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The regional pattern of the U.S. house price bubble - An application of SPC to city level data

JULIA FREESE

Zusammenfassung/ Abstract

The recent U.S. house price bubble and the subsequent deep financial crisis have renewed the interest in reliable identification methods for asset price bubbles. While there is a growing number of studies focussing on the detection of U.S. regional bubbles, estimations of the likely starting points in different local U.S. markets are still rare. Using regional data from 1990 to 2010 methods of Statistical Process Control (SPC) are used to test for house price bubbles in 17 major U.S. cities. Based on the EWMA control chart we also present estimations of the likely starting point of the regional bubbles. As a result, we find indications of house price bubbles in all 17 considered cities. Interestingly enough, the recent bubble was not a homogeneous event since regional starting points range from 1996 to 2002.

JEL-Klassifikation / JEL-Classification: C32, E44, R11

Schlagworte / Keywords: statistical process control, real estate, bubble, regional U.S. house prices

1 Introduction

During the last 15 years the U.S. real estate market was characterized by execptionally high appreciation rates of house prices. Between 1995 and 2005 the real national Case-Shiller house price index more than doubled. Since the mid of 2006 real estate prices began falling dramatically. What followed was the most severe crisis since the Great Depression hitting economies all over the world in a deep and sometimes longlasting way. Nowadays, there is a broad public consent that there was a huge bubble on the U.S. real estate market.

Due to the severe economic consequences resulting from bursting asset price bubbles, it is not surprising that there is a considerable literature concerned with the issues of bubble identification and early warning systems. In general, the different approaches can be classified into three groups: Indicator-based procedures, market-orientated analyses and econometric approaches.[1] The first group makes use of macroeconomic variables that are assumed to have a major impact on the considered asset price development such as the price-earnings ratio, price-to-income ratio or credit-to-income ratio.[2] Market-based procedures identify bubbles as significant deviations of the asset price from its long-term trend.[3] The econometric approaches include traditional cointegration tests as well as more advanced procedures such as Markov switching models or advanced state-space models for bubble identification.[4]

Although the existing identification procedures vary in their empirical approaches and clearly have virtues in detecting speculative bubbles, they mainly focus on expost identification rather than estimating the likely time point when the bubble

[1] For a more detailed description of the three classes of identification approaches see Berlemann, Freese and Knoth (2012), Gurkaynak (2008) or Mikhed and Zemcik (2009).

[2] See, e.g., Leamer (2002), Feldman (2003), Case and Shiller (2003) or Himmelberg, Mayer and Sinai (2005).

[3] See, e.g., Borio and Lowe (2002), Detken and Smets (2004) or Hülsewig and Wollmershäuser (2006).

[4] See, e.g., Campbell and Shiller (1987), Meen (2002), Funke and Sola (1994), Schaller and van Norden (2002) or Bhar and Hamori (2005).

started to develop. Up to now, there are only a few studies that tried to date the likely beginning of the recent bubble at the U.S. national level with the help of econometric approaches. Phillips and Yu (2011) date the likely starting point of the bubble with the help of a recursive regression method. Using a sequential right-sided unit root test they estimate the beginning 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 result found by Phillips and Yu (2011). Berlemann, Freese and Knoth (2012) proposed the application of methods of Statistical Process Control (SPC) to detect house price bubbles and especially, to estimate their likely starting points. Their results indicate, that the methods of SPC are useful in dating the likely beginning of the recent U.S. house price bubble. They find indications of price overvaluations at the national level as early as in between the end of 1996 and the first half of 1998.

While these studies focus on dating the bubble at the U.S. national level, regional differences in house price developments have usually been neglected. The recent bubble is often seen as a national and homogenous event that occured in different U.S. regions at roughly the same point of time. However, having a closer look at local house price dynamics during the last 15 years reveals that prices developed quite differently across regional markets. While some U.S. regions experienced high appreciation rates of house prices, others did not. Thus, a regional analysis of house price bubbles seems to be useful to account for local specifities of real estate markets and to deepen the understanding of the anatomy of the bubble and its spread across local markets. In the literature, estimations of the likely starting points in different local U.S. markets remain rare. Interestingly enough, to the best of our knowledge, there is only one empirical study that provides estimations of the likely beginning of the recent bubble at the regional level with the help of

econometric approaches.[5] We summarize this literature in section 2 of this paper. As proposed in Berlemann, Freese and Knoth (2012), methods of SPC are not only useful in detecting the recent U.S. house price bubble expost but also to date its likely beginning at the U.S. national level. In general, SPC is able to identify change points in time series of any kind and thus can be highly useful in dating the beginning of bubbles in financial markets. Interestingly enough, the bubble identification scheme also comes with an embedded estimator of the likely starting point. In this paper, we apply the methods of SPC to U.S. regional data. Using Case-Shiller house price data for 17 major U.S. cities, methods of SPC are used to examine whether past house price dynamics were in line with economic fundamentals or showed indications of house price bubbles. For every sample city we provide estimations of the likely starting point of the bubble. By doing so, we draw a likely time line across local U.S. markets and thus deliver a regional pattern of the recent U.S. house price bubble.

The paper is organized as follows: Section 2 gives a brief overview of the related literature followed by a short analysis of regional house price dynamics in major U.S. cities in section 3. The methods of SPC are presented in section 4. Section 5 explains the estimation approach and data before the results are shown in section 6. Section 7 contains some robustness checks of our baseline approach. Section 8 concludes.

2 Literature review

Throughout the last decade there is a growing interest in studying house price dynamics and especially bubbles at the U.S. regional level. This literature applies different identification methods to local U.S. data in order to test for anomalities in regional house price developments. Roughly speaking, the existing studies can

[5]The other study we found rather focusses on detecting the starting point of regional house price *booms* rather than *bubbles*. For a more detailed review of these approaches see section 2.

be divided into two groups: Studies that focus on the detection of regional bubbles using traditional identification methods and second, recently developed approaches that provide estimations of likely starting points of house price bubbles at the regional level.

The first group of studies draws a quite heterogeneous picture concerning the existence of regional house price bubbles in the U.S. throughout the last years. While a number of studies supports the existence of local bubbles, others conclude that regional price dynamics were rather due to fundamental developments than speculative behaviour.

Case and Shiller (2003) was one of the first studies concerned with house price developments at the regional level. The study finds a number of U.S. states that exhibited a bubble during the last years. As observed regional house prices between 2000 and 2002 clearly exceeded the fundamentally justified levels resulting from linear regressions, Case and Shiller draw the conclusion that bubbles existed in all eight states that are considered in their study.[6] There is also a number of studies applying traditional unit root and cointegration procedures to regional U.S. data. Clark and Coggin (2010) use quarterly data on the four U.S. census divisions from 1975 through 2005 and run several variants of unit root and cointegration tests with national and regional data. Their findings support the existence of a house price bubble both at the national and regional level. Based on panel unit root and cointegration tests, Gallin (2003) uses quarterly data from 1975 to 2002 and finds no long-run relationship between house prices and fundamentals such as per capita income, population and the stock market at the national level. The same holds for U.S. city-level data on 95 metropolitan areas. Using semi-annual data from 1990 to 2005, Mikhed and Zemcik (2009) come to similar results. Since house prices and rents in the U.S. Metropolitan Statistical Areas (MSAs) turned

[6]Case and Shiller (2003) run linear regressions on house price dynamics in Hawaii, Connecticut, New Hampshire, California, Rhode Island, Massachusetts, New Jersey and New York. The fundamental value of house prices is measured by personal income per capita, population, employment, housing starts and mortgage rates on state level.

out to be non-stationary and not cointegrated, they confirm the presence of a house price bubble in their panel data. Nneji, Brooks and Ward (2012) conduct regime-switching models for nine U.S. census divisions for the period 1991 to 2010. Their findings suggest that six regions were characterized by speculative bubbles (Mountain, Middle Atlantic, New England and West North Central, Pacific and South Atlantic regions) while there is no evidence of significant overvaluations in the East North Central, East South Central and West South Central region. Based on a standard equilibrium housing model, Füss, Zhu and Zietz (2011) derive the fundamental house price development in 20 major cities between 1998 and 2008. In a second step, the observed house price is decomposed into the fundamental part resulting from the equlibrium model and the regional bubble component which is defined as the deviation of the observable housing price from its fundamental value. Their results indicate that bubbles tend to appear more likely in coastal regions that are usually characterized by higher income levels and lower unemployment rates than interior regions.[7] Goodman and Thibodeau (2008) follow a similar approach and derive the equilibrium level of the owner-occupied housing stock and house prices from a simple housing market equilibrium models for 84 MSAs. A bubble in a specific market is assumed to occur if the actual house price is more than 30% higher than predicted by the model. By doing so, they find indications of bubbles in 39 areas in the period 2000 to 2005.[8]

Besides those studies that find indications of regional bubbles, there is also a number of studies that come to quite contrary results. Holly, Pesaran and Yamagata (2010) use annual U.S. state level data from 1975 to 2003 and test for a long-run relationship between house prices and real income. The results indicate that house

[7]To be more precise, indications of house price bubbles are found in Los Angeles, Miami, Tampa, Washington, Las Vegas, Phoenix and San Diego while real estate prices in Charlotte, Cleveland, Dallas, Denver and Boston seem to be in line with economic fundamentals.

[8]Regarding the cities that are considered in our approach, bubbles are found in Los Angeles, San Diego, Miami, Las Vegas, Tampa, Washington, San Francisco, Phoenix and Minneapolis. In Seattle, Portland, Charlotte, Denver and Chicago they find no indications of house price bubbles during 2000 and 2005.

price dynamics were in line with fundamental developments except for California, New York and Massachusetts. Smith and Smith (2006) calculate net present values for single-family houses as fundamental house price measurements in ten MSAs. Since there is no city where actual prices are far above fundamentals in 2005, the presence of house price bubbles is ruled out.[9] Himmelberg, Mayer and Sinai (2005) provide indices of imputed-to-actual-rent ratios for 46 MSAs for the period 1975 to 2004 and compare them to their 25-year average values. Their finding does not suggest widespread or large mispricings in 2004 and thus little indications of significant speculative overvaluations in nearly any of the considered local markets.

Although there is thus a number of studies that try to detect house price bubbles at the U.S. regional level which clearly have their virtues in detecting speculative bubbles, they mainly focus on expost identification of asset price bubbles. Thus, they are less useful in providing estimations of the likely starting point of bubbles in different U.S. local markets. To the best of our knowledge, there are only two studies trying to estimate local starting points in different U.S. regions with the help of econometric approaches. What is more, only one of these papers explicitly focuses on dating the beginning of regional house price *bubbles* rather than *booms*. It is important to mention that both terms essentially do not describe the same phenomena.[10] On the one hand, high growth rates of house prices can be driven by economic fundamentals. On the other hand, high growth rates in a specific period do not imply that the *bubble*, if identified, started to build up in the same period. Thus, the starting point of a house price *bubble* can differ significantly from the starting point of a house price *boom*.

Based on a purely descriptive analysis, Shiller (2007) argues that the recent house price *boom* was rather a national than a regional event since significant price growth

[9] On the contrary, there seems to be a number of cities where house prices are undervalued, e.g., Atlanta, Dallas, New Orleans and Indianapolis.

[10] While the term house price *boom* has a less negative significance and is more linked to good investment opportunities than high house prices sustained by speculative behavior, the term *bubble* does clearly state that current prices are overvalued due to irrational expectations, see Case and Shiller (2003).

rates appeared in a number of major U.S. cities in the period between 1998 and 2005. Based on regional growth rates of house prices in major U.S. cities, Shiller states that the *boom* showed its first beginning in some western cities such as San Diego, Los Angeles, San Francisco and Seattle in 1998 with high growth rates of more than 10% per year. Only one year later the *boom* became apparent in Denver and Boston. In 2001, Miami, Minneapolis, New York and Washington were characterized by price inreases around 10% per year. Las Vegas and Phoenix followed in 2004 (respectively 2005) with annual growth rates of 49% and 43%. Shiller (2007) also finds some cities that did not experience a house price *boom*. In Atlanta, Charlotte, Chicago, Cleveland, Dallas and Detroit annual house price growth rates were at a moderate level since 1998.

Another paper that focusses on the detection of the starting point of house price *booms* at the regional level is the approach of Ferreira and Gyourko (2011). In contrast to Shiller (2007) their study is based on an econometric approach with more than 23 million single-family housing transactions in 94 metropolitan areas. In a first step, they construct constant quality house price series using hedonic regressions. The house price is modeled as a function of square footage, the number of bedrooms, the number of bathrooms and the age of the home. By normalizing the estimated index to 100 in 2000, they provide the developments of house prices for 94 metropolitan areas across 29 states from 1993 to 2009. After calculating the corresponding year-on-year growth rates of the house price series, Ferreira and Gyourko (2011) estimate the quarter during which there is a global structural break in the quality-adjusted price appreciation rate series. The estimated global breakpoint is dated to the quarter in which the change in the price growth series had its greatest impact on explaining the price growth series itself. By doing so, they estimate the location of potential structural breaks that can be interpreted as likely starting point of the *boom* and construct a timeline for the recent house price *boom*. As a result, they find that the start of the *boom* was not a homogeneous event since it began at different times in different regions over a decade-long

period from 1995 to 2006. Regarding the U.S. cities that are also considered in our approach, Ferreira and Gyourko (2011) find first indications of the *boom* in Los Angeles in 1997 followed by Chicago in 2000/2001. The *boom* then spread to New York and Washington in 2002 as well as Las Vegas and Tampa in 2004. In 2005 and thus only one year before the national house price peak, the *boom* started in Phoenix, Portland and Seattle. 15 metropolitan areas inlcuding Cleveland did not experience a significant house price *boom*. Similar to Shiller (2007), the study of Ferreira and Gyourko (2011) rather focusses on dating the beginning of the house price *boom* rather than the *bubble* and is thus less comparable to our approach. Since they find that income is a major demand shifter that is strongly correlated with the timing and magnitudes of the beginning of local housing *booms*, at least the start of the *boom* was fundamentally justified by demand conditions and can not be seen as the corresponding starting point of regional *bubbles*.

To the best of our knowledge, there is only one study that explicitly provides estimations of the likely beginning of house price *bubbles* in the U.S. regions with the help of econometric approaches. Pavlidis et al. (2009) follow the more recently developed method of Phillips and Yu (2011) who conducted a recursive regression methodology for dating purposes. The approach is based on a sequential right-sided unit root test that analyses period by period whether a time series follows a unit root. A main advantage of the recursive procedure is the possibility to estimate the starting point of an upcoming house price *bubble*. Pavlidis et al. (2009) apply these tests to twenty U.S. cities for that Case-Shiller house price data are available over the period from 1987:M01 to 2008:M06. As a result, they find indications of house price *bubbles* in ten major U.S. cities that originated between 1996 and 2007. The house prices in Los Angeles, San Diego, San Francisco, Denver, Washington, Boston, Charlotte, New York, Cleveland and Portland indicate no sign of significant house price overvaluations. Regarding the regional timeline of house price bubbles across the U.S., first indications of overvaluations are found in Detroit (1996) and Atlanta (1997). One year later, *bubbles* appeared in Seattle and Minneapolis. In

the following years, *bubbles* emerged in a number of cities such as Phoenix (1999), Chicago (2001), Las Vegas (2002), Miami (2003) and Tampa (2004). First signs of a house price *bubble* appeared in Dallas in 2007 and thus almost one year after the national house price peak in 2006.

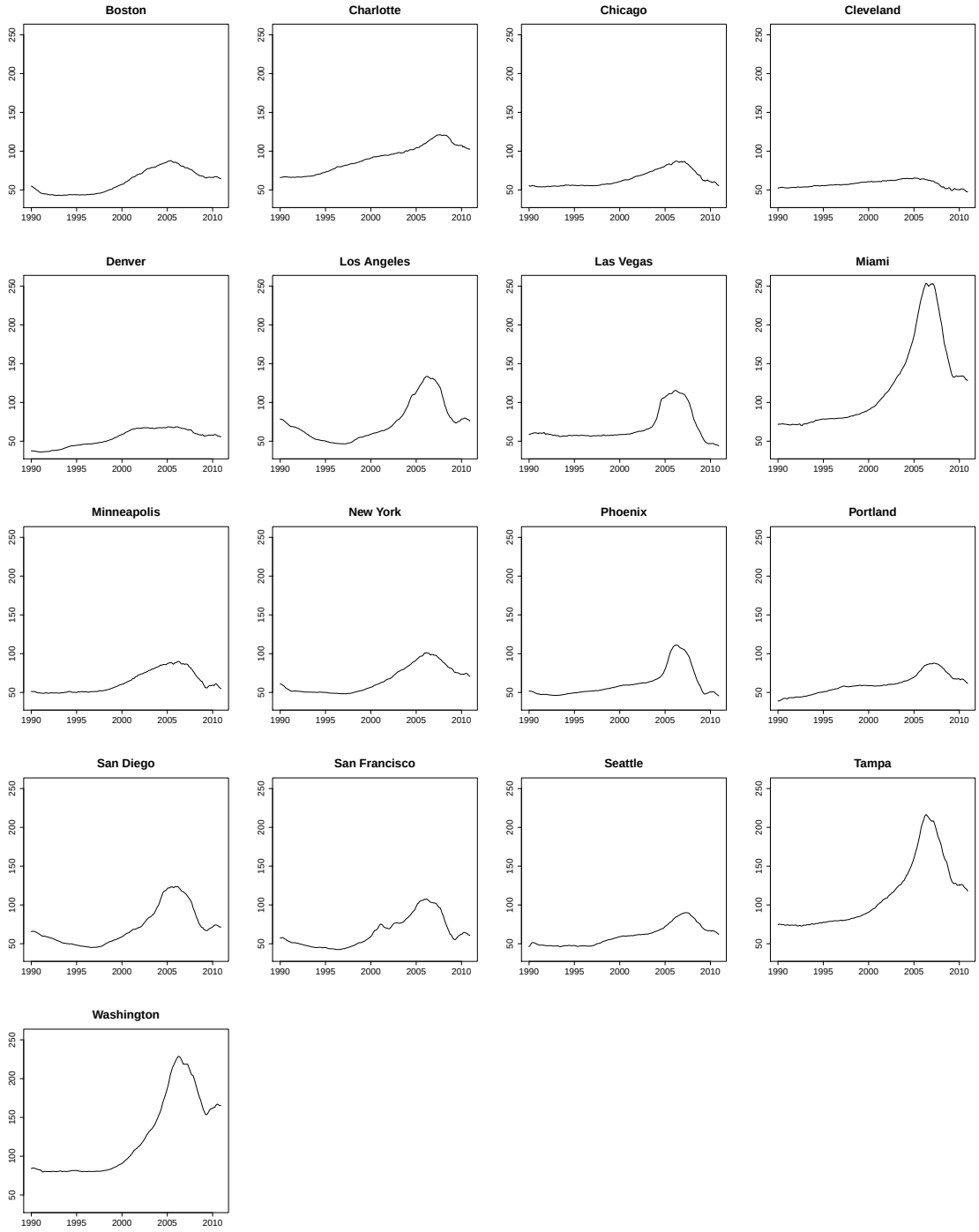
3 Regional house price dynamics

From 1995 trough 2005 aggregate house prices in the U.S. increased by 7.8% per year in real terms and in the period between 2000 and 2005 price appreciation rates with 11.4% per year were considerably higher. Taking a closer look at U.S. regional price dynamics reveals significant spatial heterogeneities across local real estate markets. While some regions were characterized by high appreciation rates, others did not experience sharp house price increases since the 90s (see Figure 1).

Table 1 reports main statistics of house price dynamics in all 17 major cities from 1990 to 2005. The highest real appreciation rates since the 1990s can be found for the real estate developments in Miami. Here, house prices increased by 7.5% per year and peaked to the end of 2005. In some other southern cities such as Tampa and Washington annual grwoth rates were above 6% per year. On the contrary, house prices in some midwest cities such as Cleveland and Chicago appreciation rates of 1.34% respectively 2.77% per year were even lower than the national average in the same period (3.66% per year). In other northeast cities for which we have data (Boston, New York), growth rates were almost in line with the national average price development.

When inspecting the time series of regional house price developments in these major cities one might have the impression that the house price bubble is easy to detect without having to use any empirical method. One might conclude that cities as Miami, Tampa and Washington experienced house price bubbles while

Figure 1: Regional house price dynamics in 17 major U.S. cities 1990-2010



Monthly data on Case-Shiller house prices in 17 major U.S. cities are seasonally adjusted and deflated by corresponding regional CPIs in the four U.S. census regions (Northeast, South, Midwest and West) (source: Standard & Poor's 2012, BLS 2012).

Table 1: Real house price indices in 17 major U.S. cities 1990-2005

City	**Trough**	**Peak**	**Growth per year 1990-2005 in %**
West			
Seattle	46.9	76.6	2.91
Los Angeles	47.0	122.2	3.25
Portland	40.9	75.2	4.14
Denver	36.4	68.1	4.15
Las Vegas	56.6	110.5	4.15
San Diego	45.6	122.6	4.35
San Francisco	42.8	122.6	4.35
Phoenix	46.6	95.9	4.38
Midwest			
Cleveland	53.0	64.7	1.34
Chicago	54.1	83.0	2.77
Minneapolis	49.2	87.8	3.75
Northeast			
New York	48.6	96.1	3.47
Boston	43.2	86.6	3.55
South			
Charlotte	66.4	106.5	3.18
Tampa	73.3	181.5	6.11
Washington	80.2	207.5	6.23
Miami	71.4	213.5	7.51

Monthly data on Case-Shiller house prices in 17 major U.S. cities are seasonally adjusted and deflated by corresponding regional CPIs in the four U.S. census regions (Northeast, South, Midwest and West) (source: Standard & Poor's 2012, BLS 2012).

prices in, e.g., Cleveland and Chicago would not cause people to worry about possible overvaluations. However, this impression is somewhat misleading since high growth rates can be driven by purely fundamental causes such as changing income conditions, interest rates or inflation. Before being able to develop an identification scheme for asset market bubbles it is therefore necessary to estimate the underlying fundamental house price process that might be helpful to judge whether house price dynamics steam from changing economic conditions or speculative behaviour.

4 Statistical Process Control

Originally, methods of SPC have been used for the control of production processes to detect anomalies in quality performance quite early. However, recently Berlemann, Freese and Knoth (2012) proposed the application of SPC to detect house price bubbles and especially to estimate the likely starting point of such a bubble.[11] One of the primary techniques of SPC is the use of so-called control charts which plot the averages of quality measurement characteristics in samples taken from the process over time. Control charts are a powerful tool to distinguish between the natural and excess variability of a process. Every control chart has upper and lower control limits which are determined from statistical considerations. A process is said to be 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 observer should then be required to investigate the process and undertake some corrective action to remove unusual sources of variability.[12] While econometric approaches look at typical measures of testing theory (size, power, error probabilities) typical performance measures within SPC are certain types of the expected time to signal. The most popular measure is the Average Run Length (ARL) measuring the time until a signal occurs for a process which is always unchanged or changed already at the beginning.

In this paper, methods of SPC are implemented similar to Berlemann, Freese and Knoth (2012): First, we choose suitable models to describe past house price developments in 17 major U.S. cities individually. Therefore we use a Vector Autoregressive Model (VAR) that also contains an equation explaining the behavior of house prices which is then utilized to create new house price residuals for the so-called monitoring period in each city. Whenever a change in the process generating house prices occurs (e. g., in the model parameters) the residuals will reflect this.

[11] See also Berlemann, Freese and Knoth (2012) for a more detailed description of SPC methods.
[12] See Montgomery (2005).

The most simple cases are shifts in the mean or in the scale of the residuals. The control charts are set up for these residuals.

By now, one can find a large number of different kinds of control charts in the literature of SPC which have been developed or enhanced during the last years. Here, we use the EWMA (Exponentially Weighted Moving Average) approach that was introduced by Roberts (1959) and was intensively discussed in Lucas and Saccucci (1990). In order to design the chart it is assumed that the behavior of the residuals is well described by a normal distribution. Assume a stream of empirical residuals ε_t which is independent and normally distributed with mean 0 and variance σ^2. Then, the design of the control chart is given by a certain sequence of statistics and a stopping time L. The EWMA series $\{Z_t\}$ is defined as:

$$Z_0 = z_0 = 0,$$

$$Z_t = (1-\lambda)Z_{t-1} + \lambda\varepsilon_t\,, t = 1, 2, 3...$$

The EWMA control chart includes all past data points 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

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

$\lambda \in (0, 1]$ is a sensivity parameter determining the historical importance of past data points. For the control chart this parameter has to be determined to calculate the corresponding alarm threshold value c_E.[13] The parameter is set by the user to most rapidly detect a shift μ_1 in the residuals' mean. There is no explicit relationship between μ_1 and λ. Even more, the optimal λ also depends on the in-

[13] We used the R library spc to calculate this threshold.

control ARL. In the corresponding literature, the smoothing parameter λ is usually chosen in the interval $0.05 \leq \lambda \leq 0.25$. In practice, $\lambda = 0.05$, $\lambda = 0.10$ and $\lambda = 0.20$ are popular choices.[14] As also done in Berlemann, Freese and Knoth (2012), we set λ to the average value 0.10 and the in-control ARL $A = 500$.

An alarm can be interpreted as an indication for a structural break which occured in the past. Interestingly enough, we can estimate the likely change point of the process which is highly useful for dating purposes. The EWMA chart comes with an embedded estimator of the change point which is given by:

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

In an evaluation of this estimator Nishina (1992) concludes that it performs suciently well. We use this change point estimator in order to date the likely beginning of the recent house price bubble at the U.S. regional level.

5 Data and estimation approach

The estimation approach followed in this paper consists of several steps. First, we estimate the fundamental relationships explaining regional house price developments for a baseline period. To account for regional specifities of local real estate markets, regional models are estimated for major U.S. cities separately. The estimated coefficents of the regional models are used to generate recursive forecasts of house prices in each city. Using methods of SPC enables us to examine whether a specific city experienced a house price bubble and to date its likely starting point. In a first step, we need an appropriate model to explain house price dynamics. In the corresponding literature, it has become standard to use a VAR approach to describe house price dynamics by macroeconomic fundamentals without deal-

[14] See Montgomery (2005), Berlemann, Freese and Knoth (2012).

ing with problems of endogeneity or describe a complex structural model of the macroeconomy.[15] Thus, 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.

House price developments are usually described by a variety of macroeconomic variables such as current business activity, inflation, monetary policy decisions, the stock market and the unemployment situation.[16] Since regional house price developments differ across markets mainly due to local economic distinctions, our models include, if available, city-level data.[17] The sample consists of monthly data ranging from 1990:M01 to 2010:M12. Thus, our empirical analysis starts well in advance of the recent house price bubble.[18]

Regional house price measures

First, we need an appropriate measure of regional house price dynamics. The S&P/Case-Shiller U.S. national house price index is a repeat-sales index which measures the value of single-family housing for the whole U.S. and is calculated by Standard & Poor's at monthly frequency. Besides national values, the index is also measured in 20 major cities in the U.S. at monthly frequency since 1987. Due to confined data availability, three cities are excluded from our empirical analy-

[15] See, e.g., Belke, Orth and Setzer (2008), Assenmacher-Wesche and Gerlach (2010), Dreger and Wolters (2009), Adalid and Detken (2007), Demary (2009), Jarocinsky and Smets (2008) or Goodhart and Hofmann (2008).

[16] See, e.g., Dreger and Wolters (2009), Goodhart and Hofmann (2008), Baffoe-Bonnie (1998) or Kuethe and Pede (2011).

[17] For a more detailed analysis of regional house price determinants see, e.g., Abraham and Hendershott (1992), Reichert (1990) or O'Donovan and Rae (1997).

[18] A detailed description of the data can be found in the appendix.

sis.[19] Thus, we estimate 17 city-level VAR models for which we have data since 1990:M01: Boston, Charlotte, Chicago, Cleveland, Denver, Las Vegas, Los Angeles, Miami, Minneapolis, New York, Phoenix, Portland, San Diego, San Francisco, Seattle, Tampa and Washington.

National production index

Since data on gdp are neither available at monthly frequency nor at the city level, we use the national index of industrial production to capture current business activities in the U.S. economy. The corresponding data steam from the OECD database.

National interest rate

To account for national monetary policy decisions, we include the national interest rate measured by the short-term market rate.[20] The data is taken from the OECD database.

National stock price

We use the Dow Jones Industrial Average Index to account for stock market developments.[21] Corresponding data steam from the EUROSTAT database.

Regional mortgage rate

Besides the national short-term interest rate, mortgage rates are often included as a measurement for long-term interest rate developments since they play an important role in buy-versus-rent decisions.[22] Interestingly enough, mortgage rates are

[19]Since Case-Shiller house prices for Texas are not available before 2000:M01, Texas is not included in the empirical analysis. Data for Atlanta and Detroit are available since 1991:M01. To keep comparability between the regional models and avoid falsifications due to different sample sizes we refrain from estimating regional models for both cities.

[20]See, e.g., Berlemann and Freese (2012), Jarocinsky and Smets (2008), Goodhart and Hofmann (2008) or Assenmacher-Wesche and Gerlach (2010).

[21]See, e.g., Assenmacher-Wesche and Gerlach (2010), Belke, Orth and Setzer (2008) or Sutton (2002).

[22]See, e.g., Reichert (1990), Baffoe-Bonnie (1998), Fratantoni and Schuh (2003), Apergis (2003) or Del Negro and Otrok (2007).

even available at the U.S. regional level. The nation's largest publisher of mortgage and consumer loan information, HSH.com, releases data on the 30-year-fixed-rate mortgage on state and even city level at monthly frequency. We collect all time series of mortgage rates for our 17 major cities since 1990:M01.[23]

Regional unemployment rate

We also include regional unemployment rates in our city-level VAR estimations. Since the employment status of a household tends to be a major driver of the ability to purchase a home, the unemployment rate in a specific region is thus a potentially important determinant of demand for housing.[24] The Bureau of Labour Statistics (BLS) offers data on unemployment rates for all MSAs since 1990 at monthly frequency. For all 17 major cities we use the monthly unemployment rate for the corresponding MSA the city is located in.

Regional inflation

Last, we employ local inflation rates in our VAR models to capture changes of the aggregate price levels in a specific region. Since corresponding time series are not calculated on the city-level we decide to use inflation rates measured for the four U.S. census regions Northeast, South, Midwest and West at monthly frequency. Data are provided by the BLS.

All time series enter the regression in seasonal adjusted form.[25] We estimate our

[23]In the case of Tampa and Minneapolis mortgage rates are not available at the city level, so we switched to state values for Florida and Minnesota in both models. For Portland and Las Vegas, both metro-level and state-level time series are available since 1993 respectively 1991, so we decided to use national mortgage rates for both cities (source: HSH.com).

[24]See, e.g., Reichert (1990), Baffoe-Bonnie (1998), Miller and Peng (2006) or Kuethe and Pede (2011).

[25]Here, the Census X12 approach has been applied except for the interest rate and mortgage rate. Regional Case-Shiller house prices are only available in seasonally adjusted form using the Census X-11 procedure. Data on production are available in seasonally adjusted form whereby the Census X12 approach has been applied. Regional inflation rates base on the seasonal adjusted regional CPI time series. Data on regional CPI steam from the BLS data base. National share prices and regional unemployment rates have been adjusted with the Census X12 approach after

VAR models in levels which has been become a common approach to model house price dynamics and macroeconomic fundamentals.[26] Data on regional house prices enter the regressions in real terms after deflating them by the CPI of the corresponding U.S. census region (Northeast, South, Midwest and West). National data on production and shares are deflated by the national CPI time series.[27] Regional house prices, national production and stocks are taken in logs.

Thus, our regional models include three national variables and four regional variables to describe house price developments over time: Regional house prices (hp_r), national production ($prod_n$), national interest rate (i_n), national share price (s_n), regional mortgage rates ($mort_r$), regional unemployment rates (u_r) and regional inflation (p_r). The vector of endogenous variables x takes the following form:

$$x = (hp_r, prod_n, i_n, s_n, mort_r, u_r, p_r) \ .$$

In a second step, we have to decide on the fitting period. In order to determine the appropriate lag lenth of the VAR models, we try different sample sizes while we allow for a maximum lag length of six months. According to the Schwarz criterion one lag turned out to be the appropriate lag order for all 17 estimations and different sample sizes. Since we have data for all 17 major cities since 1990:M01, we choose the baseline period to be 78 months which is presumably sufficient for VAR estimations.[28] Thus, we estimate our baseline VARs from 1990:M01 to 1996:M06.[29]

Next, we check for unit roots of the national and regional time series.[30] Augmented Dickey-Fuller tests reveal that the national variables follow a unit root

extracting them from the corresponding database.

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

[27]Data on national CPI steam from the BLS data base and are seasonally adjusted.

[28]The VAR models are estimated by using the R package vars (version 1.5-0).

[29]To check for robustness of our estimations, we also try some variations of the baseline period. For a more detailed view see section 7.

[30]Hereby, a linear time trend or at least a constant are included in the test equations.

process. Regional inflation and mortgage rates turned out to be non-stationarity for all 17 cities. The same holds for the city-level unemployment rates. Regional house prices in 14 cities follow a unit root process while house prices in Boston, Denver and New York are stationary. Regarding the time series that follow a unit root, augmented Dickey-Fuller tests reveal that these variables are I(1).[31] While a VAR model specified in levels is appropriate if all variables are I(0), estimating a model with unit root variables can lead to spurious regression problems. In such a framework, OLS estimations in levels can result in biased VAR results.[32] One possible solution might be the use of first differences in the VAR model. Indeed, this solution implies a loss of information contained in level variables since long-term components of time series are not regarded.[33] However, 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 coefficent 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.[34] Thus, Hamilton (1994) supports the view of Sims, Stock and Watson (1990) to estimate a VAR model in levels since the parameter of the system are estimated

[31] Here, neither a constant nor a deterministic or stochastic trend is included in the test equation.

[32] See, e.g., Sims (2001), Granger and Newbold (1974).

[33] See, e.g., Sims (1980).

[34] Regardless the existence of cointegration relations, Hamilton (1994) shows that the usual t and F tests in a VAR in levels containing unit roots are asymtotically valid. However, this is not the case for Granger-causility 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 has the standard distribution, see Watson (1994) or Sims, Stock and Watson (1990).

consistently.[35]

Since the Johansen trace statistics indicate that all 17 regional models contain up to four cointegration relations, estimating the regional VAR models in levels seems to be justified.[36]

Since we are interested in studying the development of house prices, the referring VAR equation is of special interest.[37] For all 17 models we find a positive and significant effect of the lagged value of regional house prices which is mainly due to the sluggish development of house prices. In almost all models we find that other variables have a significant impact on regional house price developments:[38] In 10 of 17 cities we find a significant negative effect of the local unemployment rate on the level of house prices in the corresponding city.[39] The employment status of a specific region is a major driver of local demand for housing since increasing unemployment tends to dampen the household's income position und thus leads to decreasing demand for housing. Given a constant level of the local housing stock, a negative demand shift decreases local house prices.[40] What is more, for the case of five cities (Boston, Cleveland, San Francisco, Seattle and Washington) the short-term interest rate has a negative impact on house prices. A restrictive monetary policy shock increases the household's costs of financing real estate and thus re-

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

[36]See also Dreger and Wolters (2009), Assenmacher-Wesche and Gerlach (2010), Belke, Orth and Setzer (2008) and Giuliodori (2005). In each regional model, we include a linear time trend in the cointegration equation. We find one cointegration relation for the model of Miami and two for the models in Chicago, Cleveland, Minneapolis, Tampa and Portland. Test results reveal three cointegration relations in Boston, New York, Charlotte, Washington, Los Angeles, Phoenix and Seattle. Four relations are found in Denver, Las Vegas, San Diego and San Francisco. We refrain from presenting the unit root and cointegration tests of all 17 models here in length. Detailed results can be provided by the author on request.

[37]For a detailed view of the estimation results of the house price equation, see Table 5 in the appendix. We refrain from reporting all estimation results of the VAR models here and rather focus on the house price equation as basis for the following application of SPC. Detailed estimation results can be obtained from the author upon request.

[38]In the case of three models (Miami, Minneapolis and New York) only the lagged house price variable has a significant effect.

[39]These cities are Charlotte, Chicago, Denver, Phoenix, Portland, San Diego, San Francisco, Seattle, Tampa and Washington.

[40]See, e.g., Apergis (2003) or Baffoe-Bonnie (1998).

duces housing demand.[41] Regarding the impact of the national production index and stock price developments, the results are somewhat heterogeneous: While for three models (Chicago, Seattle and Washington) production has a positive significant impact on house prices, in two cities (Los Angeles and Las Vegas) the opposite is true. The same holds for the effect of increasing stock prices: In Charlotte and Los Angeles higher share prices tend to increase house prices while for Seattle and Washington we find a significant negative effect. Since our VAR models form the basis of the subsequent application of SPC, we tested for the plausibility of the models by running impulse responses for each of the 17 cities. Thus, we analysed the long-run effect of the production index, interest rate, share prices, mortgage rates, unemployment rates and inflation on house prices in a specific city.[42] Regarding unemployment and interest rates, the impulse responses confirm the findings of the VAR estimation results in the long-run. While the VAR models provide quite heterogeneous results for the national production index, impulse responses point into the direction that higher production tends to increase regional house prices in the long-run, see, e.g., Chicago, Cleveland, Minneapolis, San Diego, Las Vegas and Washington.[43] This finding is also in line with existing empirical studies on house price dynamics and macroeconomic fundamentals.[44] Stock price developments turn out to have little impact on house prices in the long-run. Only for two cities (Cleveland and Phoenix) we find a positive and significant impact on house prices. Interestingly enough, regional developments of the aggregate price level seem to play an important role for local house price developments in the long-run. In 11 regional models we find a negative impact of regional inflation on house price developments. In the literature, one can find several explainations for this result.

[41] See, e.g., Sutton (2002), Rüffer and Stracca (2006) or Demary (2009).

[42] Here, we assumed that the variables effect house prices with a lag of one month. The impulse responses are studied over a period of 25 months.

[43] Interestingly enough, in the case of Las Vegas, the negative impact found in the VAR estimation results does not apply in the long-run. The same holds for Los Angeles: Here, we find a positive although insignificant effect.

[44] See, e.g., Sutton (2002), Goodhart and Hofmann (2008) or Adams and Füss (2010).

On the one hand, higher inflation rates should cause the central bank to raise the interest rate which leads to lower demand for housing. On the other hand, high inflation increases the real value of loan repayments and thus dampens housing demand.[45]

Altogether, the VAR estimation results and the corresponding impulse responses reveal that regional house price developments are driven by a number of regional and national variables such as employment, interest rates, production and inflation. In a next step, the estimated coefficients of the regional VARs are used to generate forecasts of regional house prices: Focussing on the house price equation, the estimated coefficients are used to generate forecasts of the city-level house prices throughout the monitoring period. By doing so, we obtain a time series of house price forecasts for each city from 1996:M07 to 2010:M12. Subtracting the forecasts from the realized values leads to the referring time series of residuals in the monitoring period in each city. In order to detect a house price bubble in the regional data, we apply methods of SPC on the time series of residuals from the regional Case-Shiller house price equation. Starting out from 1996:M07 we calculate the values of the EWMA chart and study whether and when the chart generates the first alarm. Whenever the EWMA series exceeds the corresponding upper threshold value, this can be interpreted as a sign for an upcoming house price bubble because actual house prices are significantly higher than predicted by the model.[46] Given the alarm, we also estimate the corresponding change point for each city. This time point can be interpreted as a structural break and thus as likely starting point of the bubble in the corresponding city. As a result, we obtain a chronology of the regional pattern of the recent U.S. house price bubble.

[45] See, e.g., Demary (2009), Debelle (2004) or Tsatsaronis and Zhu (2004).

[46] Analogous, negative alarms indicate negative bubbles: Current house prices are lower than predicted by the model. Here, we leave out the lower alarm since we are interested in detecting overvaluations of house prices in regional markets.

6 Results

In the following, we study whether and when the EWMA control chart for the 17 city-level house price developments exceeds the upper alarm threshold the first time. Table 2 shows the estimated starting points of the house price bubble for each city resulting from the EWMA procedure.[47]

Table 2: Estimated regional starting points

Estimated starting point	**City**
1996	
August	New York
August	San Diego
August	San Francisco
September	Minneapolis
1997	
February	Las Vegas
October	Los Angeles
November	Seattle
December	Boston
December	Tampa
December	Denver
1998	
December	Washington
1999	
February	Chicago
October	Phoenix
December	Miami
2002	
February	Portland
September	Charlotte
October	Cleveland

We find indications of regional house price bubbles in all 17 major cities. Ordering the change points estimated by the EWMA control chart for each city chronologically enables us to follow the likely regional pattern of the recent house price

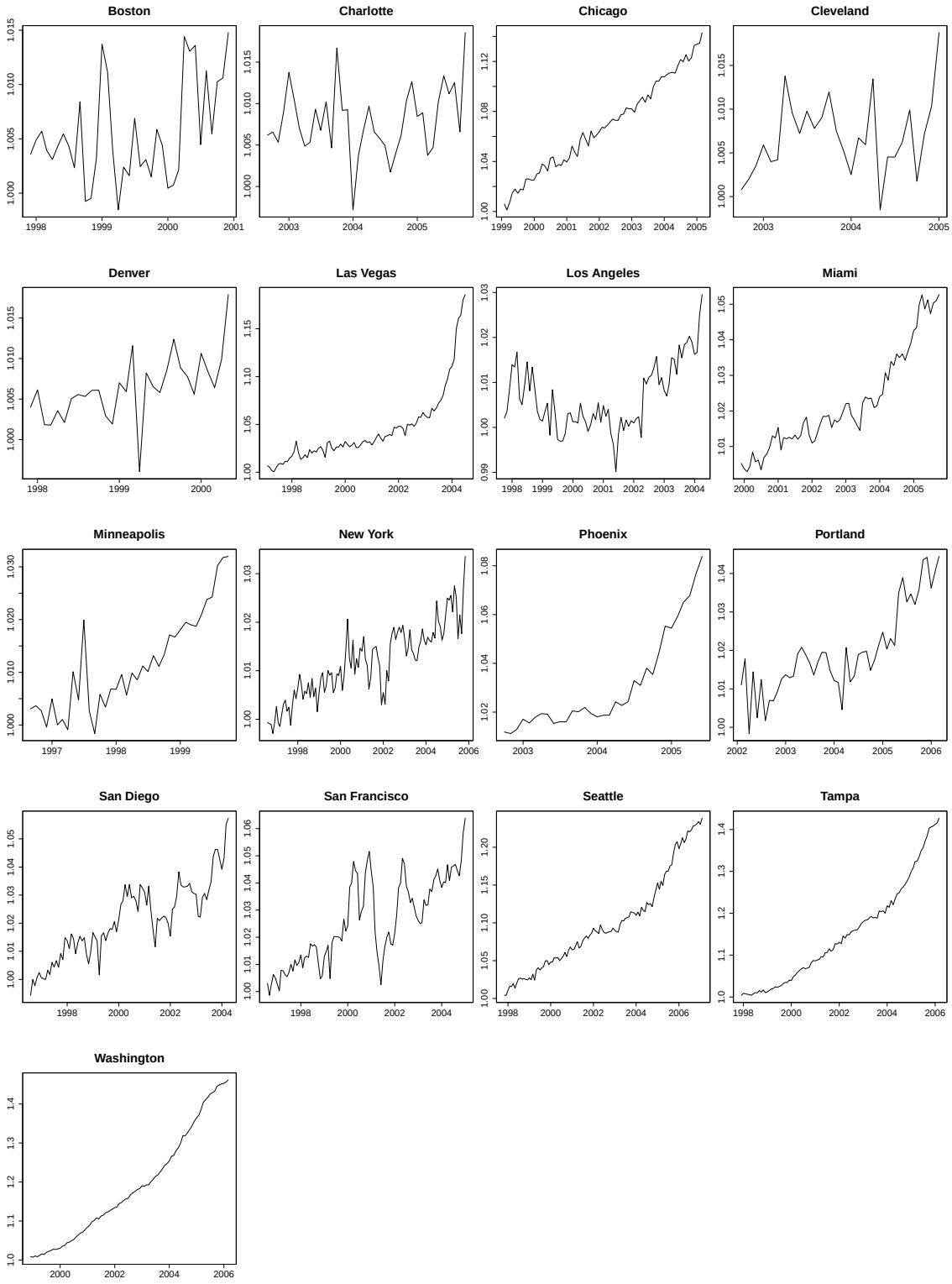
[47]For a detailed view of all 17 EWMA series see Figure 11 in the appendix.

bubble across markets. The first indications of house price overvaluations can be found in New York, San Diego and San Francisco as early as 1996:M08, followed by Minneapolis only one month later in 1996:M09. In the following year bubbles evolved in Las Vegas (1997:M02), Los Angeles (1997:M10), Seattle (1997:M11), Boston, Tampa and Denver (1997:M12). To the end of 1998 we find indications of a house price bubble in Washington (1998:M12). The bubble then appeared in Chicago (1999:M02), Phoenix and Miami (1999:M10). In three cities house price bubbles started to develop quite late in 2002 (Portland 2002:M02, Charlotte 2002:M09 and Cleveland 2002:M10).

Since we use the estimated change points as likely starting points of regional house price bubbles, one would expect increasing forecast errors since the estimated change point is a sign for an upcoming house price bubble in a specific city. To ensure that the estimated starting points for the 17 major cities indeed indicate the beginning of a house price bubble, we analyse the development of the house price forecast errors in between the time point of the estimated change point and the maximum value of the forecast error series. Figure 2 reveals that in almost all cities, forecast errors increased significantly since the estimated change point in a specific city. We also applied the augmented Dickey-Fuller test to test for stationarity of the resulting house price forecast errors from the regional models. The results reveal that house price forecast errors in all 17 cities contain a unit root confirming the plausibility of the EWMA control chart results.[48]

[48]The test statistics do not allow for a constant or a linear time trend of the VAR residuals. We refrain from reporting all test results here in length. Detailed results can be obtained by the author upon request.

Figure 2: Forecast errors resulting from regional VAR models.



Forecast errors are calculated on the base of the city-level VAR models of the fitting period.

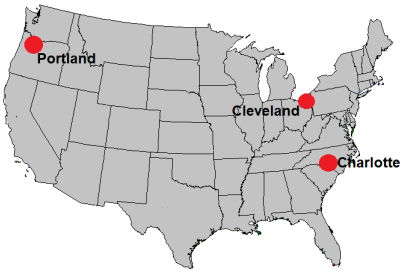
Figures 3 to 6 display the estimated regional pattern of the U.S. house price bubble. According to the SPC results bubbles started to develop in six western, one midwestern, two northeastern and one southern city during the years 1996 and 1997. To the end of the century bubbles in two cities located in the northeastern respectively midwestern region, one city in the western and one in the southern region followed. In 2002 bubbles appeared in one western, one midwestern and one southern city. These findings draw a quite heterogeneous picture regarding the spatial distribution of local bubbles. According to the SPC approach, we find no indications that the bubble first appeared in a specific U.S. region and spread to other neighbouring regions in the following years thereby following a specific regional pattern.

Figure 3: 1996

Figure 4: 1997

Figure 5: 1998/99

Figure 6: 2002



Since Shiller (2007) and Ferreira and Gyourko (2011) rather focus on regional house price *booms* than *bubbles*, our findings are less comparable to their results. However, we can compare our findings to those of Pavlidis et al. (2009) who also focus on dating the beginning of local house price bubbles in 20 major cities where Case-Shiller house price data are available.

Figure 7: Regional pattern of the U.S. housing bubble.

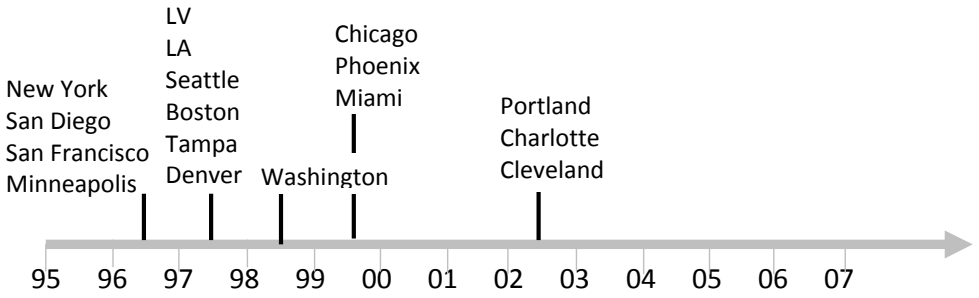
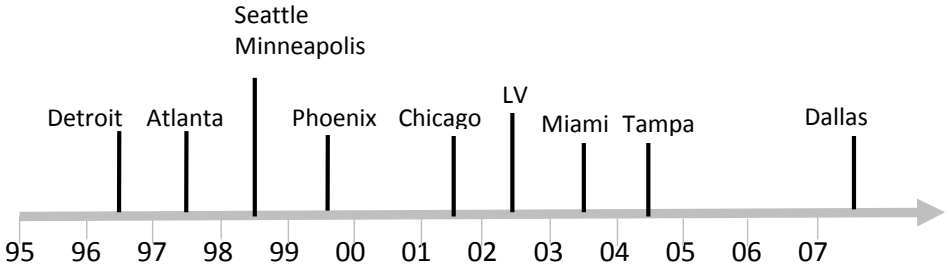


Figure 8: Regional pattern of the U.S. housing bubble (Pavlidis et al. (2009)).



No bubble: Los Angeles, San Diego, San Francisco, Denver, Washington, Boston, Charlotte, New York, Cleveland and Portland

Figure 7 and Figure 8 show the regional timeline of the recent house price bubble across U.S. cities estimated by the SPC procedure compared to the findings of Pavlidis et al. (2009). A main difference is the number of identified house price bubbles in regional U.S. markets. While Pavlidis et al. (2009) find a number of cities that did not experience a bubble, we find indications of house price bubbles in all 17 U.S. cities considered in our approach. Moreover, there are differences regarding the resulting chronological sequence of the cities.

Interestingly enough, similar to Pavlidis et al.(2009) we find significant heterogeneities in when the bubble started to grow up in different U.S. cities. Regarding the regional pattern of the bubble, both studies find no indications that the recent bubble evolved in a specific region and spread to another neighboured region in the following years. According to Pavlidis et al. (2009), bubbles emerged in the northeastern, southern, western and midwestern region until the end of the century. During the years 2001 until 2004, other midwestern, western and southern cities followed. Similar to our results, these findings evolve a quite heterogeneous picture regarding the spatial distribution of local bubbles.

7 Robustness checks

To test for the robustness of our results from the baseline model we try eleven alternative specifications and check whether they have an impact on the estimated starting points of the regional bubbles.

Since the regional VAR models are the main basis of the subsequent application of SPC methods we run some variations of our regional baseline models to ensure that the results are independent of the baseline model specification.

First, we change the size of the fitting period up to 84 respectively 90 months for every VAR model and re-run the corresponding EWMA control charts. Second, since both the national interest rate and regional mortgage rates to some extend measure the stance of monetary policy, we re-estimate the city-level models without the national interest rate. However, since the US is characterized by a mortgage market where either fixed rate contracts or variable rate contracts are supplied while there is a growing use of variable-rate loans during the last years, we also drop the regional 30 year fixed mortgage rates from the VAR specifications.[49] Fourth, regional house price dynamics might be rather driven by regional economic

[49]See, e.g., Sellon (2002), Demary (2009).

conditions than national variables. Thus, we drop all national variables from the models so that the regional VAR specifications include only regional variables such as house prices, mortgage rates, unemployment rates and inflation. Fifth, we exclude the national stock market development from the regional models. Since the stock market is characterized by speculative behaviour in the same manner as the real estate market, we thus control for the possibility that the stock market contains a speculative bubble during the fitting period.

What is more, we run some variations of the applied SPC procedure. In general, the higher the sensivity parameter λ is chosen, the more sensitive the control chart is towards alarm signals. First, to test for the impact of the smoothing parameter on regional starting points, we run two variations of the EWMA scheme with $\lambda = 0.05$ and $\lambda = 0.2$. Second, we apply a different kind of control chart, the CUSUM chart with three different reference values to test for regional bubbles and compare the results to our findings using the EWMA control chart in the previous section.

The CUSUM procedure (Cumulative sum) is a popular alternative to test for anomalities of a process.[50] In contrast to the EWMA procedure, the CUSUM control chart deploys only a short window with random size of the last data points. Here, a positive and a negative series S is calculated which is set to zero at the beginning and is determined by the past value of S^+ respectively S^-, the current value of the residuals and the a-priori defined reference value k:

$$S_0^+ = S_0^- = 0\,,$$

$$S_t^+ = \max\{0, S_{t-1}^+ + \varepsilon_t - k\}\,,$$

$$S_t^- = \min\{0, S_{t-1}^- + \varepsilon_t + k\}\,.$$

[50] See Page (1954).

The design of the control chart is given by its stopping time L:

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

The parameter $k \geq 0$ for CUSUM is a design knob to increase the scheme's sensitivity for a pre-defined shift in the mean of the residuals. Assuming that σ is the shift of interest (in standard deviation units), then k is usually set at half the value of that shift: $k = 0.5 \cdot \sigma$.[51] A widely used value in practice is a reference value of $k = 0.5$.[52] Thus, a shift of about 1σ can be detected while a good ARL performance is provided.[53]

The CUSUM chart comes, due to the re-setting behavior at 0, with an embedded estimator of the change point τ, which is given by:

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

To test for speculative bubbles we apply the CUSUM procedure with three different values of k in the same manner as the EWMA procedure on the estimated regional models for the 17 cities. Here, we focus on the upper CUSUM series S_t^+ and analyse when exactly the series exceeds the upper threshold value since we are interested in studying an upcoming house price bubble.[54]

Instead of presenting the detailed results of the estimated local change points, we analysed in how far the alternative specifications affect the local starting points on average. Table 3 provides the average deviation in months resulting from the eleven variations with regard to the change points found in the baseline specification.

The results indicate that even though the alternative estimations indeed have

[51] See, e.g., Hawkins and Olwell (1998).

[52] To test for the robustness of the CUSUM results, we also run the control charts with $k = 0.25$ and $k = 1.0$, see also Berlemann, Freese and Knoth (2012).

[53] See Montgomery (2005).

[54] Similar to the EWMA approach, negative alarms would indicate undervaluations of the current regional house prices.

Table 3: Deviations resulting from robustness checks

Stadt	**Starting point from baseline model**	**Average deviation in months**
New York	1996:M08	5.3
San Diego	1996:M08	4.7
San Francisco	1996:M08	2.6
Minneapolis	1996:M09	5.9
Las Vegas	1997:M02	3.7
Los Angeles	1997:M10	6.1
Seattle	1997:M11	5.4
Boston	1997:M12	5.8
Tampa	1997:M12	2.6
Denver	1997:M12	3.3
Washington	1998:M12	5.5
Chicago	1999:M02	5.6
Phoenix	1999:M10	6.5
Miami	1999:M12	3.2
Portland	2002:M02	27.4
Charlotte	2002:M09	9.3
Cleveland	2002:M10	23.6
Total		**7.44**

an impact on the results, the average deviations of eleven robustness checks amount to only a few months in almost all regional models. Regarding all 17 models, the average deviation is about seven months. In the case of San Francisco, Las Vegas, Tampa, Denver and Miami we find only slight differences in the estimated starting points of less than four months. For nine of the considered cities the average deviations vary in between the range of four and seven months. In the case of Charlotte, the average deviation is about nine months and in two cities (Portland and Cleveland) we find significant changes in the estimated starting points of 27 respectively 24 months. However, regarding the regional timeline of the house price bubble, these average shifts would not change the likely bubble chronology found by the baseline specification. Even if the likely starting points in Portland, Charlotte and Cleveland would be estimated nine months respectively two years earlier, house

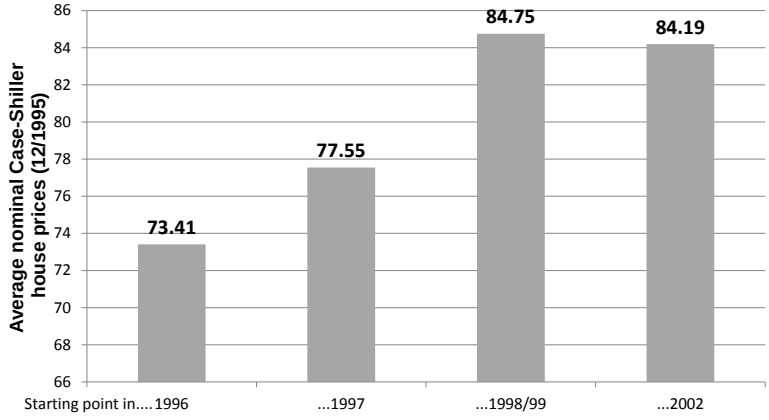
price bubbles in all three cities would appear later than in other considered cities.

8 Disussion and conclusions

In this paper we provide a time line of the recent U.S. house price bubble on the regional level. According to the results of the SPC procedure we find indications of house price overvaluations in all 17 considered cities. In some cities these bubbles started evolving as early as in 1996 respectively 1997. However, four U.S. cities followed to the end of the century and in three cities we find that house price bubbles emerged not before 2002.

It is an interesting question which factors can explain the regional pattern of the U.S. house price bubble as detected in this paper. We found two empirical factors which might contribute to explaining the picture. First, it seems that bubbles first evolved in those regions with the lowest nominal house price level measured at the end of 1995.

Figure 9: Nominal house prices in 1995 and regional starting points



Source: Standard and Poor's (2012). Average nominal house prices of a specific year result from the average of nominal house prices to the end of 1995 in those cities where the bubble started in the corresponding year.

Figure 9 shows the average nominal house prices to the end of 1995 in the 17

cities that are divided into their estimated starting points 1996, 1997, 1998/99 and 2002. Interestingly enough, in those cities where we find indications of house price bubbles quite early, the average nominal house price in 1995 was lower than in those cities with later starting points. On average, the lower the nominal house prices in 1995, the earlier a bubble appeared in a specific city. One reason behind this finding might be the relaxed lending conditions of mortgage banks especially to households of low income-classes. There is a broad public consent that relaxed lending conditions of mortgage banks especially to households of low income-classes coupled with low-interest rates contributed to the bubble.[55] Since the 1990s an increasing number of subprime mortgage loans to less credit-worthy borrowers, the so-called "'NINJA"' loans ("no income, no job and no assets") could be observed.[56] This allowed even households of low-income classes to purchase their own home especially in regions with low house prices. Given a constant level of housing stock in these cities, this positive shift of housing demand increased future house prices in the corresponding region. Increasing house prices and positive future expectations coupled with lax lending conditions led to speculative price increases of real estate and became apparent in a regional house price bubble that formed earlier than in other regions.[57]

Second, if this assumption holds true, it seems that the regional density of subprime mortgage loan specialists might have been a contributing factor to regional bubbles. Thus, one would expect higher subprime lending activities in those cities where the house price bubble emerged quite early. Since 1993, the U.S. Department of Housing and Urban Developments (HUD) publishes a list of lenders who specialize in subprime mortgage lending in order to identify subprime mortgage lending trends in the U.S.[58] To the end of 1995, HUD reports 101 lenders across the U.S.

[55]See, e.g., Shiller (2008), The President's Working Group on Financial Markets (2008) or Mizen (2008).

[56]See, e.g., Chomsisengphet and Pennington-Cross (2006).

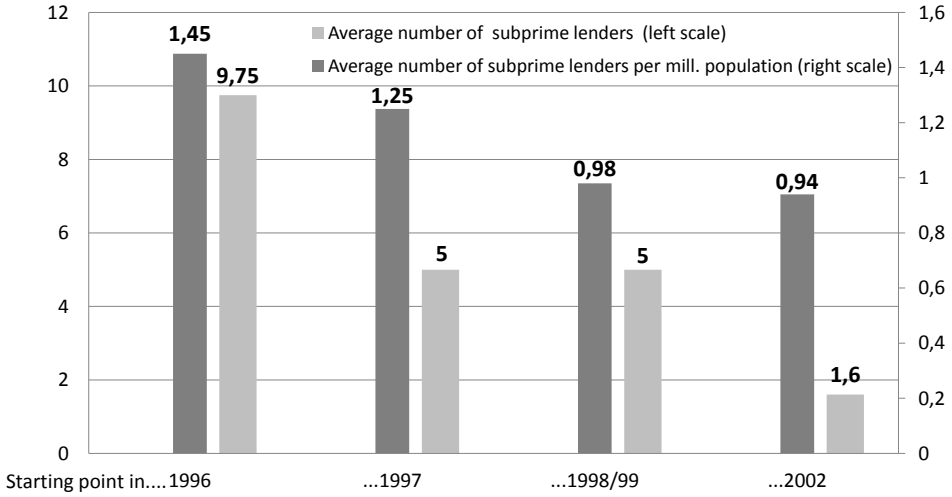
[57]See Shiller (2008).

[58]Therefore, the HUD uses a number of indicators that identify lenders as subprime lender specialists such as origination rates, shares of subprime lenders' total originations and prime

as suprime mortgage specialists. We use this list as a proxy for the presence of subprime lending activities in all 17 U.S. cities to the end of 1995. Therefore, the regional distribution of each subprime lender in 1995 is estimated by determing the number of regional offices of each lender in each of the 17 cities.[59]

Figure 10 shows the average presence of subprime lender specialists to the end

Figure 10: Subprime lenders in 1995 and regional starting points



Source: U.S. Department of Housing and Urban Development (HUD) (2012). Average number of subprime lenders in a specific year results from the average number of subprime lenders to the end of 1995 in those cities where the bubble started in the corresponding year.

of 1995 in the 17 cities that are divided into their estimated starting points 1996, 1997, 1998/99 and 2002. Interestingly enough, in those cities where we find indications of house price bubbles quite early, the total average number of subprime lenders is higher than in those regions with later starting points. Since the absolute number of regional offices should be larger in large cities we accounted for the size of each city by determing the number of suprime lenders per million population.[60]

lenders' originations. For a more detailed description of the methodology, see www.huduser.org.

[59]If a subprime lender has a regional office in a specific city, we assumed that the regional offices of a suprime lender already existed to the end of 1995. Whenever other information from the subprime lender's homepage or other online business communities are available, regional offices are excluded from the sample if they were not present to the end of 1995 in a specific city. If a regional office is located less than 50 miles from the city center, it is assigned to the corresponding city.

[60]Data on population steam from the Bureau of Economic Analysis (BEA) and refer to the end of 1995. Since we assign regional offices to a specific city if the distance is less than 50 miles, we chose the population data in the corresponding city core and close economic ties throughout the

By doing so, we estimate the market penetration of subprime mortgage lenders in a specific city to the end of 1995. Interestingly enough, Figure 10 reveals that this causality even holds when accounting for the city size. On average, the earlier the starting point of the house price bubble in a specific city is estimated, the higher is the number of subprime lenders per million capita in these cities.

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9 Appendix

Table 4: Data sources.

Name	Description	Source
National production	National index of industrial production, OECD base year=100, seasonal adjusted (Cenus X12).	OECD (2012)
National interest rate	Short-term interest rates (90-day rates).	OECD (2012)
National share price	Dow Jones Industrial Average Index (2005=100), national average values, not seasonally adjusted.	EUROSTAT (2012)
National CPI	Consumer Price Index all items, all urban consumers, U.S. city average (1982-1984=100), seasonally adjusted (Census X12).	BLS (2012)
Regional house price	The S&P/Case-Shiller house price index is a repeat-sales index and measures the value of single-family housing. The index reflects changes in housing market prices given a constant level of quality. Changes in the types and sizes of houses or the physical characteristics of houses are specifically excluded from the calculations to avoid incorrectly affecting the index value. Therefore, data on properties that have sold at least twice are considered in order to capture the true appreciated value of each specific sales unit. The S&P/Case-Shiller house price index is available for 20 major cities in the USA. Data are seasonally adjusted (Census X11).	S&P (2012)
Regional mortgage rate	30 Year Fixed Rate Mortgage. Data are derived from weekly editorial surveys of between 2.000 and 3.000 lenders in all 50 states while every institution is contacted directly, branch by branch.	HSH (2012)
Regional CPI	Consumer Price Index for the U.S. census regions Northeast, South, Midwest and West, all items (1982-1984=100), seasonally adjusted (Census X12).	BLS (2012)
Regional Inflation	Percentage change on the same month of the previous year, based on the Regional CPI data.	BLS (2012)
Regional unemployment rate	Rates on MSA-level: Phoenix-Mesa-Glendale (AZ), Los Angeles-Long Beach-Santa Ana (CA), San Diego-Carlsbad-San Marcos (CA), San Francisco-Oakland-Fremont (CA), Denver-Aurora-Broomfield (CO), Washington-Arlington-Alexandria (DC-VA-MD-WV), Miami-Fort Lauderdale-Pompano Beach (FL),Tampa-St.Petersburg-Clearwater (FL), Chicago-Joliet-Naperville (IL-IN-WI), Boston-Cambridge-Quincy (MA-NH), Minneapolis-St.Paul-Bloomington (MN-WI), Charlotte-Gastonia-Rock Hill (NC-SC), Las Vegas-Paradise (NV), New York-Northern New Jersey-Long Island (NY-NJ-PA), Cleveland-Elyria-Mentor (OH), Portland-Vancouver-Hillsboro (OR-WA), Seattle-Tacoma-Bellevue (WA). Extracted data are not seasonally adjusted.	BLS (2012)

Table 5: VAR estimation results of regional house price equations.

```
VAR Estimation Results:
=========================
Endogenous variables: prod, i, p, mort, u, s, hp
Deterministic variables: const
Sample size: 77
Log Likelihood: 967.033
Roots of the characteristic polynomial:
1.003 0.9354 0.9354 0.9104 0.9104 0.827 0.827
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1
------------------------------------------------------------------------------
BOSTON
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1 -0.0671422  0.0553927  -1.212   0.2296
i.l1    -0.0023531  0.0010202  -2.307   0.0241 *
p.l1    -0.0007186  0.0007725  -0.930   0.3555
mort.l1  0.0017089  0.0011665   1.465   0.1475
u.l1    -0.0022494  0.0016467  -1.366   0.1764
s.l1     0.0134268  0.0079005   1.699   0.0937 .
hp.l1    0.9908883  0.0195985  50.559   <2e-16 ***
const    0.2638225  0.1781761   1.481   0.1432
Residual standard error: 0.003487 on 69 degrees of freedom
Multiple R-Squared: 0.9966,     Adjusted R-squared: 0.9963
F-statistic:  2932 on 7 and 69 DF,  p-value: < 2.2e-16
------------------------------------------------------------------------------
CHARLOTTE
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1 -0.0321317  0.0320579  -1.002  0.31970
i.l1     0.0002363  0.0006567   0.360  0.72014
p.l1    -0.0010527  0.0006378  -1.650  0.10339
mort.l1  0.0001442  0.0009373   0.154  0.87820
u.l1    -0.0022850  0.0007390  -3.092  0.00287 **
s.l1     0.0263471  0.0099454   2.649  0.01000 **
hp.l1    0.9431251  0.0235004  40.132  < 2e-16 ***
const    0.2965670  0.1541575   1.924  0.05851 .
Residual standard error: 0.002458 on 69 degrees of freedom
Multiple R-Squared: 0.9983,     Adjusted R-squared: 0.9981
F-statistic:  5857 on 7 and 69 DF,  p-value: < 2.2e-16
```

```
CHICAGO
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
         Estimate Std. Error t value Pr(>|t|)
prod.l1  0.107763   0.051271   2.102  0.03922 *
i.l1    -0.001416   0.001074  -1.319  0.19138
p.l1    -0.002354   0.001392  -1.691  0.09528 .
mort.l1 -0.001898   0.001388  -1.367  0.17601
u.l1    -0.002579   0.001204  -2.141  0.03578 *
s.l1    -0.014375   0.009131  -1.574  0.11999
hp.l1    0.667514   0.090203   7.400 2.49e-10 ***
const    1.010052   0.315190   3.205  0.00205 **
Residual standard error: 0.004089 on 69 degrees of freedom
Multiple R-Squared: 0.9115,     Adjusted R-squared: 0.9026
F-statistic: 101.6 on 7 and 69 DF,  p-value: < 2.2e-16
------------------------------------------------------------------------------
CLEVELAND
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1  0.0118314  0.0318121   0.372   0.7111
i.l1    -0.0020797  0.0009582  -2.170   0.0334 *
p.l1     0.0006564  0.0009092   0.722   0.4728
mort.l1  0.0004643  0.0009888   0.470   0.6401
u.l1    -0.0027295  0.0013768  -1.983   0.0514 .
s.l1     0.0116891  0.0074746   1.564   0.1224
hp.l1    0.8564292  0.0443054  19.330   <2e-16 ***
const    0.5146993  0.1943667   2.648   0.0100 *
Residual standard error: 0.002988 on 69 degrees of freedom
Multiple R-Squared: 0.9858,     Adjusted R-squared: 0.9844
F-statistic: 683.9 on 7 and 69 DF,  p-value: < 2.2e-16
------------------------------------------------------------------------------
DENVER
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1 -3.022e-02  3.968e-02  -0.762    0.449
i.l1    -2.071e-03  1.113e-03  -1.861    0.067 .
p.l1    -6.563e-05  8.230e-04  -0.080    0.937
mort.l1 -5.759e-04  9.427e-04  -0.611    0.543
u.l1    -4.290e-03  2.017e-03  -2.127    0.037 *
s.l1     2.831e-04  6.823e-03   0.041    0.967
hp.l1    9.806e-01  2.192e-02  44.735   <2e-16 ***
const    2.258e-01  1.142e-01   1.978    0.052 .
Residual standard error: 0.002979 on 69 degrees of freedom
Multiple R-Squared: 0.999,      Adjusted R-squared: 0.9989
F-statistic: 1.027e+04 on 7 and 69 DF,  p-value: < 2.2e-16
```

```
LOS ANGELES
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1 -0.0796629  0.0343023  -2.322  0.02317 *
i.l1    -0.0016286  0.0017722  -0.919  0.36129
p.l1    -0.0011034  0.0008953  -1.232  0.22198
mort.l1  0.0032811  0.0012364   2.654  0.00988 **
u.l1    -0.0031720  0.0017446  -1.818  0.07338 .
s.l1     0.0175574  0.0066788   2.629  0.01055 *
hp.l1    0.9902327  0.0075143 131.780  < 2e-16 ***
const    0.2952454  0.1429895   2.065  0.04270 *
Residual standard error: 0.00346 on 69 degrees of freedom
Multiple R-Squared: 0.9996,     Adjusted R-squared: 0.9996
F-statistic: 2.429e+04 on 7 and 69 DF,  p-value: < 2.2e-16´
------------------------------------------------------------------------------
LAS VEGAS
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1 -0.2022691  0.1002807  -2.017  0.04759 *
i.l1     0.0013975  0.0016217   0.862  0.39179
p.l1    -0.0006384  0.0014734  -0.433  0.66616
mort.l1  0.0033802  0.0020422   1.655  0.10244
u.l1    -0.0054913  0.0035060  -1.566  0.12186
s.l1    -0.0032734  0.0106550  -0.307  0.75960
hp.l1    0.7841863  0.0663064  11.827  < 2e-16 ***
const    1.6699761  0.5377431   3.106  0.00276 **
Residual standard error: 0.00585 on 69 degrees of freedom
Multiple R-Squared:  0.95,      Adjusted R-squared: 0.945
F-statistic: 187.4 on 7 and 69 DF,  p-value: < 2.2e-16
------------------------------------------------------------------------------
MIAMI
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1  0.0360910  0.0598861   0.603    0.549
i.l1    -0.0010683  0.0013878  -0.770    0.444
p.l1    -0.0009846  0.0014426  -0.683    0.497
mort.l1 -0.0005865  0.0018324  -0.320    0.750
u.l1    -0.0016285  0.0015489  -1.051    0.297
s.l1    -0.0040682  0.0103171  -0.394    0.695
hp.l1    0.9663027  0.0343513  28.130   <2e-16 ***
const    0.0465586  0.2898214   0.161    0.873
Residual standard error: 0.00498 on 69 degrees of freedom
Multiple R-Squared: 0.9876,     Adjusted R-squared: 0.9864
F-statistic: 785.7 on 7 and 69 DF,  p-value: < 2.2e-16
```

```
MINNEAPOLIS
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1  0.0194276  0.0520174   0.373   0.7099
i.l1    -0.0003759  0.0010498  -0.358   0.7214
p.l1     0.0010246  0.0013228   0.775   0.4412
mort.l1 -0.0023921  0.0014945  -1.601   0.1140
u.l1    -0.0029506  0.0016621  -1.775   0.0803 .
s.l1    -0.0071898  0.0085061  -0.845   0.4009
hp.l1    0.8557199  0.0708485  12.078   <2e-16 ***
const    0.5423718  0.2549058   2.128   0.0369 *
Residual standard error: 0.004081 on 69 degrees of freedom
Multiple R-Squared: 0.9308,     Adjusted R-squared: 0.9238
F-statistic: 132.6 on 7 and 69 DF,  p-value: < 2.2e-16
------------------------------------------------------------------------------
NEW YORK
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1 -0.0209257  0.0439958  -0.476    0.636
i.l1    -0.0018200  0.0012075  -1.507    0.136
p.l1    -0.0006687  0.0007489  -0.893    0.375
mort.l1  0.0016065  0.0011389   1.411    0.163
u.l1    -0.0006484  0.0011050  -0.587    0.559
s.l1     0.0058742  0.0076546   0.767    0.445
hp.l1    0.9726080  0.0194270  50.065   <2e-16 ***
const    0.1703223  0.1282553   1.328    0.189
Residual standard error: 0.003407 on 69 degrees of freedom
Multiple R-Squared: 0.996,      Adjusted R-squared: 0.9956
F-statistic:  2434 on 7 and 69 DF,  p-value: < 2.2e-16
------------------------------------------------------------------------------
PHOENIX
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1  0.0279443  0.0408694   0.684  0.49642
i.l1    -0.0005601  0.0011832  -0.473  0.63745
p.l1    -0.0013176  0.0006986  -1.886  0.06352 .
mort.l1  0.0003016  0.0011486   0.263  0.79365
u.l1    -0.0023359  0.0007704  -3.032  0.00342 **
s.l1     0.0060879  0.0060668   1.003  0.31914
hp.l1    0.9262925  0.0478438  19.361  < 2e-16 ***
const    0.1745411  0.1234451   1.414  0.16188
Residual standard error: 0.002939 on 69 degrees of freedom
Multiple R-Squared: 0.9937,     Adjusted R-squared: 0.9931
F-statistic:  1562 on 7 and 69 DF,  p-value: < 2.2e-16
```

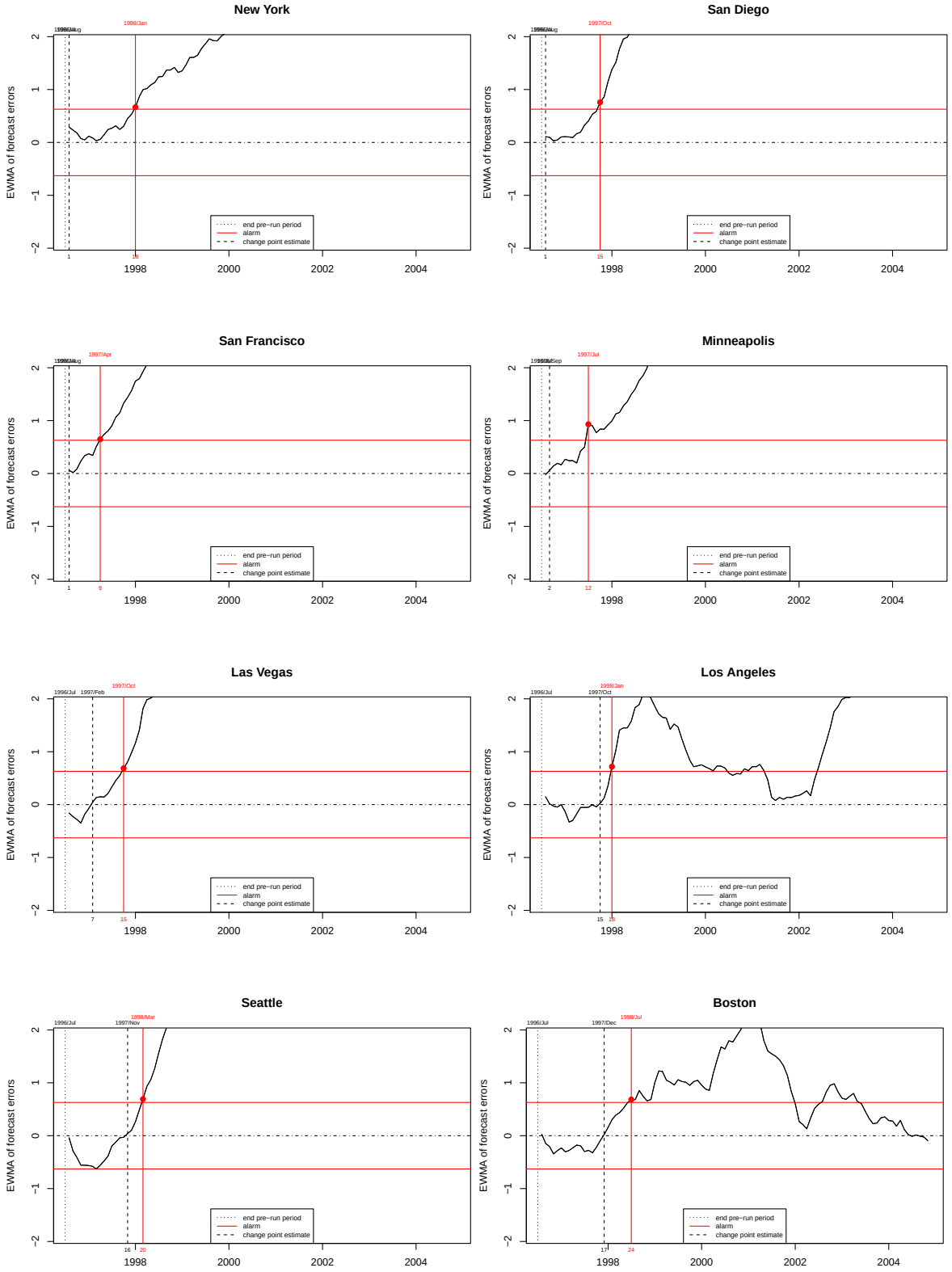
```
PORTLAND
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1  0.0218588  0.0526205   0.415   0.6791
i.l1    -0.0016885  0.0016559  -1.020   0.3115
p.l1    -0.0010345  0.0012597  -0.821   0.4143
mort.l1 -0.0008775  0.0017135  -0.512   0.6102
u.l1    -0.0047264  0.0018823  -2.511   0.0144 *
s.l1     0.0191835  0.0130541   1.470   0.1462
hp.l1    0.9143145  0.0230218  39.715   <2e-16 ***
const    0.2315282  0.2361826   0.980   0.3304
Residual standard error: 0.004908 on 69 degrees of freedom
Multiple R-Squared: 0.9973,     Adjusted R-squared: 0.9971
F-statistic:  3686 on 7 and 69 DF,  p-value: < 2.2e-16
------------------------------------------------------------------------------
SAN DIEGO
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1 -0.0460935  0.0458181  -1.006   0.3179
i.l1    -0.0017485  0.0012650  -1.382   0.1714
p.l1    -0.0008390  0.0010238  -0.819   0.4153
mort.l1 -0.0001996  0.0012082  -0.165   0.8693
u.l1    -0.0058983  0.0023593  -2.500   0.0148 *
s.l1    -0.0174512  0.0117640  -1.483   0.1425
hp.l1    0.9653618  0.0201992  47.792   <2e-16 ***
const    0.4193074  0.2586456   1.621   0.1095
Residual standard error: 0.003956 on 69 degrees of freedom
Multiple R-Squared: 0.9989,     Adjusted R-squared: 0.9988
F-statistic:  9147 on 7 and 69 DF,  p-value: < 2.2e-16
------------------------------------------------------------------------------
SAN FRANCISCO
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1 -0.0019458  0.0403482  -0.048   0.9617
i.l1    -0.0028201  0.0013578  -2.077   0.0415 *
p.l1    -0.0009657  0.0009501  -1.016   0.3130
mort.l1  0.0014858  0.0012378   1.200   0.2341
u.l1    -0.0055322  0.0023404  -2.364   0.0209 *
s.l1    -0.0104338  0.0095587  -1.092   0.2788
hp.l1    0.9564542  0.0217319  44.012   <2e-16 ***
const    0.2401300  0.1935719   1.241   0.2190
Residual standard error: 0.003946 on 69 degrees of freedom
Multiple R-Squared: 0.9982,     Adjusted R-squared: 0.998
F-statistic:  5385 on 7 and 69 DF,  p-value: < 2.2e-16
```

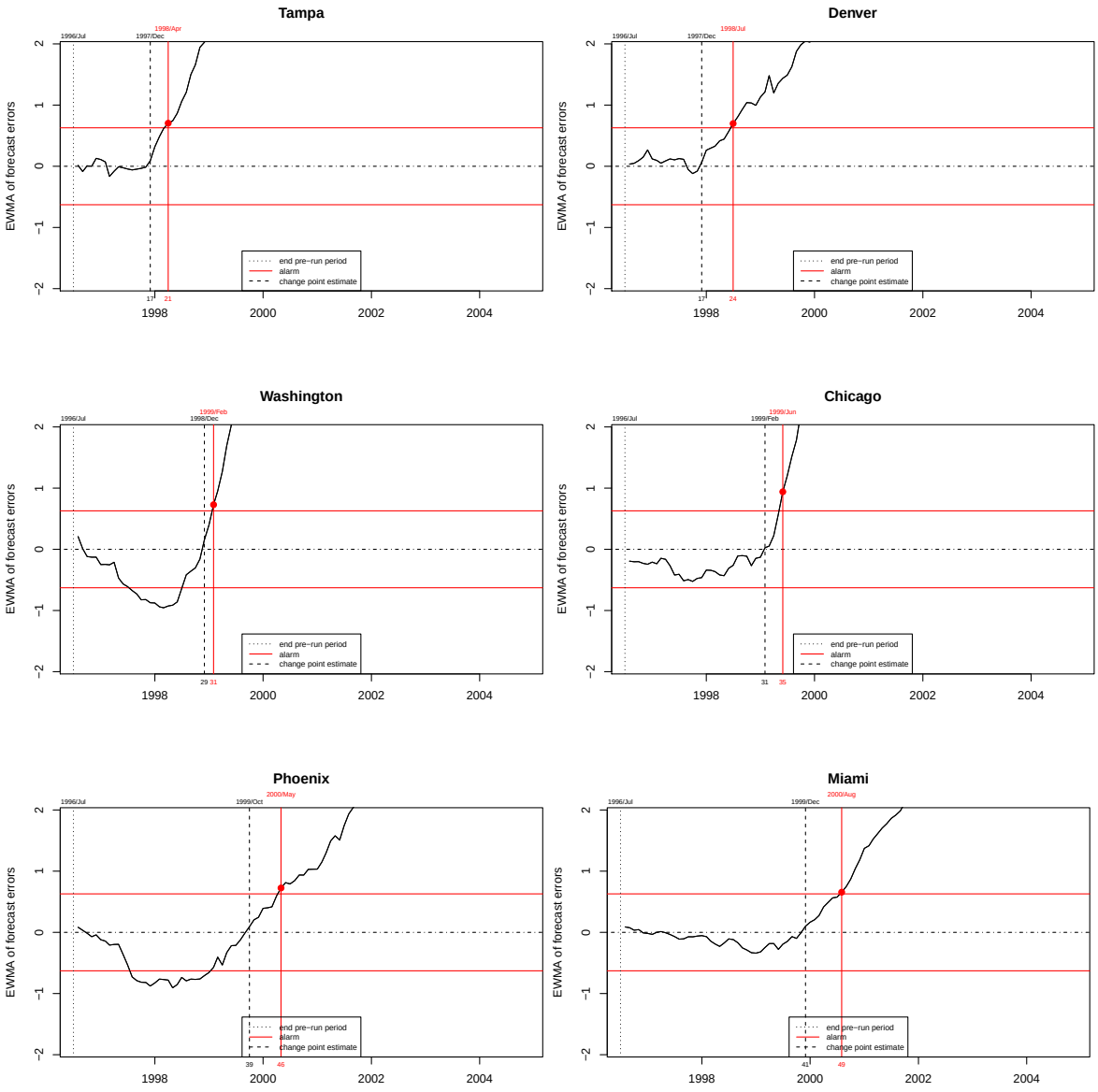
```
SEATTLE
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1  2.656e-01  6.298e-02   4.218 7.37e-05 ***
i.l1    -5.135e-03  2.052e-03  -2.502  0.01472 *
p.l1    -4.186e-05  1.459e-03  -0.029  0.97719
mort.l1  1.848e-03  1.889e-03   0.978  0.33126
u.l1    -1.118e-02  4.335e-03  -2.579  0.01203 *
s.l1    -2.930e-02  1.098e-02  -2.668  0.00949 **
hp.l1    6.764e-01  5.181e-02  13.055  < 2e-16 ***
const    3.866e-01  3.180e-01   1.216  0.22827
Residual standard error: 0.006267 on 69 degrees of freedom
Multiple R-Squared: 0.9405,     Adjusted R-squared: 0.9344
F-statistic: 155.8 on 7 and 69 DF,  p-value: < 2.2e-16

------------------------------------------------------------------------------
TAMPA
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1 -8.346e-02  5.024e-02  -1.661 0.101166
i.l1     5.505e-05  1.056e-03   0.052 0.958554
p.l1    -1.487e-03  9.996e-04  -1.488 0.141383
mort.l1 -1.575e-03  1.331e-03  -1.184 0.240619
u.l1    -8.329e-03  2.230e-03  -3.736 0.000382 ***
s.l1     1.581e-02  1.007e-02   1.571 0.120804
hp.l1    6.372e-01  9.918e-02   6.425 1.44e-08 ***
const    1.910e+00  5.482e-01   3.483 0.000864 ***
Residual standard error: 0.003707 on 69 degrees of freedom
Multiple R-Squared: 0.9825,     Adjusted R-squared: 0.9807
F-statistic: 552.1 on 7 and 69 DF,  p-value: < 2.2e-16

------------------------------------------------------------------------------
WASHINGTON
Estimation results for equation hp:
hp = prod.l1 + i.l1 + p.l1 + mort.l1 + u.l1 + s.l1 + hp.l1 + const
          Estimate Std. Error t value Pr(>|t|)
prod.l1  0.1879371  0.0517862   3.629 0.000541 ***
i.l1    -0.0029910  0.0007717  -3.876 0.000239 ***
p.l1     0.0005889  0.0007288   0.808 0.421868
mort.l1  0.0019899  0.0010177   1.955 0.054602 .
u.l1    -0.0041667  0.0015871  -2.625 0.010650 *
s.l1    -0.0187173  0.0074266  -2.520 0.014042 *
hp.l1    0.6407249  0.0785728   8.155 1.04e-11 ***
const    0.9235836  0.3008448   3.070 0.003060 **
Residual standard error: 0.002826 on 69 degrees of freedom
Multiple R-Squared: 0.9698,     Adjusted R-squared: 0.9667
F-statistic:   316 on 7 and 69 DF,  p-value: < 2.2e-16
```

Figure 11: EWMA control charts for 17 major U.S. cities.




Tampa
Denver
Washington
Chicago
Phoenix
Miami
EWMA of forecast errors
end pre−run period
alarm
change point estimate
1998
2000
2002
2004

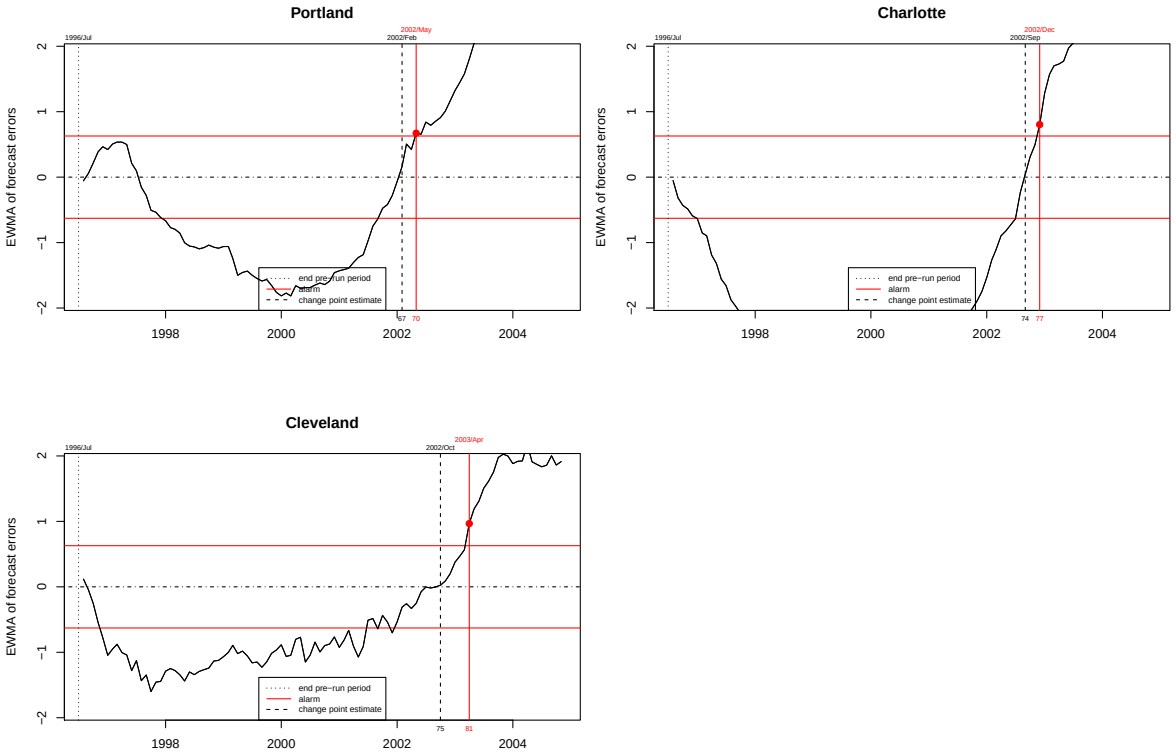


Figure 11 shows the EWMA series of the house price forecast errors resulting from the regional base models for $\lambda = 0.1$ in each of the 17 U.S. major cities. The vertical red line in every figure indicates the alarm threshold calculated for the EWMA procedure. The left horizontal dashed line shows the left-sided margin of the monitoring period. The vertical red line indicate when exactly the system generates the first alarm. Given this signal, the likely change point (structural break) is shown by the second vertical dashed line in the figure.

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