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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.

JEL-Code: C320, E440.

Keywords: statistical process control, real estate, asset prices bubbles, early warning systems.

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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 a bubble on the U.S. house market which derived as the consequence of the booming subprime segment triggered the global crisis.[1] Some authors go even further and argue that the global financial crisis is the logical consequence of a series of sequential events.[2]

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. While a number of methods have been developed to identify speculative bubbles, 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

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

[2]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.

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

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

to ensure that it doesn't not change its properties unnoticedly. For this purpose, SPC uses typically 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 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. housing market. In order to do so, we apply SPC to U.S. data under 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. By comparing the forecasts to the realizations we yield a time series of house price forecast errors. We then monitor this time series using two different control charts (EWMA, CUSUM). Based on occurring alarms we proceed by estimating the likely change point of the house price time series. Both employed control charts deliver quite similar results. Using the EWMA control chart we identify 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 turmoils.

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

Identifying asset price bubbles is a difficult task. In order to be able to do so, the fundamental part of asset prices has to be separated from speculative components. Neither is the fundamental value of an asset price easy to calculate nor is the speculative element easy to measure. Because speculation is driven by unobservable expectations it is hard to decide whether current asset prices deviate from their fundamentally justified values or whether an asset price bubble is evolving. It is thus not surprising that there is a considerable literature concerned with the issues of bubble identification and early warning systems. 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 will 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 for a possibly upcoming (or bursting) bubble. An indicator which is often employed in the context of house prices is the price-earnings-ratio (P/E-ratio) which 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 but somewhat arbitrary 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 long-term relationship exists explosive bubbles can be ruled out. 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 vary in their empirical approaches and clearly have 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, Hoang, Powell and Shi (2002), Zeileis, Leisch, Kleiber and Hornik (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 allow 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 belongs to the field of structural change. Roughly speaking, structural change methods provide a toolset for identifying rather general types of changes in complex time series models. Typically, the methods developed in the existing literature are based on functional central limit theorems. These models are evaluated within the framework of fixed sample theory and thus, can detect changes in time series only retrospectively.

Only recently, the first papers taking a sequential perspective appeared in the econometric literature.[5] However, as Zeileis et al. (2005) mention, this problem has already been discussed extensively in SQC. SPC, the related sub-field of SQC, delivers methods for detecting changes in time series in a sequential fashion.[6] Originally, SPC methods were used 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 the control of production

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

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

processes in order to detect anomalies in quality performance early. One of the primary tools of SPC are control charts plotting sample averages or other suitable statistics of quality measurement against time. Control charts have proved to be quite powerful in distinguishing between the natural and excess variability of a process.

Every control chart has one or two (upper and lower) control limits which are determined from statistical considerations. A process is flagged as out-of-control whenever the utilized statistic exceeds these 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. In production processes the sources for the occurred changes will then be removed whenever possible.[7] While econometric approaches consider measures of testing theory such as size, power or error probabilities[8], classic SPC performance measures are based on the expected time to signal. The most popular measure is the Average Run Length (ARL), i.e., the time until a signal occurs for an undisturbed or initially out-of-control process.

The SPC approach has various advantages compared to the competing structural change procedures. First, the sequential properties of control charts are well studied. For evaluating and designing traditional structural change procedures, limit theorem results have to be exploited. For small size data sets as they are common for quarterly, monthly or even daily time series this procedure is often inappropriate. As an alternative, Monte Carlo studies have to be used. The setup of SPC algorithms is much simpler and accurate results are readily available. Second, at least some optimality properties of control charts have been proven.[9] Third, from a practitioner's point of view the application of SPC techniques is much easier. Fourth, during the last 20 years highly complex models such as multivariate time series or profiles were considered in the SPC literature. The results can be easily transferred to economic data. Finally, at least one scheme, the CUSUM control chart, comes with a built-in change point estimator. For the EWMA control chart, the change point can also be estimated in a reasonable way.

[7]See Montgomery (2005).

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

[9]See Moustakides (1986).

For our purposes we consider three different control charts: the classical Shewhart chart, the CUSUM chart and the EWMA chart.[10] We shall outline their operation briefly in the following.

Assume a stream of empirical residuals ε_t which is independent and normally distributed with mean 0 and variance σ^2. Then, the designs of the control charts are given by a certain sequence of statistics and a stopping time L.

The traditional Shewhart chart uses only the most recent residual. The corresponding stopping time L is given by

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

Shewhart control charts are extremely useful in a first phase of implementing SPC because they are relatively easy to construct and to interpret. What is more, they are able to detect both large and sustained shifts in the process parameters.[11]

In contrast to the simple Shewhart procedure, the EWMA and CUSUM control charts use more than just the most recent data and include past developments. The EWMA chart was introduced by Roberts (1959) and was intensively discussed in Lucas and Saccucci (1990). For the design of the EWMA control chart, the series $\{Z_t\}$ with

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

has to be calculated. Thus, EWMA employs all sample data, although with decreasing weights through the smoothing parameter λ. The natural center line for monitoring residuals is zero. This effects the initializing at $z_0 = 0$ and the shape of the stopping rule. The EWMA chart gives an out-of-control signal if the current value of Z_t exceeds the threshold

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

The normalizing term resembles the asymptotic standard deviation of Z_t ($t \to \infty$).

[10]See Shewhart (1926), Page (1954), Roberts (1959).
[11]See Montgomery (2005).

CUSUM[12] in contrast uses just the last data points within a small and random sized window.[13] In the two-sided case which is the natural counterpart to EWMA both a positive and a negative series $S_t^{\pm}$ have to be calculated:

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

Whenever the upper (respectively lower) series exceeds the corresponding threshold the system signals an alarm:

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

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 these patterns. All three charts are calibrated for an in-control process to yield the same expected time $A = 500$ to signal.

The alarm thresholds c_S, c_E and c_C are determined accordingly by using the R package spc.[14] The three profiles show the ARL as a function of the true expectation μ of the residuals. Their standard deviation σ is set to 1. Note that steep profiles indicate powerful charts. Figure 1 exhibits the usual order: Shewhart charts are dominated by EWMA and CUSUM for shifts smaller than about 2. Only for values larger than 2.5 the classical Shewhart chart is considerably better.[15]

The parameters $\lambda \in (0, 1]$ and $k \geq 0$ for EWMA and CUSUM, respectively, are set by the user to most rapidly detect a shift μ_1 in the residuals' mean. The design rule for CUSUM's k is simple: Set $k = \mu_1/2$.[16] It is more subtle for EWMA. There is no explicit relationship between μ_1 and λ. Even more, the optimal λ also depends on the in-control ARL A. For ease of application, there are some

[12] For more details see the monography of Hawkins and Olwell (1998).

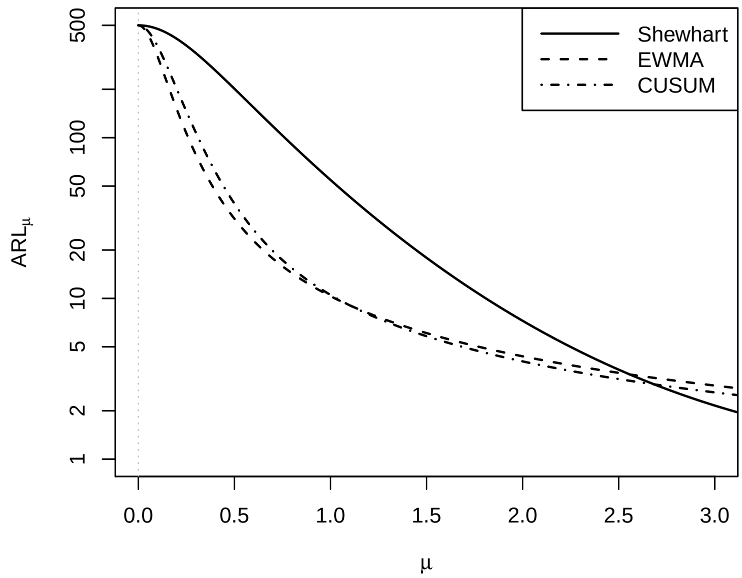
[13] In Zeileis et al. (2005) either all data or a moving window with fixed size are used. Note that the CUSUM process of the structural change literature differs from the one in statistical process control. Both designs are also known in the SPC literature (repeated significance tests and moving average charts, respectively), but are not frequently used for change point detection, because they are dominated by other methods such as namely CUSUM, EWMA and a further one called Shiryaev-Roberts procedure.

[14] See Knoth (2011).

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

[16] See for optimality Moustakides (1986) and for a more detailed discussion Hawkins and Olwell (1998).

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



general recommendations such as $\lambda = 0.05$, $\lambda = 0.10$ and $\lambda = 0.20$.[17] Some nice design rules are provided in Srivastava and Wu (1997) who constructed certain simple approximations. It should be noted that there are pitfalls while searching the optimal λ especially for one-sided EWMA schemes.[18] It turns out that not the regular ARL should be the target for optimizing λ but more complex measures like the steady-state ARL, i.e., the expected detection delay for a long running monitoring process without false alarm.

An alarm signal might be interpreted as an indication for a structural break in the (recent) past. Both, EWMA and CUSUM come with a built-in estimator for the change point which is highly useful for dating purposes. No comparable estimator is available for the Shewhart control chart. In the remainder of this paper we therefore concentrate on the implementation of the EWMA and the CUSUM chart.

The CUSUM estimator of the change point τ is given by:

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

[17]See Lucas and Saccucci (1990) and Montgomery (2005).
[18]See Knoth (2006).

Since the EWMA chart lacks such re-setting behavior, the change-point estimator which is given by

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

needs some more justification. In an evaluation of this estimator Nishina (1992) concludes that it performs sufficiently well. Even though other authors have contributed to the discussion, there has not been much progress since then.[19] Hence, for the present analysis we also chose the popular built-in estimators.

4 Empirical Approach and Data

In this paper we apply SPC methods similarly to the structural change analysis proposed in Zeileis et al. (2005). To begin, we estimate a model of the U.S. 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 was 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)

[19] The classic is Hinkley (1971) while some more recent references are Srivastava and Wu (1999), Pignatiello and Samuel (2001), Wu (2004) and Lou (2008). They considered typical properties of the built-in estimators (mainly of CUSUM). Only Pignatiello and Samuel (2001) introduced an estimator whose design does not depend on the control chart that triggers the alarm signal.

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.

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 sold at least twice in order to capture the true appreciated value of each specific

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	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

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 easy 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 causes. Before being able to detect an asset market bubble it is therefore necessary to estimate the underlying fundamental house price process.

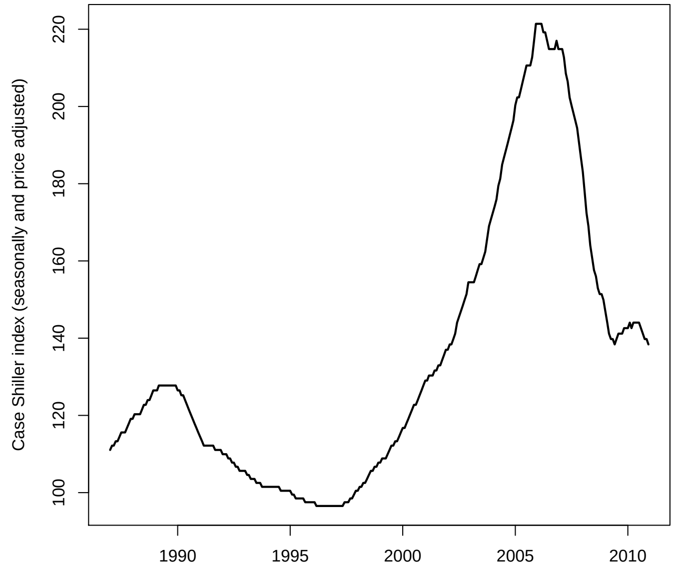
We estimate our VAR model in levels. Thus, the vector of endogenous variables x has the form:

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

In the light of our data frequency we allowed for a maximum lag order of six. According to the Schwarz criterion one lag turned out to be the appropriate lag order. Unit-root tests reveal that all time series turned out to be non-stationary and are integrated of order one. Since estimating a model with unit root variables leads to

[20] For a detailed description see S&P's (2012).

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



spurious regression problems one might think about using first differences. Indeed, this solution implies a loss of information contained in level variables. However, as Sims, Stock and Watson (1990) show, VAR estimations containing some unit-root variables lead to consistent OLS estimators when there are cointegration relations among the variables. According to the Johanson procedure there are at least two cointegration relationship between the variables of the VAR model.[21] 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.[22] 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 variable, 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

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

[22]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 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
--------------------------------------------------------------------------------
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1
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
```

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 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.

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 schemes and an econometric approach. Finally we apply SPC to the data and compare the results with those from the literature.

5.1 Previous Evidence

There is yet no common agreement on when exactly the U.S. house price bubble started developing (Hagerty (2009)). While some authors date back the origin of the bubble 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 to the years 1997/98. One of the most prominent advocates of this theory 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 increases at that time were 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 90s due to the increasing wealth of the households and led to higher consumption and especially positive demand shifts towards housing. 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 statistical areas in the U.S. and 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) they 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.

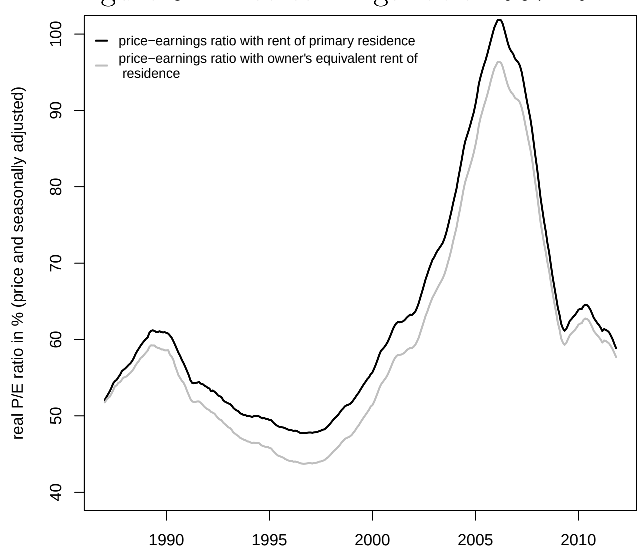
A second group of authors argues that the likely starting point of the U.S. house price bubble was roughly four years later, i.e. in the years 2001/2002. Phillips and Yu (2011) date the likely starting point of the house price bubble with the help of a recursive regression method. Using a sequential right-sided unit root test they date the beginning of the bubble to the fourth quarter of 2001. 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 result 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 year.

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, market-based and at least some econometric identification methods using our dataset and sample period before turning to our application of SPC to the data.

We start out with some popular indicators of house price bubbles as 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.

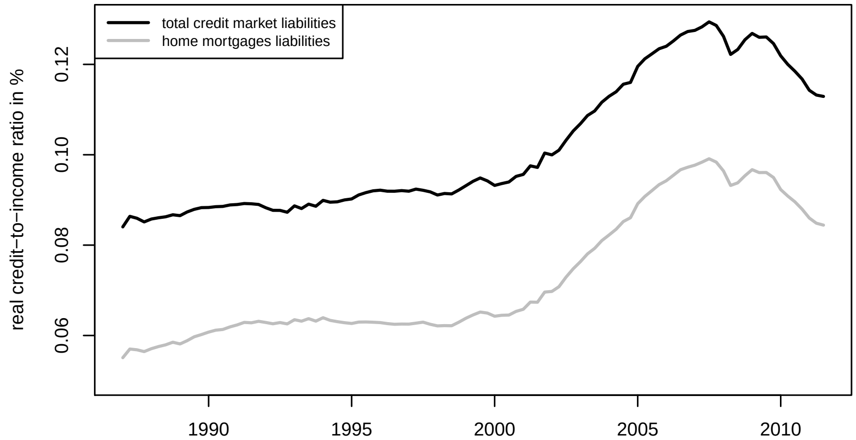
Figure 3: Price-earnings ratio 1987-2011



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.

A main drawback of the indicator-based identifcation 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

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.

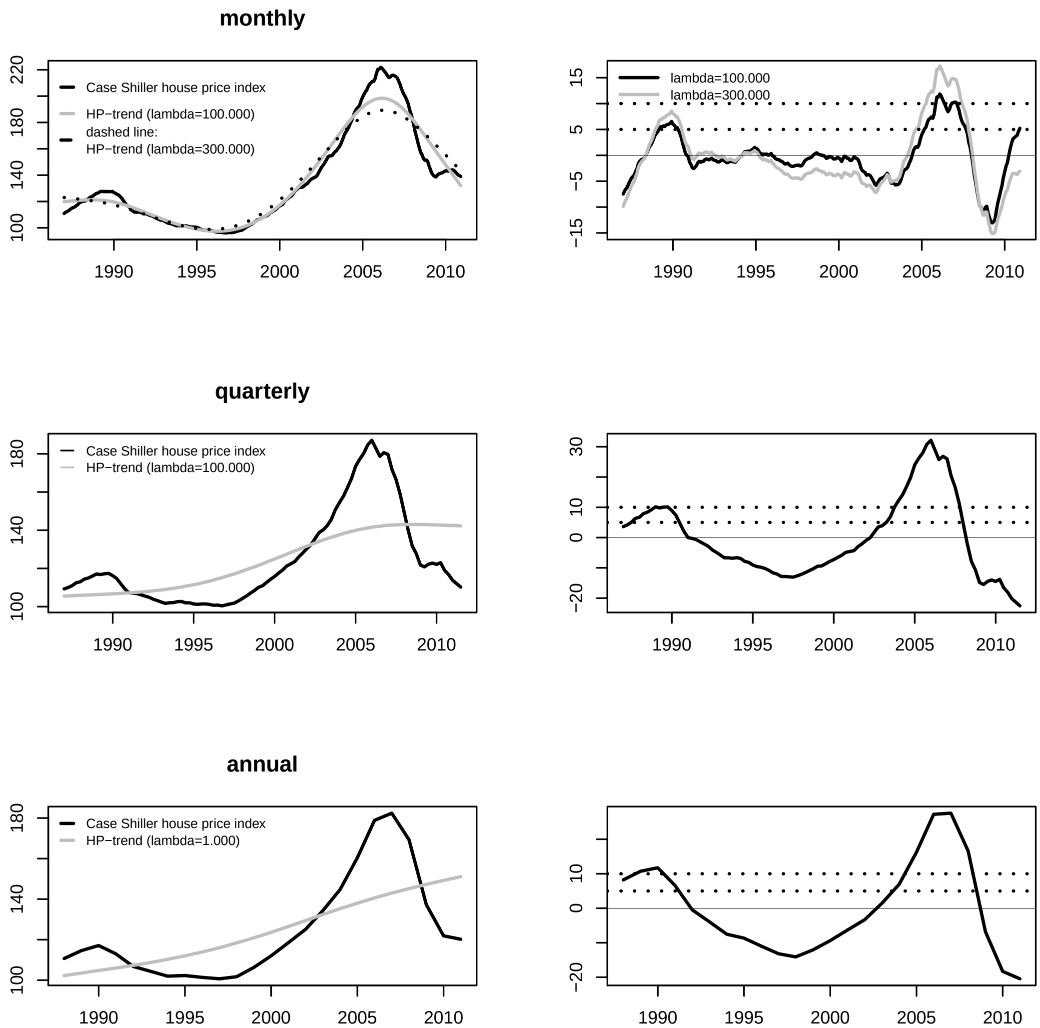
Figure 5: Price-to-income ratio 1987-2011

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

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

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



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).[23] The exact results of

[23]While Goodhart and Hofmann (2008) use a 5% deviation from the trend, Adalid and Detken

the market-based identification procedure depend on the employed data frequency, the smoothing parameter and the threshold level.[24] 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).

Finally, we conducted traditional cointegration tests as it is done in parts of the econometric literature[25] concerned with identifying house price bubbles. We tested for a long-run relationship between real house prices and other variables such as mortgage rates, real broad money, real share prices, the unemployment rate, real disposable personal income and real rents. Following the Johansen-procedure we test for the existence of such a relationship between house prices and each of the fundamental variables for the period 1987 to 2011. As the results reveal, we find no indication of a stable long-run relationship between house prices and any of the considered fundamentals. The cointegration tests indicate that house price developments were not in line with economic fundamentals during the sample period.[26] Thus, according to this identification approach the existence of a house price bubble can not be ruled out. A main drawback of this approach is that traditional cointegration tests do not allow for the estimation of the likely period in which the bubble came up or to date the likely starting point of that bubble. In the literature, they are therefore rather used to test for the existence of a bubble for a finite sample than to date the beginning and the time point when the bubble bursts.

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

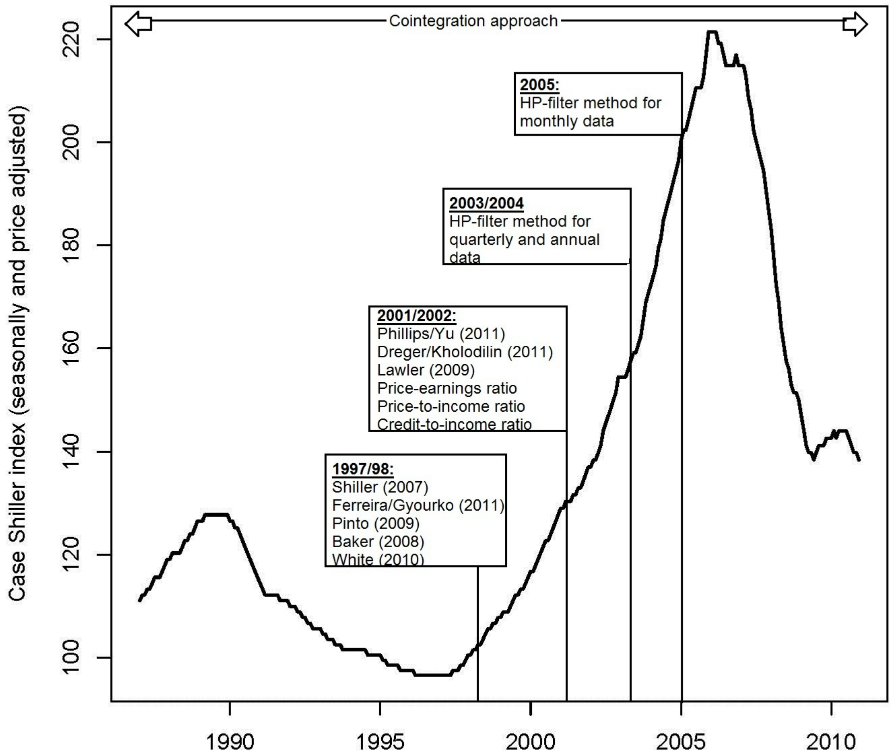
(2007) apply a 10% deviation.

[24]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%).

[25]See Campbell and Shiller (1987), Diba and Grossmann (1988), Meen (2002) or Gallin (2003, 2004).

[26]See Table 8 in the appendix for detailed test results.

Figure 7: Starting point of the recent U.S. housing bubble found by previous studies and traditional identification methods



application of the SPC techniques.

5.3 SPC Evidence

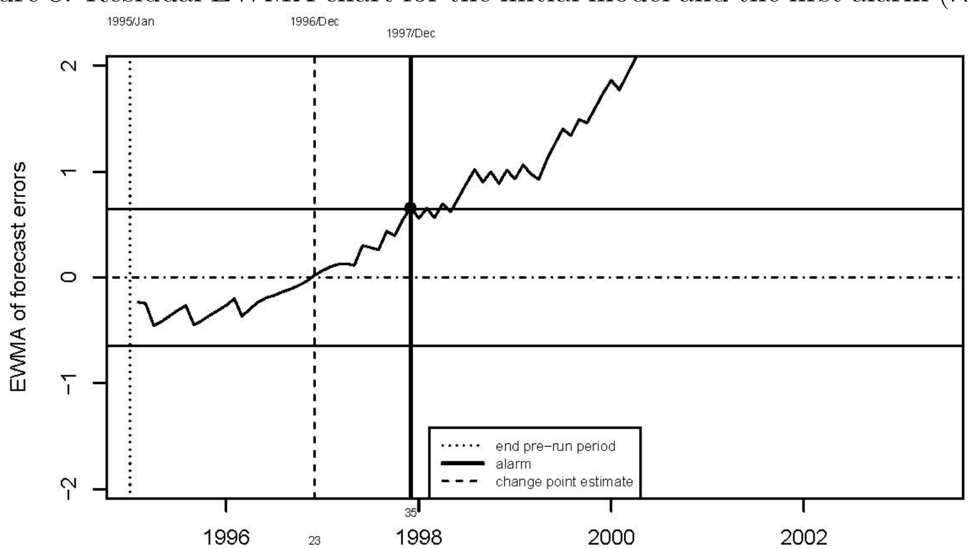
Our applied estimation procedure simulates a surveillant engaged in controlling the U.S. house price development over the sample period using the described two control charts: EWMA and CUSUM.

We start out with employing the EWMA control chart. In a first run we apply a smoothing parameter of $\lambda = 0.1$ which is the average value of the interval recommended in the corresponding literature.[27] 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 with the average value of $\lambda = 0.1$. The upper and 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

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

1995:M01. The vertical lines indicate when exactly the referring chart generate alarms. 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 (structural break) is shown by the second dashed vertical line and is estimated exactly one year earlier to 1996:M12. Figure 9 marks the first alarm and the corresponding change point estimation along the Case Shiller house price series.

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



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 time points of first alarm and the corresponding change points found by the EWMA procedure for different smoothing parameters.

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).[28] Obviously the change point estimations of our three EWMA specifications with different smoothing parameters λ are only slightly different. We thus might date the likely beginning of the U.S. house price bubble to the time period between 1996:M09 and 1997:M04 using the EWMA control chart.

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

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

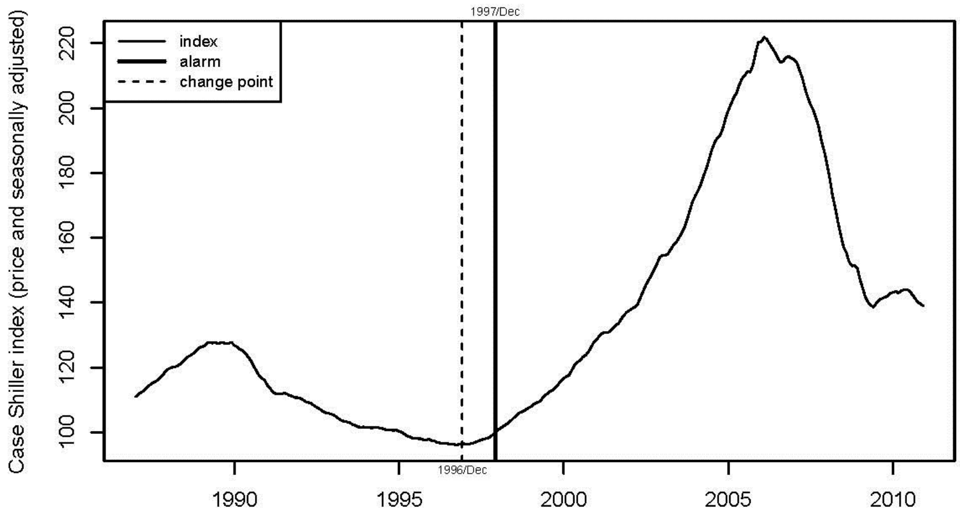
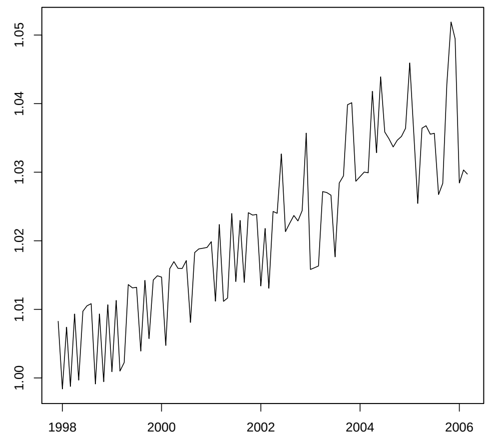


Table 3: EWMA results for different values of λ.

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

The positive alarm signal shown by the EWMA control chart for the benchmark model indicates that the observed house prices exceed those prices explained by the fundamentals of the VAR. To ensure that this alarm in fact indicates an upcoming house price bubble, one would expect increasing forecast errors after the first alarm until the house price peak in mid 2006. Figure 10 shows the development of the house price forecast errors since 1997:M12. The corresponding ADF-test reveals that the house price forecast errors since the first alarm until 2006 contain a unit root confirming the plausibility of the EWMA control chart results.[29]

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



In the next step we employ the CUSUM control chart and set the tuning parameter k to 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 run chart and the left-sided margin of the monitoring period is indicated by the left vertical left line. In doing so, the first alarm generated by the CUSUM procedure is dated to 1998:M04. 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.

Similar to our EWMA procedure, we also run the CUSUM control chart for different specifications of k. Table 4 shows the corresponding estimation results for different values of k.[30] 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 to 1998:M06. We conclude that the

[29]See Table 9 in the appendix for detailed test results.
[30]The detailed CUSUM series can be found in Figure 16 and 17 in the appendix.

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

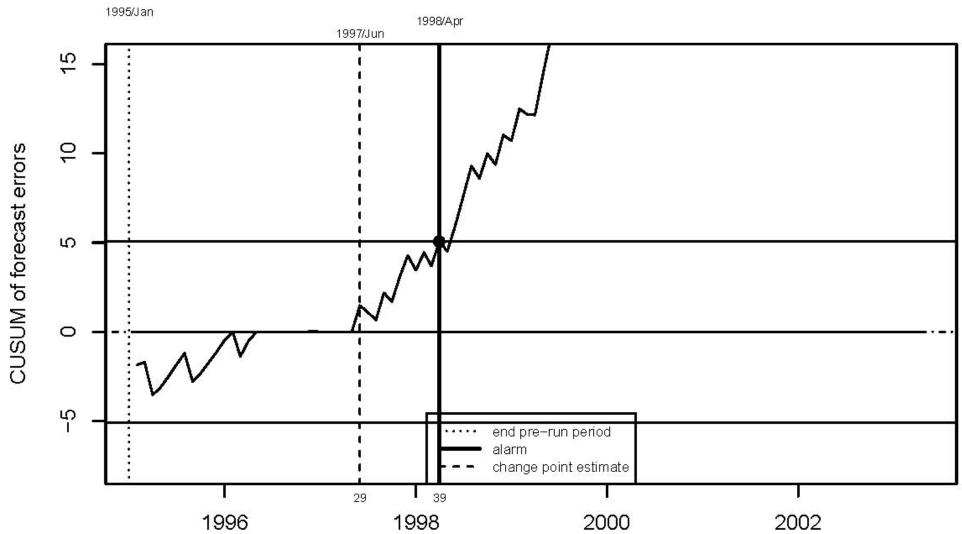
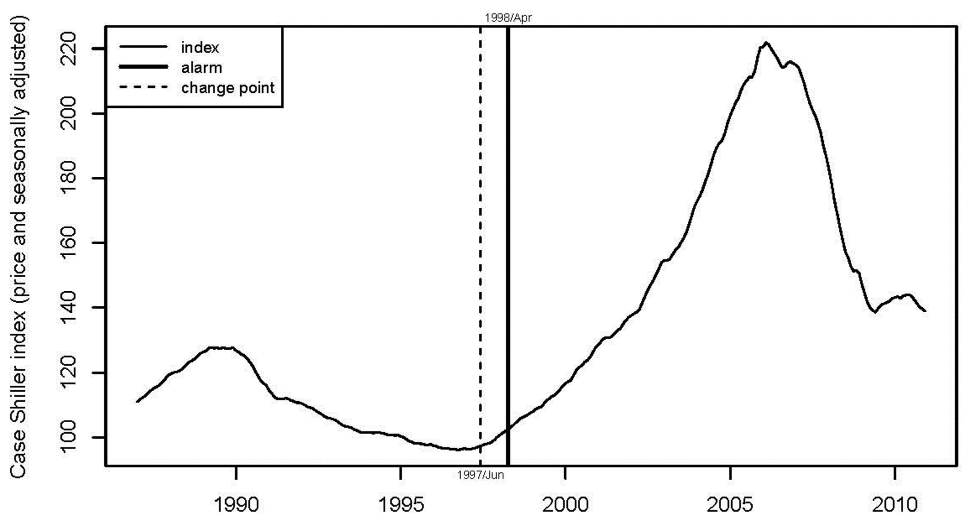


Figure 12: First CUSUM chart alarms marked along the Case Shiller house price series ($k = 0.5$).



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.

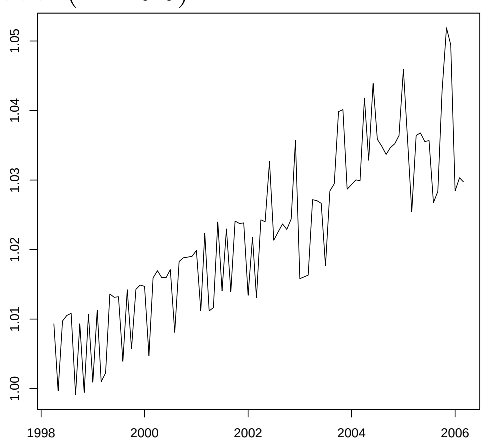
As in the EWMA approach, we find that the empirical residuals of the baseline model between the first alarm and the house price peak in 2006 follow a unit-root process (see Figure 13).[31]

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

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

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



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 with respect to different parameter specifications to the period 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 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 a natural candidate 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

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

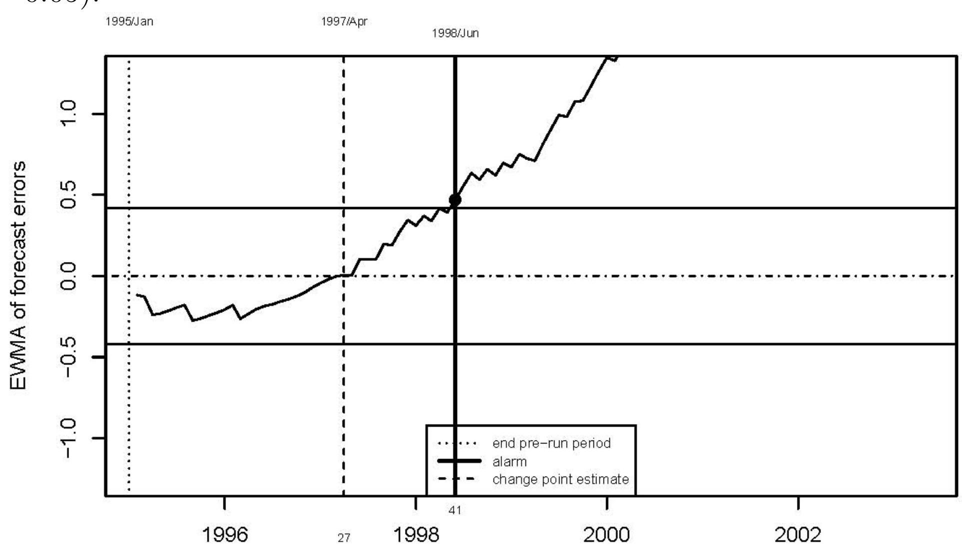

Figure 15: Residual EWMA chart for the initial model and the first alarm ($\lambda = 0.2$).

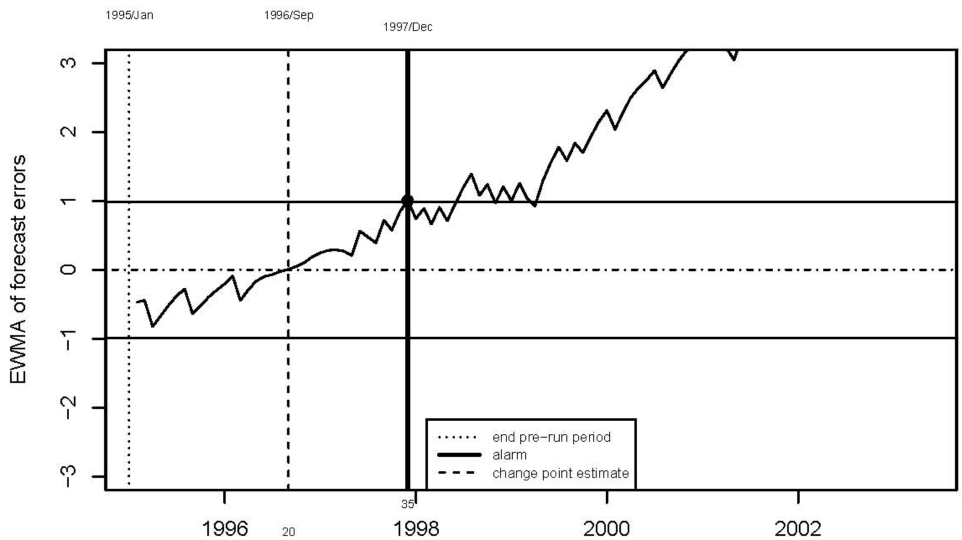

Figure 16: Residual CUSUM chart for the initial model and the first alarm ($k = 0.25$).

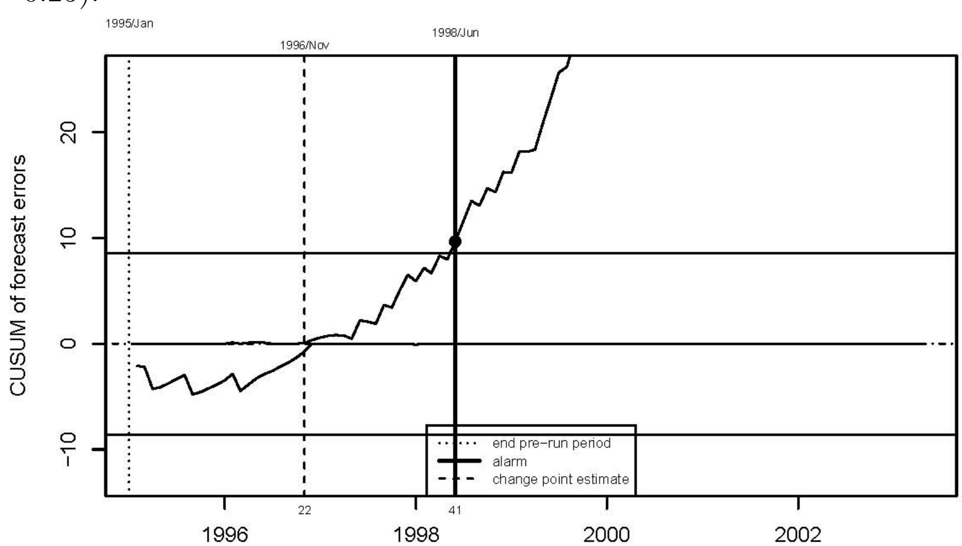

Table 9: ADF-test of house price forecast errors for the EWMA control chart ($\lambda = 0.1$).

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

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

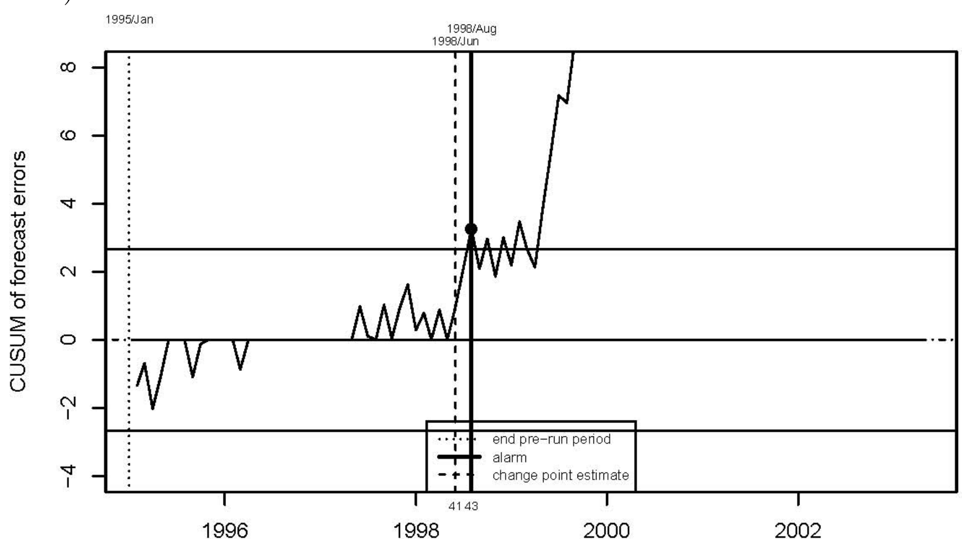

Table 10: ADF-test of house price forecast errors for the CUSUM control chart ($k = 0.5$).

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