewhart chart, the EWMA chart allows estimating when the break in the underlying time series occurred most likely. The change-point estimator for the EWMA chart is given by

$$\hat{\tau}_{\text{EWMA}} = 1 + \begin{cases} \max\{1 \le t \le L_{\text{EWMA}} : \; Z_t \le 0\} & , Z_{L_{\text{EWMA}}} > 0 \\ \max\{1 \le t \le L_{\text{EWMA}} : \; Z_t \ge 0\} & , Z_{L_{\text{EWMA}}} < 0 \end{cases}$$

In an evaluation of this estimator Nishina (1992) concludes that it performs sufficiently well.

[13]See e.g. Lucas and Saccucci (1990) and Montgomery (2013).

[14]It should be noted that there are some pitfalls in determining the optimal λ, especially for one-sided EWMA schemes. See Knoth (2006) for a discussion of this issue.

3.3 Cumulated Sum Chart (CUSUM)

The third control chart, we consider here, the CUSUM chart,[15] uses just the last data points within a small and randomly sized window.[16] Different from the EWMA chart, the CUSUM chart monitors two time series series S_t^+ and S_t^-, which are calculated as

$$
\begin{aligned}
&S_0^+ = S_0^- = 0\,,\\
&S_t^+ = \max\{0, S_{t-1}^+ + \varepsilon_t - k\}\,,\ S_t^- \ = \ \min\{0, S_{t-1}^- + \varepsilon_t + k\}\,.
\end{aligned}
$$

The most important design parameter of the CUSUM chart is the slack value $k \geq 0$.[17] Similar as in the case of the EWMA chart, the slack variable k is chosen in accordance to the shift in the process μ one is interested in detecting quickly. It is typically expressed in standard deviation units. Moustakides (1986) showed that the optimal choice of the slack value is $k = \frac{\mu}{2}$.[18]

The CUSUM chart delivers an out-of-control signal whenever S_t^+ exceeds or S_t^- falls below the symmetric control limits $\pm c_C\sigma$. Thus, the stopping time is given by

$$
L_{\text{CUSUM}} = \inf\left\{t \in \mathbb{N} : \max\{S_t^+, -S_t^-\} > c_C\sigma\right\}.
$$

As in the previous subsection, the critical value c_C of the CUSUM chart is calculated numerically for a given slack value k and a predefined ARL.

[15]See Page (1954). For more details see the monography of Hawkins and Olwell (1998).

[16]In Zeileis et al. (2005) either all data or a moving window with fixed size are used. Note that the CUSUM process of the structural change literature differs from the one in statistical process control. Both designs are also known in the SPC literature (repeated significance tests and moving average charts, respectively). However, since the CUSUM test in the structural change literature is dominated by the described CUSUM chart and the EWMA chart, it is rarely used in the SPC literature.

[17]The parameter k is also called reference value or allowance. See Montgomery (2013).

[18]For a more detailed discussion see Hawkins and Olwell (1998) and Montgomery (2013).

As the EWMA chart, the CUSUM comes with an estimator of the likely change point τ. It is given by

$$\hat{\tau}_{\text{CUSUM}} = 1 + \begin{cases} \max\{1 \leq t \leq L_{\text{CUSUM}} : \ S_t^+ = 0\} & , S^+_{L_{\text{CUSUM}}} > c_C\sigma \\ \max\{1 \leq t \leq L_{\text{CUSUM}} : \ S_t^- = 0\} & , S^-_{L_{\text{CUSUM}}} < -c_C\sigma \end{cases}$$

3.4 Relative Performance

While the classical Shewhart control chart is more effective in detecting larger shifts, the EWMA and CUSUM procedures perform considerably better with regard to smaller shifts. Figure 1 illustrates this phenomenon for normally distributed data with $0 \leq \mu \leq 3$ and unit variance. For the EWMA chart we use $\lambda = 0.1$ and for the CUSUM chart we set $k = 0.5$. The control limits are determined to provide an ARL of 500 (time units, observations etc.) for the unchanged process ($\mu = 0$).

Figure 1 about here

The three visualized profiles show the ARL as a function of the true expectation μ of the residuals. Note that steep profiles indicate powerful charts. The ARL values, on the vertical axis, are given on a log scale. Figure 1 exhibits the usual order: Shewhart charts are dominated by EWMA and CUSUM for shifts smaller than about 2 standard deviation units. Only for values larger than 2.5 the classical Shewhart chart is considerably better.[19]

4 Empirical Approach and Data

In this paper we apply SPC methods similarly to the structural change analysis proposed in Zeileis et al. (2005). We start out by estimating a model of the U.S.

[19] For a more thorough discussion of performance evaluation of SPC procedures see, e.g., Knoth (2006).

economy for a base (fitting) period for which we assume that no house price bubble was present. On the one hand, the fitting period has to be long enough to allow estimating a stable model, on the other hand the fitting period should end well before the house price bubble started evolving. According to the literature, the earliest estimates of the beginning of the U.S. house price bubble range in between 1997 and 1998. The necessary data for the U.S. economy is available since 1987 in monthly frequency. We thus chose the period of 1987:M01 to 1994:M12 as fitting period. Doing so leaves us with 96 time series observations which is sufficient for estimating a stable macroeconometric model. Moreover, according to the Business Cycle Dating Committee of the NBER the second half of the 1980s was classified as an economic expansion. This expansion started in November 1982 and reached its peak in July 1990. Three quarters later, in the beginning of 1991, the U.S. economy reached a through. One thus might argue that our fitting period roughly consists of a whole business cycle which seems to be necessary to qualify as a base period. We also could not detect any further empirical evidence indicating that this period was "abnormal" in any respect.

It has become common to use VAR models in the tradition of Sims (1980) to explain house price developments by macroeconomic fundamentals (see, e.g., Belke, Orth and Setzer (2008), Assenmacher-Wesche and Gerlach (2009), Dreger and Wolters (2009), Adalid and Detken (2007), Demary (2009), Jarocinsky and Smets (2008) or Goodhart and Hofmann (2008)). In VAR models each endogenous variable is regressed on its own lags and the lags of all other variables in the model. In contrast to other econometric approaches, VAR models do not refer to structural relations between the variables but rather specify their own structure to describe interactions of the variables. The predominance of the VAR approach might be attributed to the fact that VARs are capable of dealing with possible endogeneity problems in an adequate way (see Dreger and Wolters (2009)). In our study we follow this approach and use a VAR approach to model the U.S. economy.

More precisely, we estimate the following unrestricted VAR in reduced form:

$$x_t = c + \sum_{i=1}^{p} A_i \, x_{t-i} + u_t \, ,$$

where x_t is a vector of n endogenous variables at time t, A_i are the $n \times n$ matrices of reduced-form parameters and c is a $n \times 1$ vector of constants. u_t denotes a $n \times 1$ vector of unobservable error terms.

In line with the literature, our VAR model contains the following six variables that are usually included to explain house price developments over time: production index ($prod$), inflation (p), mortgage rates (i), broad money (m), housing prices (hp) and share prices (s) (see, e. g., Dreger and Wolters (2009), Goodhart and Hofmann (2008), Baffoe-Bonnie (1998)). Data on the index of industrial production, inflation and broad money M3 were taken from the OECD database. House prices are measured by the Case Shiller house price index which is constructed by Standard and Poor's. For stock prices we use the Dow Jones Industrial Average from EUROSTAT. Mortgage rates are taken from the Federal Finance Housing Agency (FHFA). Table 1 provides a summary of the data sources. All variables are seasonally adjusted, deflated by the consumer price index and taken in logs except inflation and mortgage rates. Thus, the vector of endogenous variables x has the form:

$$x = (gdp, p, i, m, hp, s) \ .$$

The focus of our analysis is on the development of the house price index. The Case Shiller house price index is a repeat-sales index which measures the development of single-family house prices by considering data on properties that have been

Table 1: Data sources.

Name	Description	Source
Production (*prod*)	Index of industrial production, OECD base year=100, seasonally adjusted, deflated by CPI and taken in logs.	OECD 2012
Inflation (p)	Measured as %-change on the same period of the previous year, based on the CPI, 2005=100.	OECD 2012
Broad money (m)	M3 index, 2005=100, deflated by the CPI, seasonally adjusted and taken in logs.	OECD 2012
Housing prices (hp)	The S&P/Case-Shiller U.S. National Home Price Index Composite 10 measures the value of single-family housing within the United States. The indices measure changes in housing market prices given a constant level of quality. Changes in the types and sizes of houses or changes in the physical characteristics of houses are specifically excluded from the calculations to avoid incorrectly affecting the index value. Data are deflated by the CPI, seasonally adjusted and taken in logs.	Standard & Poor's 2012
Share prices (s)	Dow Jones Industrial Average, price adjusted using the CPI, seasonally adjusted and taken in logs.	EUROSTAT 2012
Mortgage rates (i)	Terms on the conventional single-familiy mortgages, monthly national averages, all homes, contract interest rates.	FHFA 2012

sold at least twice in order to capture the true appreciated value of each specific sales unit.[20] In Figure 2 we show the development of the Case Shiller house price index over the sample period.

When inspecting the displayed time series one might have the impression that the house price bubble is easily detectable without any empirical methods. However, this impression is somewhat misleading since we can not rule out that the observed development of house prices is driven by purely fundamental factors. Before being able to detect an asset market bubble it is therefore necessary to estimate the underlying fundamental house price process.

Figure 2 about here

In the light of our data frequency we allowed for a maximum lag order of six.

[20]For a detailed description see Standard & Poor's (2012).

According to the Schwarz criterion one lag turned out to be the appropriate lag order.

As it is common in the literature on modeling house price dynamics we estimate the VAR model in levels.[21] However, unit-root tests reveal that all employed time series turned out to be non-stationary and are integrated of order one. While VAR models specified in levels are appropriate if all variables are I(0), estimating VARs with unit root variables can lead to spurious regression problems.[22] A possible solution to this problem is to estimate the VAR model in first differences. However, this solution implies a loss of information contained in the level of the variables as the long-term components of the time series are disregarded (Sims (1980)). VAR estimations containing some unit root variables lead to consistent OLS estimators when there are cointegration relations among the variables. Sims, Stock and Watson (1990) show for the case of a trivariate VAR model that the coefficient estimators are asymtotically normally distributed and all test statistics have the usual asymptotic χ^2-distribution when there is a long-run relationship between the variables. In their conclusion, they favor the use of VARs in levels instead of using differenced variables or cointegration operators. Hamilton (1994) shows that OLS estimations in levels do not lead to spurious regression problems when the variables are I(1) with zero drift and there are some cointegration relationships between the endogeneous variables. Asymptotically, several functions of the parameters have the standard asymtotic distributions in the presence unit root variables in the VAR model.[23] Thus, Hamilton (1994) supports the view of Sims,

[21] See, e.g., Adalid and Detken (2007), Jarocinsky and Smets (2008) or Dreger and Wolters (2009).

[22] Sims (2001), Granger and Newboldt (1974).

[23] Regardless of the existence of cointegration relations, Hamilton (1994) shows that the usual t and F tests in a VAR in levels, containing unit roots, are asymptotically valid. However, this is not the case for Granger-Causality tests that do not follow the usual χ^2-distribution (see also Watson (1994), Park and Phillips (1988,1989)). If the variables are cointegrated, the test statistic follows a standard distribution (see Watson (1994) or Sims, Stock and Watson (1990)).

Stock and Watson (1990) to estimate a VAR model in levels since the parameter of the system are estimated consistently.[24] According to the Johanson procedure there are at least two cointegration relationships between the variables in the VAR model.[25] Thus, estimating the VAR in levels seems to be justified. The VAR model is estimated by using the R package vars (version 1.5-0).

Since we are interested in studying the development of house prices, the referring VAR equation is of special interest. We display the estimated coefficients of the house price equation of the VAR model in Table 2.[26] Three variables turn out to have a significant effect on house prices in the base period: The lagged value of the price index, industrial production and inflation. More than 99% of the house price developments in the base period can be explained by the baseline VAR which is mainly due to the sluggish development of house prices. Although current house prices are mainly driven by their lagged value, industrial production and inflation turn out to play a significant role.

The estimation results for the base period presented in Table 2 are also robust to changes of the sample size: We increased respectively decreased the base period to 102 and 108 months respectively to 90 and 84 months to ensure that our following results are robust of the choice of the length of the base period.

In a next step we use the estimated VAR to generate a time series of house price forecasts under quasi real-time conditions. Using the realized values of gdp, p, i, m, hp, s we therefore apply a recursive procedure and generate a time series of one-month-ahead out-of-sample forecasts of house prices. By subtracting the forecasts from the realized values we yield a time series of house price forecast

[24]See also Mitra (2006) for a similar approach. In addition, Clements and Mizon (1991) show that a differenced model implies a loss in information if there is cointegration among the variables.

[25]See Table 5 and Table 7 in the appendix for detailed results of all unit root tests and the VAR cointegration test.

[26]For a detailed view of the estimation results of the baseline VAR see Table 6 in the appendix.

Table 2: VAR estimation results of house price equation.

```
Endogenous variables: hp, prod, s, m, p, i
Deterministic variables: const
Sample size: 95
Log Likelihood: 1399.869
Roots of the characteristic polynomial:
0.993 0.9936 0.9471 0.9471 0.7299 0.7299
Estimation results for equation house prices (hp):
===================================
hp = hp.l1 + prod.l1 + s.l1 + m.l1 + p.l1 + i.l1 + const

          Estimate     Std. Error   t value   Pr(>|t|)
hp.l1      0.9809       0.0225       43.563    < 2e-16 ***
prod.l1    0.0707       0.0184        3.842    0.0002  ***
s.l1      -0.0105       0.0088       -1.200    0.2333
m.l1      -0.0206       0.0704       -0.292    0.7711
p.l1      -0.0020       0.0010       -1.993    0.0494  *
i.l1       0.0003       0.0014        0.256    0.7988
const     -0.1027       0.3114       -0.330    0.7423
-------------------------------------------------------------------------------
Residual standard error: 0.004934 on 88 degrees of freedom
Multiple R-Squared: 0.9965, Adjusted R-squared: 0.9963
F-statistic:  4231 on 6 and 88 DF,  p-value: < 2.2e-16
-------------------------------------------------------------------------------
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1
hp: house prices, prod: industrial production, s: share prices,
m: broad money, p: inflation, i: mortgage rate
```

errors

$$\hat{\varepsilon} = hp - \hat{h}p$$

After doing so we apply two different control charts (EWMA, CUSUM) to the time series of house price forecasts $\hat{\varepsilon}$ and study when the first alarm occurs. Based on the first alarm we then estimate the likely change point of the house price time series. In order to do so we make use of the R package spc.[27]

[27]See Knoth (2011).

5 Dating the Bubble

In this section we study when exactly the U.S. house price bubble started unfolding. We start out with reviewing the findings of earlier studies on this aspect. In a second step we study the development of various of the earlier mentioned indicator variables as well as a market-based identification scheme. Finally we apply SPC to the data and compare the results with those found in the literature.

5.1 Previous Evidence

There is yet no common agreement on the answer on the question, when exactly the U.S. house price bubble started developing (Hagerty (2009)). While some authors date the origin of the bubble back to 1997/1998, others argue the bubble started in 2001/2002 or even later.

First, some economists date the likely beginning of the bubble quite early, more precisely to the years 1997/98. One of the most prominent advocates of this hypothesis is Shiller (2007). He argues that regional bubbles in some U.S. states developed as early as in 1998 which then culminated in a nationwide bubble in the subsequent years. According to his view the house price boom at that time was not justified by economic fundamentals such as construction costs or the owner's equivalent rent, but rather driven by psychological factors such as speculative behavior. Pinto (cited in Hagerty (2009)), Baker (2008) and White (2010) come to similar results. Pinto (cited in Hagerty (2009)), a former Fannie Mae expert, and White (2010) blame the misguided government efforts to raise the homeownership rate, lax lending conditions to households of low income classes and the expansion and securitization of residential mortgage finance since the early and mid 90s for the upcoming bubble in 1997. According to Baker (2008), the housing bubble built up alongside the stock bubble in the mid 1990s. Due to the increasing wealth of households at that time consumption increased and there was a demand shift towards housing expenses. While none of these authors delivers a detailed empirical study supporting his line of argument, Ferreira and Gyourko (2011) use regional U.S. housing transaction data to construct hedonic house price indices for all metropolitan areas in the U.S. They then identify likely structural breaks by estimating the quarter in which the change in the price growth series has the greatest impact on the explanation of the price growth series itself. Broadly in line with Shiller (2007) the authors find house price booms in some metropolitan areas in the mid of the last decade, which then spread to other regions in the following years. However, Ferreira and Gyourko (2011) do not use the term "speculative bubble" for this development but rather speak of a "house price boom" which is more linked to the existence of good investment opportunities than to excessively high house prices as the consequence of speculative behavior. One might therefore conclude from the results of Ferreira and Gyourko (2011) that the crisis was at least initially based on a favourable fundamental development of the housing market in some metropolitan areas.

A second group of authors argues that the likely starting point of the U.S. house price bubble was roughly four years later, i.e. in the years 2001/2002. Phillips and Yu (2011) date the likely starting point of the house price bubble with the help of a recursive regression method. Using a sequential right-sided unit root test they date the beginning of the bubble to 2002:M02. Dreger and Kholodilin (2011) use a signaling approach and logit/probit models to construct bubble chronologies in 12 OECD countries. For the U.S. housing market, the estimation results indicate that the bubble started in the second quarter of 2001, which is quite similar to the results found by Phillips and Yu (2011). Even some housing market experts like Lawler (cited in Hagerty (2009)) argue that the crisis started not before 2002. Lawler blames the loose monetary policy of the Federal Reserve System since the bursted DotCom Bubble in 2001 for the upcoming house price bubble in the following years.

5.2 Application of Traditional Identification Methods

Since almost all of the earlier cited authors argue on the basis of more or less differing data and sample periods it is not easy to compare these results to our following empirical analysis. It thus seems to be useful to first give an overview on the results of indicator-based and a market-based identification method using our dataset and sample period, before turning to our own empirical analysis.

We start out with some popular indicators of house price bubbles, as they have been discussed earlier. Figure 3 shows the development of the price-earnings ratio over the sample period. We consider two different measurements of the rent component: the rent of primary residence and the owner's equivalent rent of residence. Both are taken from the Bureau of Labour Statistics (BLS) database and are often used to calculate historical developments of the price-earnings ratio. Figure 3 reveals clearly that the price-earnings ratio increased significantly in between the mid of the 90s until the house price peak in 2006. However, it is obviously hard to use the price-earnings ratio to date the beginning of the house price bubble. While the price-earnings ratio increased since 1997, it did exceed the values from the late 1980s not before the early 2000 years.

Figure 3 about here

A similar picture arises when switching to the development of the credit-to-income and the price-to-income ratio (see Figure 4 and Figure 5). While the price-to-income ratio shows almost the same development as the price-earnings-ratio, leaving us with the same interpretation problems, the credit-to-income ratio rose only slightly over the 1990s and increased significantly since the early 2000s.

Figures 4 and 5 about here

A main drawback of the indicator-based identification schemes is the obvious lack of a properly derived threshold up to which price increases might be qualified as justified and thus can serve as a sort of yardstick to identify an asset price bubble. There is little consensus in the literature on the question how to judge shifts in the development of house-price-related indicators. One approach is to compare current indicator values to their long-term average value (see, e.g., McCarthy and Peach (2004), Himmelberg, Mayer and Sinai (2005)). Following this approach, both price-earnings-ratios from Figure 3 started to exceed their long-run averages (63,3% for rent of primary residence and 59,9% for the owner's equivalent rent of residence from 1987 until 2011) in the beginning of 2002. Similar results hold for the credit-to-income ratio and the price-to-income ratio which exceed their long-term trends in 2002 for the first time. However, it seems questionable in how far it is reasonable to include the bubble period itself into the calculation of the long-term averages.

In a next step we consider market-based identification procedures and use traditional HP-filter methods to detect the U.S. house price bubble. Following the approach of Goodhart and Hofmann (2008) we use real house prices measured by the Case Shiller house price index of different frequencies (monthly, quarterly, annual) and calculate their long-term trend with different smoothing parameters as used in the related literature. Figure 6 shows the resulting long-term trend and current values of house prices for the sample period. We calculated the percentage deviation of house prices from their HP-trend for each period (right column) and examined whether and when these deviations exceed the threshold values in Goodhart and Hofmann (2008) and Adalid and Detken (2007).[28] The exact results of the market-based identification procedure depend on the employed data frequency, the smoothing parameter and the threshold level.[29] Using the highest available data frequency (which is also used in our following empirical analysis) dates the bubble to the year 2005 and thus almost 8 years later than the estimate of Shiller (2007).

Figures 6 and 7 about here

Figure 7 summarizes the results from the previous literature and the application of traditional identification methods to our dataset. In the light of the evolving heterogeneous picture it is an interesting question which result is supported by the application of SPC techniques.

5.3 SPC Evidence

We now turn to the SPC approach and start out with employing the EWMA control chart. In a first round we apply a smoothing parameter of $\lambda = 0.1$, which is the average value of the interval recommended in the corresponding literature.[30] Figure 8 and 9 show the results for the EWMA control charts. Figure 8 shows the development of the EWMA series of the house price forecast errors $\hat{\varepsilon}$ resulting from the VAR coefficients of the inital model in the base period. The upper and

[28] While Goodhart and Hofmann (2008) use a 5% deviation from the trend, Adalid and Detken (2007) apply a 10% deviation.

[29] Given a threshold of 5% (respectively 10%), monthly house prices exceed the threshold levels the first time in 2005:M03 (respectively 2005:M12) for a HP–smoothing parameter of λ=100.000. Choosing a smoothing parameter of λ=300.000 which is the more appropriate choice with respect to monthly data the threshold of 5% is achieved in 2004:M10 and the 10%-boundary in 2005:M05. For quarterly and annual house price data, the results are quite different; for quarterly data and a smoothing parameter of λ=100.000 the observed house prices pass the 5%-threshold the first time in 2003:Q4 and the 10%-boundary in 2004:Q1 and thus nearly two years earlier than for monthly data. The same holds for annual data. House prices exceed the thresholds in 2003 (5%) respectively 2004 (10%).

[30] For both, the EWMA and CUSUM approach, we choose the in–control ARL to be 500.

lower horizontal lines mark the alarm thresholds calculated for the EWMA series and the left dashed line the left-sided margin of the monitoring period starting in 1995:M01. The vertical lines indicate when exactly the referring chart generates an alarm. According to the EWMA control chart shown in Figure 8, the first alarm occurs in 1997:M12. Here, the EWMA residuals exceed the upper alarm threshold and thus a signal occurs. Given this signal, the likely change point is shown by the second dashed vertical line and is estimated exactly one year earlier (1996:M12). Figure 9 shows the first alarm and the corresponding change point estimation along the Case Shiller house price series.

Figures 8 and 9 about here

To test for the robustness of our results we repeated the analysis for an upper und lower value of the interval of the smoothing parameter ($\lambda = 0.05$ and $\lambda = 0.20$) as it was recommended in the related literature. Table 3 shows the first alarms and the corresponding change points under the EWMA procedure for the two different smoothing parameters.

Table 3: EWMA results for different values of λ.

Parameter value	**First alarm**	**Change point**
$\lambda = 0.1$ (Reference value)	1997:M12	1996:M12
$\lambda = 0.05$	1998:M06	1997:M04
$\lambda = 0.2$	1997:M12	1996:M09

When choosing a smoothing parameter of $\lambda = 0.05$, the change point is estimated only five months later than in our benchmark model (1997:M04) while the EWMA control chart set up for $\lambda = 0.20$ dates the likely starting point three months earlier (1996:M09).[31] Obviously, the change point estimations of our three EWMA specifications with different smoothing parameters λ lead to similar results. Based on the EWMA chart we thus might date the likely beginning of the U.S. house price bubble to the time period between 1996:M09 and 1997:M04.

The positive alarm signal generated by the EWMA control chart for the benchmark model indicates that the observed house prices exceed the prices explained by the VAR model. To ensure that this alarm in fact indicates an upcoming house price bubble, forecast errors after the first alarm should increase until the house price peak in mid 2006. Figure 10 shows the development of the house price forecast errors since 1997:M12. An ADF-test reveals that the time series of house price forecast errors throughout the period in between the first alarm and 2006 contain a unit root, thereby confirming the plausibility of the EWMA control chart results.[32]

Figure 10 about here

In the next step we employ the CUSUM control chart and set the tuning parameter k to the optimal value of 0.5. The estimation results for the CUSUM control charts are shown in Figure 11 and 12. The residual CUSUM charts $\hat{\varepsilon}$ for both the upper and lower CUSUM series S_t^+ and S_t^-, based on the initial model and the first alarm are displayed in Figure 11. Similar to EWMA, the upper und lower horizontal red lines mark the alarm thresholds calculated for the EWMA chart and the left-sided margin of the monitoring period is indicated by the left vertical left line. The first alarm generated by the CUSUM procedure occurs in 1998:M04.

[31] For the corresponding EWMA series with $\lambda = 0.05$ and $\lambda = 0.20$ see Figure 14 and 15 in the appendix.

[32] See Table 9 in the appendix for detailed test results.

Here, the CUSUM residuals exceed the upper threshold and thus a positive signal occurs which is in line with the implication of an upcoming positive house price bubble. Based on this alarm, the likely change point of the house price series and thus the beginning of the U.S. house price bubble is estimated to be 1997:M06.

Figures 11 and 12 about here

Similar to our EWMA procedure, we also run the CUSUM control chart for different specifications of k. Table 4 shows the corresponding estimation results.[33] Similar to the results found for different EWMA specifications, the parameter k affects the time of the first alarm occuring. For $k = 0.25$, the first alarm occurs in 1998:M06. The corresponding change point estimation for $k = 0.25$ is 1996:M11. For $k = 1.0$ the first alarm occurs in 1998:M08 and the likely beginning is dated two months earlier (1998:M06). We conclude that the CUSUM control chart dates the likely beginning of the U.S. house price bubble to the time period in between 1996:M11 and 1998:M06.

Table 4: CUSUM results for different values of k.

Parameter value	**First alarm**	**Change point**
$k = 0.5$ (Reference value)	1998:M04	1997:M06
$k = 0.25$	1998:M06	1996:M11
$k = 1.0$	1998:M08	1998:M06

[33]The detailed CUSUM series can be found in Figure 16 and 17 in the appendix.

As under the EWMA approach, we find that the empirical residuals of the baseline model between the first alarm and the house price peak in 2006 follow a unit-root process (see Figure 13).[34]

Figure 13 about here

Interestingly enough, there are only slight differences between the two applied control charts concerning the likely starting point of the bubble. While the EWMA control chart dates the likely beginning to the time in between 1996:M09 and 1997:M04, the CUSUM control chart estimates the likely starting point to the period in between 1996:M11 and 1998:M06. Although the change point estimations of the EWMA and CUSUM control chart thus differ slightly, they both indicate that the house price bubble started already in the end of the 1990s.

6 Summary and conclusions

While the literature on dating the U.S. house price bubble yet reached no consensus on the question when the bubble started developing, the empirical evidence derived from the application of two SPC control charts, presented in this paper, points into the direction that the bubble originated quite early. Depending on the exact specification of the control charts, the derived change point estimators range in between the end of 1996 and the first half of 1998. Both control charts are thus supportive to the results of Shiller (2007), Ferreira and Gyourko (2011), Pinto (cited in Hagerty (2009)), Baker (2008) and White (2010) arguing that the U.S. house price bubble originated in the years 1997/98.

However, the application of the methods of Statistical Process Control are not only useful in dating the U.S. house price bubble (or more general the estimation

[34]See Table 10 in the appendix for the corresponding ADF-test results.

of change points in time series of asset prices). They also have the advantage to be designed for the use under real-time conditions. This makes them natural candidates for the construction of early warning systems. In our application of SPC to the US housing market the two control charts performed quite well in detecting the occurring change points. For the EWMA control chart the time-to-signal ranged in between 12 and 15 months. The CUSUM chart sent alarms in between 2 and 19 months after the likely change in the house price time series occurred. It thus seems to be adequate to add SPC techniques to the construction set of early warning systems.

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7 Appendix

Figure 1: ARL profiles of Shewhart, EWMA ($\lambda = 0.1$) and CUSUM ($k = 0.5$) control charts with in-control ARL of 500.

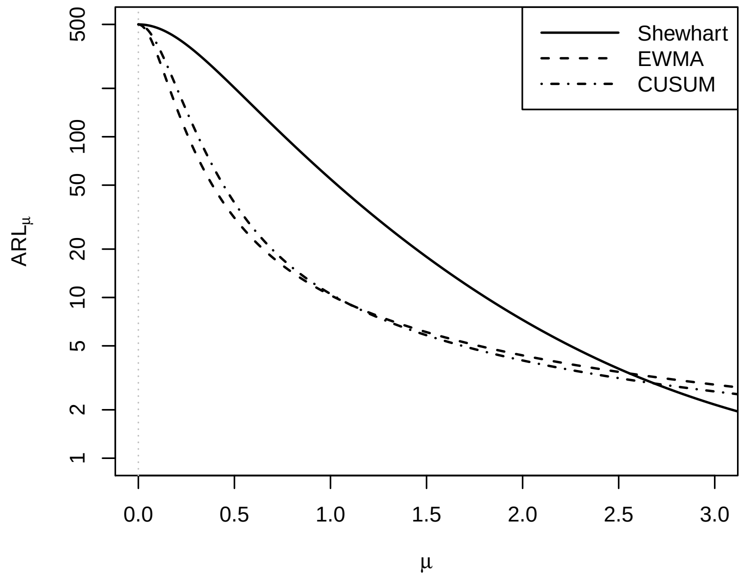


Figure 2: Case Shiller house price index 1987-2010.

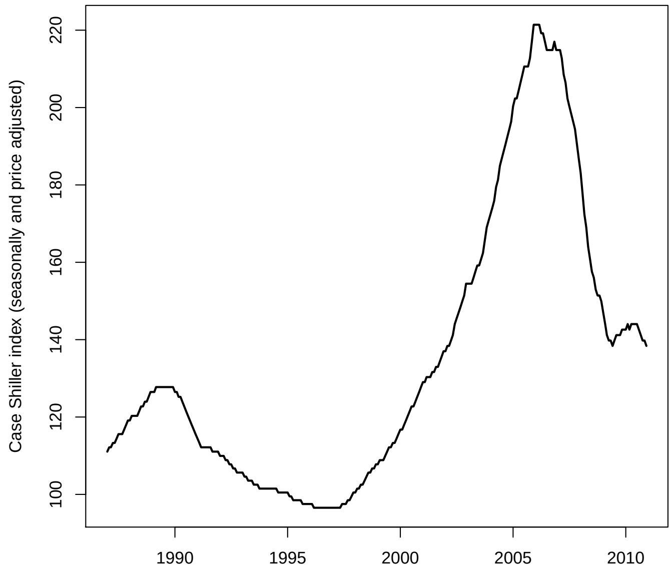


Figure 3: Price-earnings ratio 1987-2011

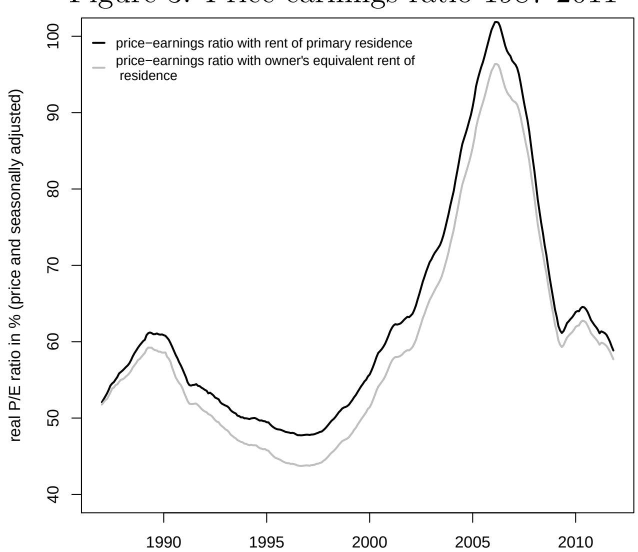
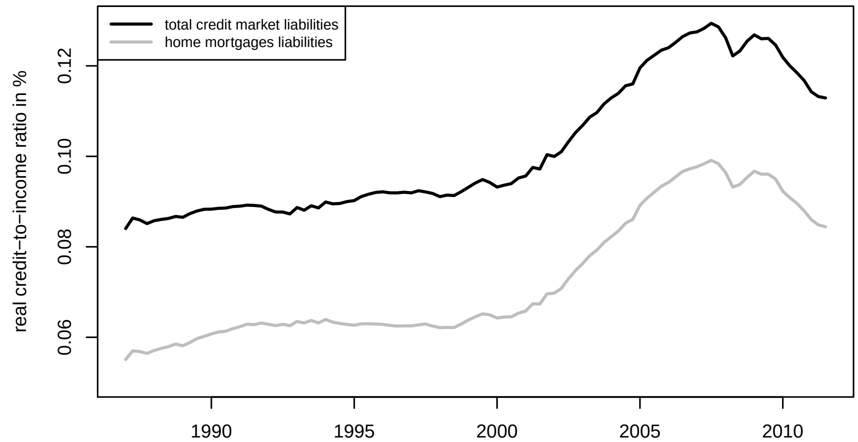


Figure 4: Credit-to-income ratio 1987-2011



Credit market instruments of households a. non profit organizations in Bio. USD (FRB 2012), disposable personal income in Bio. USD (BEA 2012) seasonally and price adjusted.

Figure 5: Price-to-income ratio 1987-2011

Income: real GDP per head, US $, OECD base year (OECD 2012) seasonally adjusted.

Figure 6: HP-filter of real house prices and cyclical components

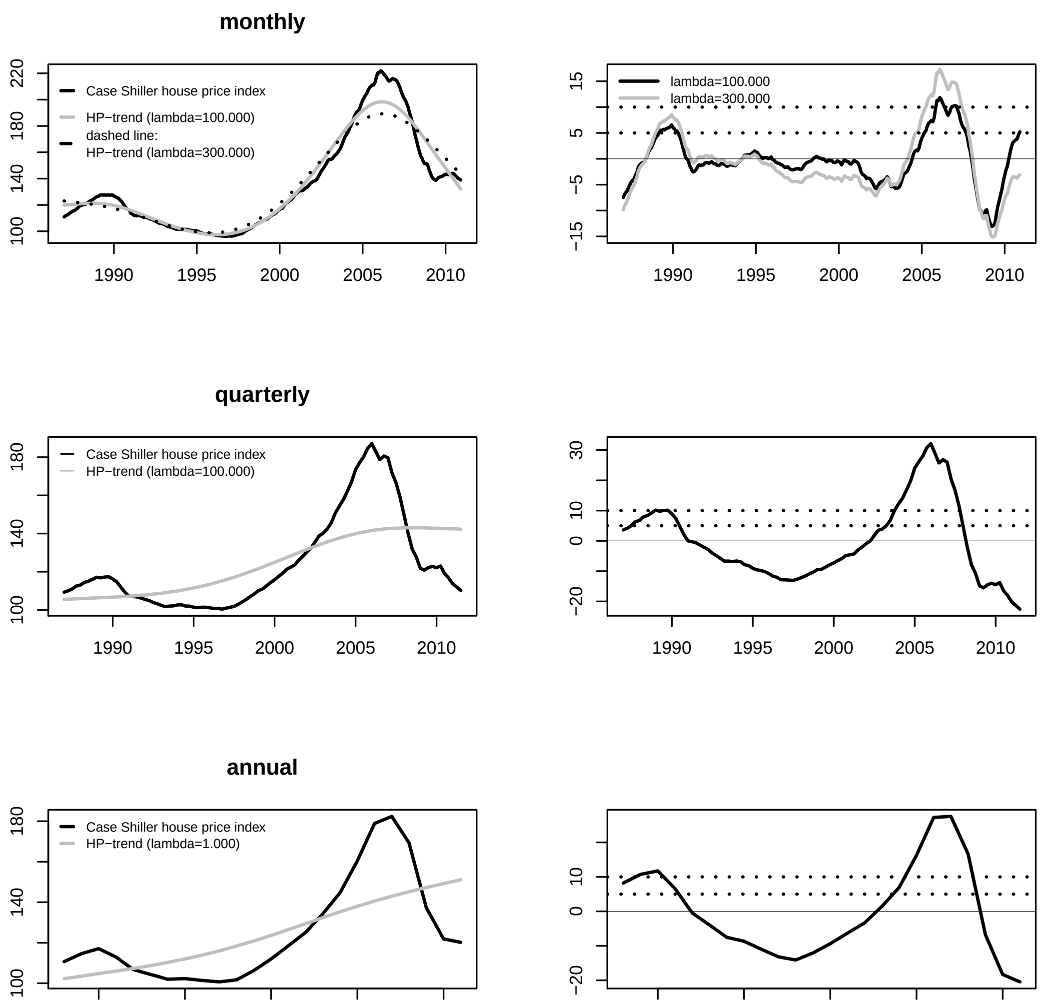


Figure 7: Starting point of the recent U.S. housing bubble as detected in previous studies using traditional identification methods

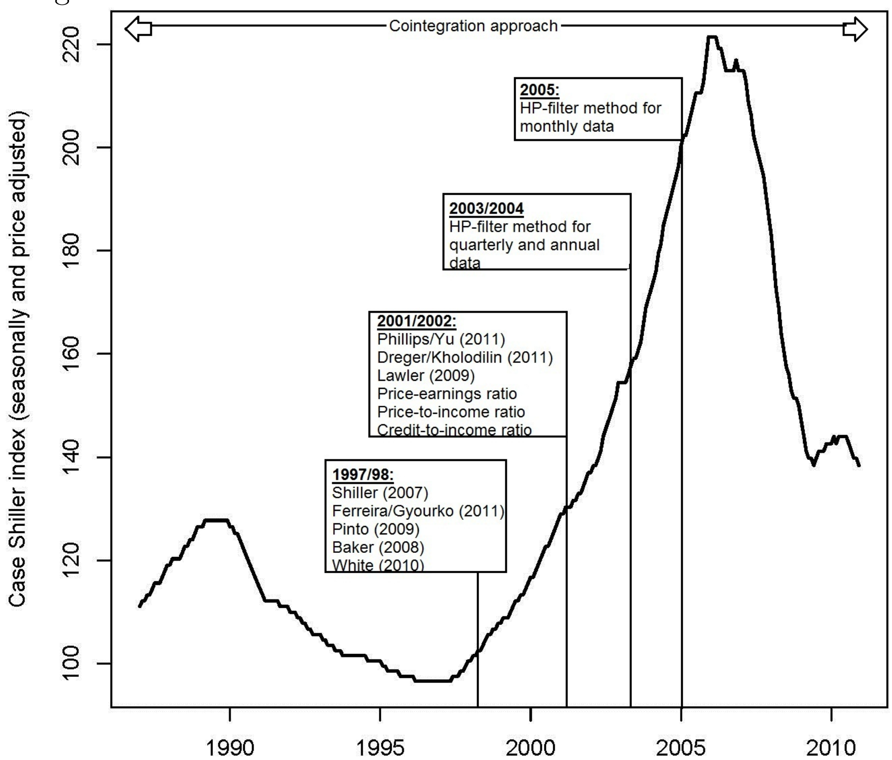


Figure 8: Residual EWMA chart for the initial model and first alarm ($\lambda = 0.1$).

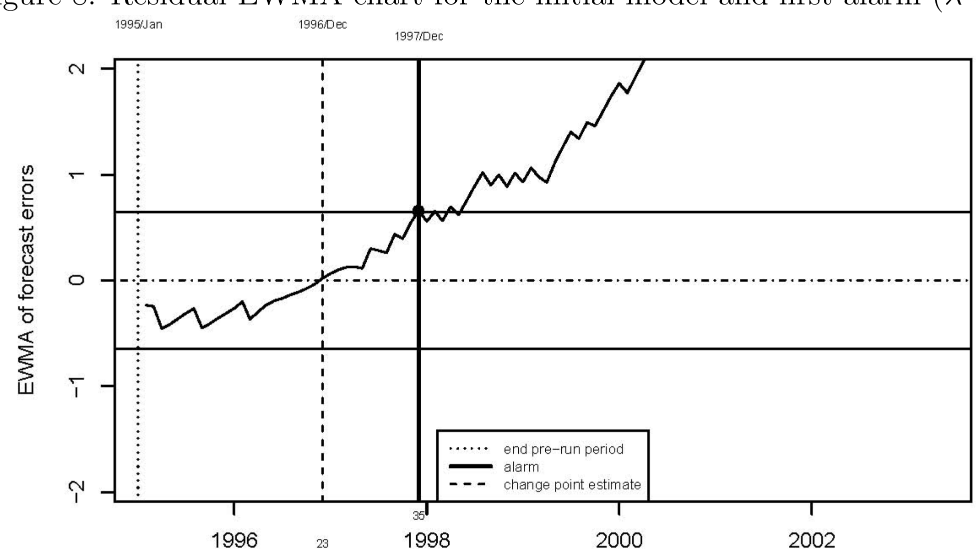


Figure 9: First EWMA chart alarm and Case Shiller house price series ($\lambda = 0.1$).

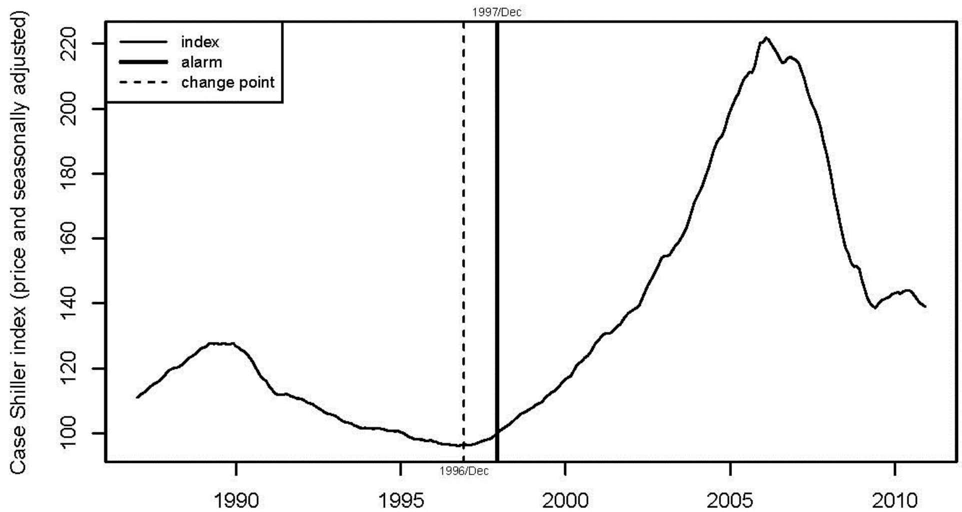


Figure 10: House price forecast errors 1997:M12–2006:M03 for the EWMA control chart and the initial model ($\lambda = 0.1$).

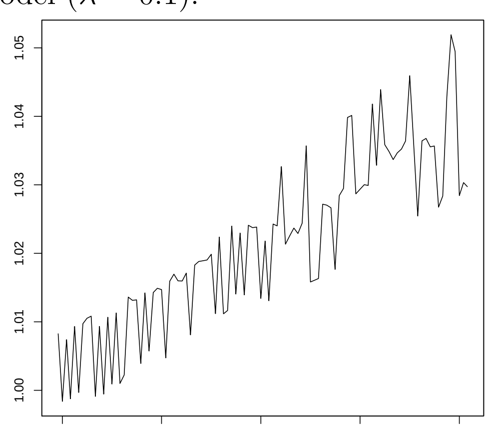


Figure 11: Residual CUSUM chart for the initial model and the first alarm ($k = 0.5$).

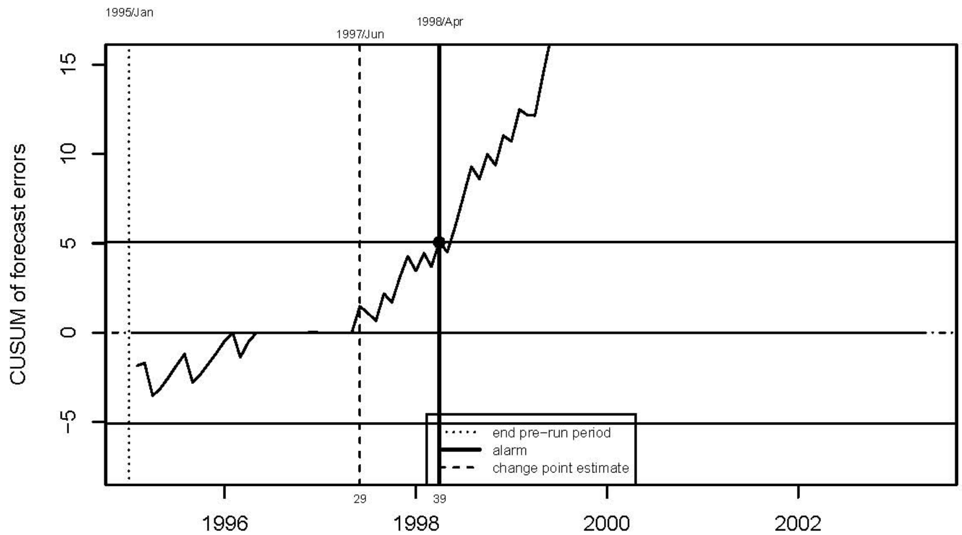


Figure 12: First CUSUM chart alarms and Case Shiller house price series ($k = 0.5$).

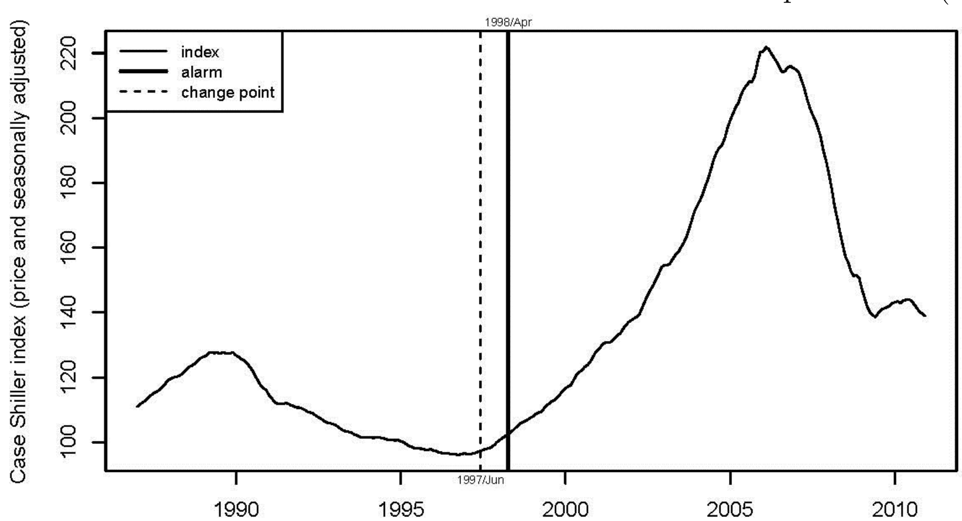


Figure 13: House price forecast errors 1998:M04–2006:M03 for the CUSUM control chart and the intial model ($k = 0.5$).

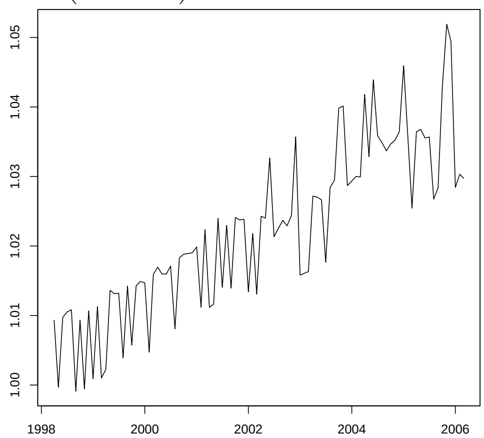


Figure 14: Residual EWMA chart for the initial model and the first alarm ($\lambda = 0.05$).

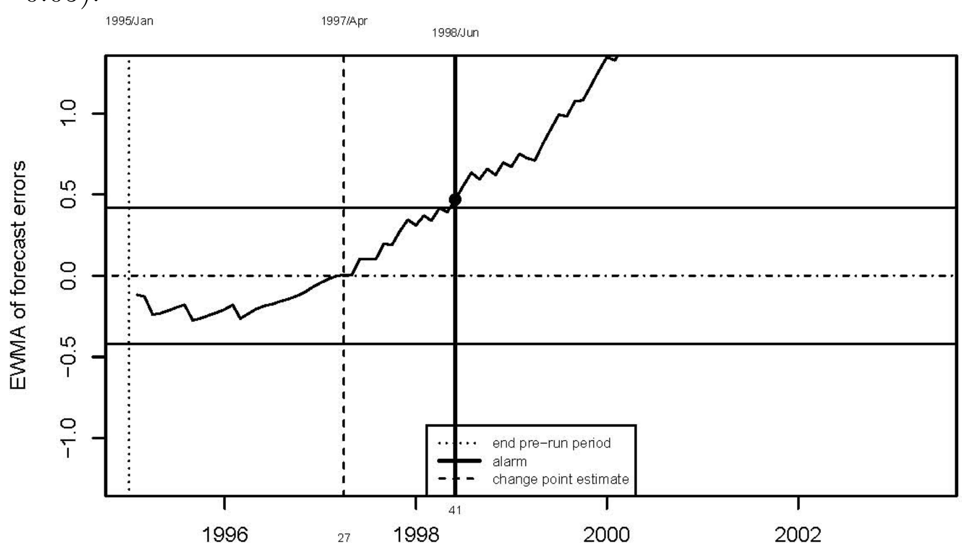


Table 5: Results of Unit Root tests of the baseline VAR (ADF-Test).

```
Augmented Dickey-Fuller Test of prod
    Lag Order: 0
    Dickey-Fuller: -0.9433
  P VALUE: 0.7058
-----------------------------------------------------------------------------
Augmented Dickey-Fuller Test of p
    Lag Order: 0
    Dickey-Fuller: -0.1073
  P VALUE: 0.5787
------------------------------------------------------------------------------
Augmented Dickey-Fuller Test of i
Test Results:
    Lag Order: 0
  STATISTIC:
    Dickey-Fuller: -1.0084
  P VALUE: 0.9326
------------------------------------------------------------------------------
 Augmented Dickey-Fuller Test of m
    Lag Order: 0
    Dickey-Fuller: -2.2844
  P VALUE: 0.4589
------------------------------------------------------------------------------
Augmented Dickey-Fuller Test of hp
    Lag Order: 0
    Dickey-Fuller: 1.096
  P VALUE: 0.99
------------------------------------------------------------------------------
Augmented Dickey-Fuller Test of s
    Lag Order: 0
    Dickey-Fuller: -2.566
  P VALUE: 0.3425
```

Table 6: Estimation Results of the baseline VAR.

```
Endogenous variables: hp, prod, s, m, p, i
Deterministic variables: const, Sample size: 95
Log Likelihood: 1399.869 , Roots of the characteristic polynomial:
0.9936 0.9936 0.9471 0.9471 0.7299 0.7299
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1
===================================
Estimation results for equation hp:
hp = hp.l1 + prod.l1 + s.l1 + m.l1 + p.l1 + i.l1 + const
          Estimate Std. Error t value Pr(>|t|)
hp.l1    0.9809263  0.0225174  43.563  < 2e-16 ***
prod.l1  0.0706616  0.0183896   3.842 0.000229 ***
s.l1    -0.0105396  0.0087828  -1.200 0.233348
m.l1    -0.0205574  0.0704262  -0.292 0.771050
p.l1    -0.0019660  0.0009866  -1.993 0.049388 *
i.l1     0.0003469  0.0013570   0.256 0.798810
const   -0.1026841  0.3113986  -0.330 0.742372
Residual standard error: 0.004934 on 88 degrees of freedom
Multiple R-Squared: 0.9965,     Adjusted R-squared: 0.9963
F-statistic:  4231 on 6 and 88 DF,  p-value: < 2.2e-16
=====================================
Estimation results for equation prod:
prod = hp.l1 + prod.l1 + s.l1 + m.l1 + p.l1 + i.l1 + const
         Estimate Std. Error t value Pr(>|t|)
hp.l1   -0.038914   0.029073  -1.338    0.184
prod.l1  1.034533   0.023743  43.572   <2e-16 ***
s.l1     0.011615   0.011340   1.024    0.308
m.l1     0.051893   0.090929   0.571    0.570
p.l1    -0.001739   0.001274  -1.365    0.176
i.l1     0.001387   0.001752   0.791    0.431
const   -0.245115   0.402056  -0.610    0.544
Residual standard error: 0.006371 on 88 degrees of freedom
Multiple R-Squared: 0.988,      Adjusted R-squared: 0.9872
F-statistic:  1205 on 6 and 88 DF,  p-value: < 2.2e-16
==================================
Estimation results for equation s:
s = hp.l1 + prod.l1 + s.l1 + m.l1 + p.l1 + i.l1 + const
         Estimate Std. Error t value Pr(>|t|)
hp.l1    0.257134   0.140440   1.831 0.070498 .
prod.l1 -0.453395   0.114695  -3.953 0.000156 ***
s.l1     0.773834   0.054778  14.127  < 2e-16 ***
m.l1    -1.252820   0.439246  -2.852 0.005410 **
p.l1    -0.019346   0.006153  -3.144 0.002272 **
i.l1     0.010982   0.008463   1.298 0.197829
const    7.049082   1.942182   3.629 0.000476 ***
Residual standard error: 0.03077 on 88 degrees of freedom
Multiple R-Squared: 0.9449,     Adjusted R-squared: 0.9411
F-statistic: 251.3 on 6 and 88 DF,  p-value: < 2.2e-16
```

```
Estimation results for equation m:
m = hp.l1 + prod.l1 + s.l1 + m.l1 + p.l1 + i.l1 + const
          Estimate Std. Error t value Pr(>|t|)
hp.l1    0.0400782  0.0224203   1.788 0.077285 .
prod.l1 -0.0269356  0.0183102  -1.471 0.144838
s.l1    -0.0212663  0.0087449  -2.432 0.017048 *
m.l1     0.7532458  0.0701223  10.742  < 2e-16 ***
p.l1    -0.0012016  0.0009823  -1.223 0.224519
i.l1     0.0010680  0.0013511   0.790 0.431401
const    1.0654048  0.3100547   3.436 0.000903 ***
Residual standard error: 0.004913 on 88 degrees of freedom
Multiple R-Squared: 0.9331,     Adjusted R-squared: 0.9286
F-statistic: 204.7 on 6 and 88 DF,  p-value: < 2.2e-16
==================================
Estimation results for equation p:
p = hp.l1 + prod.l1 + s.l1 + m.l1 + p.l1 + i.l1 + const
         Estimate Std. Error t value Pr(>|t|)
hp.l1    -0.77824    1.13024  -0.689  0.49291
prod.l1   2.44802    0.92305   2.652  0.00949 **
s.l1      0.86782    0.44084   1.969  0.05215 .
m.l1      5.35068    3.53498   1.514  0.13370
p.l1      0.87319    0.04952  17.633  < 2e-16 ***
i.l1      0.09873    0.06811   1.449  0.15076
const   -34.01671   15.63039  -2.176  0.03221 *
Residual standard error: 0.2477 on 88 degrees of freedom
Multiple R-Squared: 0.9474,     Adjusted R-squared: 0.9438
F-statistic:   264 on 6 and 88 DF,  p-value: < 2.2e-16
==================================
Estimation results for equation i:
i = hp.l1 + prod.l1 + s.l1 + m.l1 + p.l1 + i.l1 + const
        Estimate Std. Error t value Pr(>|t|)
hp.l1    0.63242    0.49496   1.278   0.2047
prod.l1  1.15329    0.40422   2.853   0.0054 **
s.l1     0.25196    0.19306   1.305   0.1953
m.l1    -0.80236    1.54805  -0.518   0.6055
p.l1     0.05043    0.02169   2.326   0.0223 *
i.l1     0.90793    0.02983  30.439   <2e-16 ***
const   -5.17764    6.84490  -0.756   0.4514
Residual standard error: 0.1085 on 88 degrees of freedom
Multiple R-Squared:  0.99,      Adjusted R-squared: 0.9893
F-statistic:  1445 on 6 and 88 DF,  p-value: < 2.2e-16
```

Table 7: Results of the Johansen cointegration test for the baseline VAR.

```
Test type: maximal eigenvalue statistic (lambda max),
with linear trend in cointegration
Eigenvalues (lambda):
[1] 4.899709e-01 4.040799e-01 2.301118e-01 1.149592e-01 1.065815e-01
6.602200e-02 2.071605e-17
Values of teststatistic and critical values of test:

          test 10pct  5pct  1pct
r <= 5 |  6.42 10.49 12.25 16.26
r <= 4 | 10.59 16.85 18.96 23.65
r <= 3 | 11.48 23.11 25.54 30.34
r <= 2 | 24.58 29.12 31.46 36.65
r <= 1 | 48.66 34.75 37.52 42.36
r = 0  | 63.29 40.91 43.97 49.51
```

Table 8: Results of Cointegration tests of house prices and macroeconomic fundamentals 1987-2011.

```
HOUSE PRICES AND MORTGAGE RATES
Test type: trace statistic , with linear trend in cointegration
Eigenvalues (lambda): 0.05451555 0.01640961 0.00000000
Values of teststatistic and critical values of test:
          test 10pct  5pct  1pct
r <= 1 |  4.73 10.49 12.25 16.26
r = 0  | 20.76 22.76 25.32 30.45
-------------------------------------------------------------------------------
HOUSE PRICES AND BROAD MONEY
Test type: trace statistic , with linear trend in cointegration
Eigenvalues (lambda): 3.249828e-02 1.252162e-02 8.326673e-17
Values of teststatistic and critical values of test:
          test 10pct  5pct  1pct
r <= 1 |  3.60 10.49 12.25 16.26
r = 0  | 13.05 22.76 25.32 30.45
-------------------------------------------------------------------------------
HOUSE PRICES AND SHARE PRICES
Test type: trace statistic , with linear trend in cointegration
Eigenvalues (lambda): 1.605125e-02 1.154054e-02 6.938894e-18
Values of teststatistic and critical values of test:
         test 10pct  5pct  1pct
r <= 1 | 3.32 10.49 12.25 16.26
r = 0  | 7.95 22.76 25.32 30.45
```

```
HOUSE PRICES AND UNEMPLOYMENT RATE
Test type: trace statistic , with linear trend in cointegration
Eigenvalues (lambda): 2.506483e-02 8.968171e-03 2.428613e-17
Values of teststatistic and critical values of test:
         test 10pct  5pct  1pct
r <= 1 | 2.58 10.49 12.25 16.26
r = 0  | 9.84 22.76 25.32 30.45
-------------------------------------------------------------------------------
HOUSE PRICES AND RENTS
Test type: trace statistic , with linear trend in cointegration
Eigenvalues (lambda): 4.567518e-02  1.915823e-02 -1.387779e-17
Values of teststatistic and critical values of test:
          test 10pct  5pct  1pct
r <= 1 |  5.53 10.49 12.25 16.26
r = 0  | 18.90 22.76 25.32 30.45
-------------------------------------------------------------------------------
HOUSE PRICES AND INCOME
Test type: trace statistic , with linear trend in cointegration
Eigenvalues (lambda): 1.172571e-01 1.539660e-02 1.629943e-16
Values of teststatistic and critical values of test:
          test 10pct  5pct  1pct
r <= 1 |  1.51 10.49 12.25 16.26
r = 0  | 13.60 22.76 25.32 30.45
```

Figure 15: Residual EWMA chart for the initial model and the first alarm ($\lambda = 0.2$).

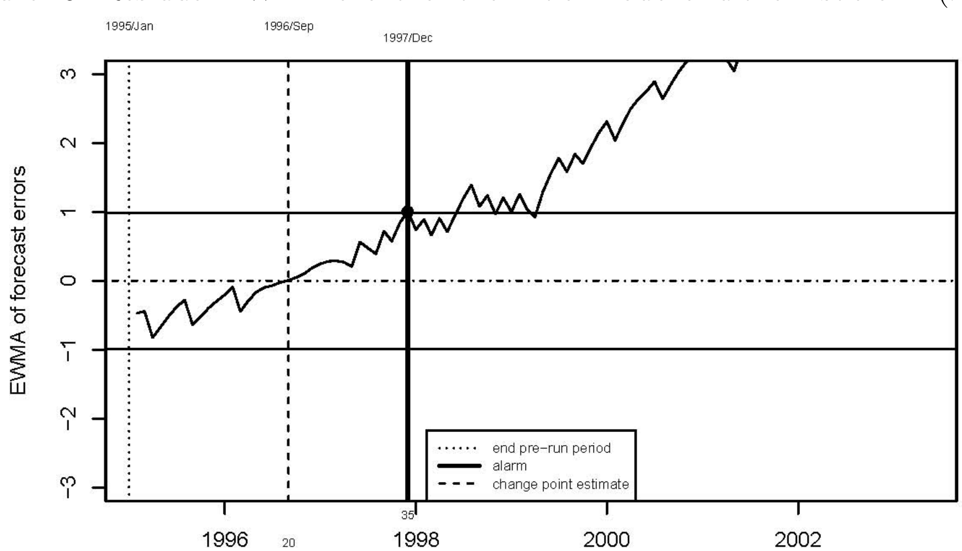


Figure 16: Residual CUSUM chart for the initial model and the first alarm ($k = 0.25$).

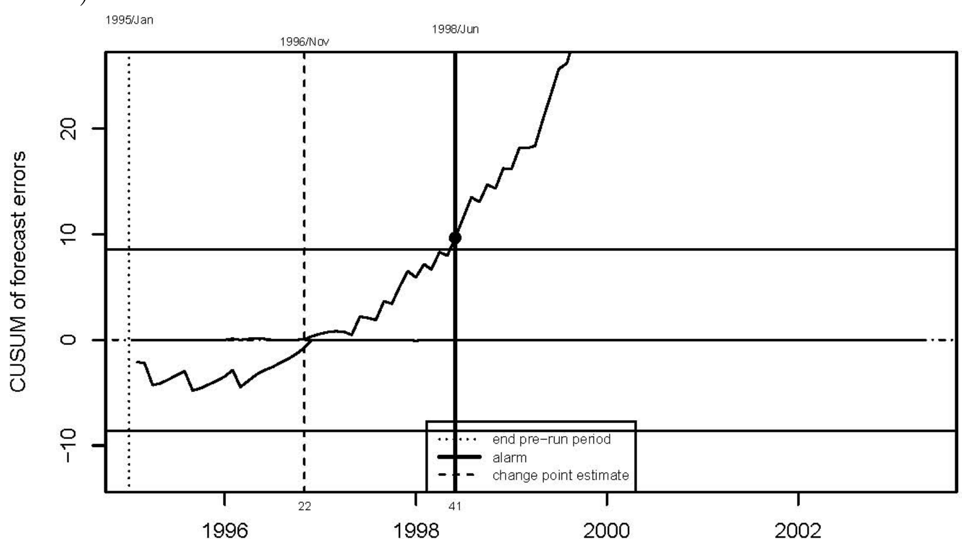


Figure 17: Residual CUSUM chart for the initial model and the first alarm ($k = 1.0$).

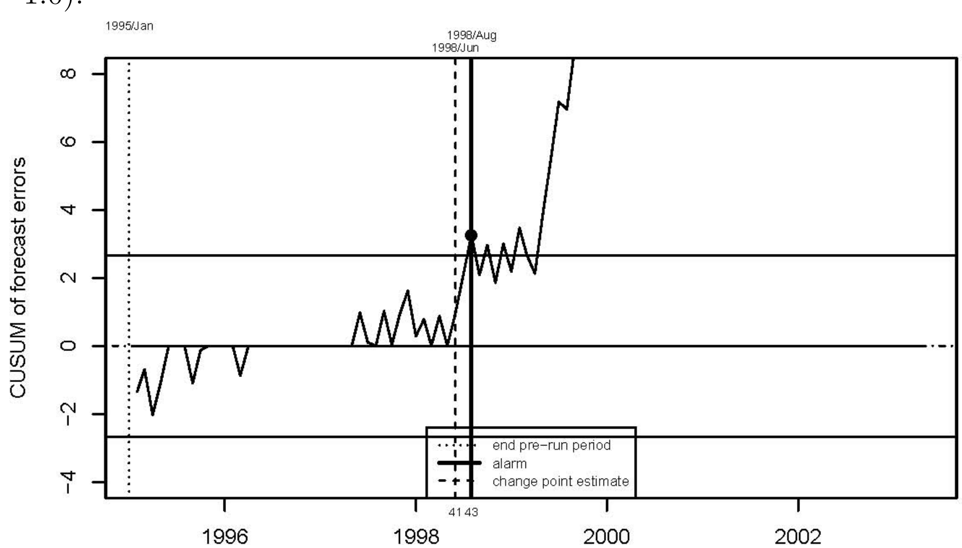


Table 9: ADF-test of house price forecast errors for the EWMA control chart ($\lambda = 0.1$).

```
Test Results:
  PARAMETER:
    Lag Order: 0
  STATISTIC:
    Dickey-Fuller: -1.4162
  P VALUE: 0.1617
```

Table 10: ADF-test of house price forecast errors for the CUSUM control chart ($k = 0.5$).

```
Test Results:
  PARAMETER:
    Lag Order: 0
  STATISTIC:
    Dickey-Fuller: -1.3384
  P VALUE: 0.1865
```