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Abstract

To promote the financial stability, there is a need for an early warning system to signal the formation of asset price misalignments. This research provides two novel methods to accomplish this task. Results in this research shows that the conventional unit root tests in modified forms can be used to construct early warning indicators for bubbles in financial markets. More precisely, the conventional augmented Dickey-Fuller unit root test is shown to provide a basis for two novel bubble indicators. These new indicators are tested via MC simulations to analyze their ability to signal emerging unit roots in time series and to compare their power with standard stability and unit root tests. Simulation results concerning these two new stability tests are promising: they seem to be more robust and to have more power in the presence of changing persistence than the standard stability and unit root tests. When these new tests are applied to real US stock market data starting from 1871, they are able to signal most of the consensus bubbles, defined as stock market booms for example by the IMF, and they also flash warning signals far ahead of a crash. Also encouraging are the results with these methods in practical applications using equity prices in the UK, Finland and China as the methods seem to be able to signal most of the consensus bubbles from the data. Finally, these early warning indicators are applied to data for several housing markets. In most of the cases the indicators seem to work relatively well, indicating bubbles before the periods which, according to the consensus literature, are seen as periods of sizeable upward or downward movements. The scope of application of these early warning indicators could be wide. They could be used eg to help determine the right timing for the start of a monetary tightening cycle or for an increase in countercyclical capital buffers.

Key words: asset prices, financial crises, bubbles, indicator, unit-root

JEL classification: C15, G01, G12

Tiivistelmä

Rahoitusvakauden edistämiseksi tarvitaan työkaluja, joiden avulla ennakkovaroitusjärjestelmä viestii varallisuushintojen vääristymistä. Tässä tutkimuksessa kehitetään kaksi uutta menetelmää tämän päämäärän saavuttamiseksi. Tutkimuksen tulokset osoittavat, että perinteisiä modifioituja yksikköjuuritestejä voidaan soveltaa kehitettäessä rahoitusmarkkinakuplista viestiviä ennakkovaroitusindikaattoreita. Tarkemmin sanoen tavanomaista laajennettua Dickey–Fuller-testiä voidaan käyttää näiden kahden uuden kuplaindikaattorin perustana. Uusia indikaattoreita testataan Monte Carlo -simuloinneilla, joissa analysoidaan indikaattorien kykyä viestiä aikasarjojen mahdollisista yksikköjuurista ja verrataan niiden suorituskykyä suhteessa vakiomuotoisiin vakaus- ja yksikköjuuritesteihin. Näitä kahta uutta vakaustestiä koskevat simulointitulokset ovat lupaavia: testit näyttävät olevan luotettavampia ja prosessin stationaarisuuden muuttuessa suorituskyvyltään parempia kuin aiemmat vakaus- ja yksikköjuuritestit. Kun näissä kahdessa uudessa testissä käytetään vuodesta 1871 lähtien koottuja aikasarjoja Yhdysvaltain reaalisista osakemarkkinoista, testit pystyvät osoittamaan suurimman osan konsensusarvion mukaisista kuplista, jotka esimerkiksi IMF määrittelee osakemarkkinabuumeiksi, ja ne myös varoittavat hyvissä ajoin ennen romahdusta. Rohkaisevia ovat niin ikään näiden kahden menetelmän muut käytännön sovellukset, joissa käytetään Ison-Britannian ja Suomen sekä Kiinan osakemarkkinahintatietoja. Menetelmät näyttävät pystyvän osoittamaan suurimman osan näihin markkinoihin liittyvistä konsensusarvion mukaisista kuplista. Lopuksi näitä ennakkovaroitusindikaattoreita sovelletaan useiden asuntomarkkinoiden aineistoihin. Useimmissa tapauksissa indikaattorit näyttävät toimivan suhteellisen hyvin ja kertovat kuplista ennen ajanjaksoja, jotka konsensustutkimuksessa katsotaan huomattaviksi nousu- tai laskukausiksi. Näiden ennakkovaroitusindikaattorien soveltamisala saattaisi olla laaja, koska indikaattoreita voitaisiin käyttää apuvälineenä muun muassa silloin, kun päätetään rahapolitiikan kiristämisen aloittamisen tai esimerkiksi vastasyklisten pääomapuskureiden kasvattamisen oikeasta ajoituksesta.

Asiasanat: omaisuuserien hinnat, rahoitusmarkkinakriisi, kuplat, indikaattori, yksikköjuuri

JEL-luokat: C15, G01, G12

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Sipoo, October 2012
Katja Taipalus

Contents

1 Introduction

Recent decades have witnessed a surge of interest in asset market developments and asset pricing. Academics as well as policymakers have increasingly paid attention to price misalignments (bubbles) in the asset prices, since bubbles can at worst have severe repercussions for the functioning of the financial system and the economy as a whole.[1] Special attention has been devoted to means and techniques for spotting bubbles.

Though every bubble has its own features, there are some common early symptoms. One is the emergence of overconfident expectations of emerging trends. Overconfidence in asset prices means overly positive expectations concerning the duration of rising prices, ie the existence of rational bubbles. Because overconfidence is hard to detect, a constantly diminishing dividend-price ratio can serve as a reference: if price expectations are rising, but higher dividends fail to materialize, the price rise is probably not based on fundamentals. In such case the price can be seen as a composite of fundamental value and a rational bubble component.

A bubble is hazardous for financial and macro stability, especially as it can amplify a credit boom by inflating collateral values and causing misallocation of economic resources. In order to cushion the negative macroeconomic effects of a bubble, one needs to detect it early – as soon as prices begin to rise. The warning alarm should be simple and easy to interpret. Unfortunately, traditional stability tests have several limitations due to which they are unable to achieve high accuracy in the case of a periodically collapsing process. One of the major difficulties in using traditional unit root tests is the I(1) dominance, which biases the test results. As Morrison (1991) has stated 'The trick is to observe behavior in the real world and similar behavior in a computation and then identify these as equivalent within a certain range of scales and to a limited level of precision'.

This research consists of four parts. The first part begins with a more thorough definition of 'bubble'. This is followed by an analysis of historical bubble periods aimed identifying their common features as well as the common symptoms distinguishable from the periods

[1] For the effects, see Bean (2004), Herrera and Perry (2003), Mishkin (2001), Dupor and Conley (2004), von Goetz (2004), Mishkin and White (2003), Kindleberger (2000), Kent and Lowe (1997), Allen and Gale (2000), Filardo (2000), Goodhart (1993), Bernanke and Gertler (1999), Cecchetti et al (2000), Bryan et al (2002), Goodfriend (2003), Mussa (2003), Gilchrist et al (2004), Lansig (2003a) and Lansig (2003b).

preceding their emergence. In the latter part of the section, the aim is to explain, why bubbles should be identified from asset price series and to present some of the tools, for responding to bubbling prices in different policy settings.

The second part of the research presents two modified uses of traditional unit root test parameters to construct two new early warning indicators. New statistical limits are found via extensive Monte Carlo simulations for use in interpreting the signals sent by ADF-regression coefficients and pure AR-regression coefficients. To overcome the problem of I(1) dominance, I make repeated use of tests based on rolling samples. Different window lengths are tested to find the fastest, yet the most robust, length of subsample, by which to evaluate the dividend-yield process, which displays constant growth without mean reversion.

In the third part these novel methods are compared to the most powerful unit-root and stabilization tests. All of the tests are run through the same MC simulations. Though the novel methods presented here are fairly simple, the Monte Carlo simulations show that the modified indicators have more power than the older testing methods. One major advantage is these new indicators' ability to react quickly to changes in the underlying data (at best, the bubble alarms were received after 7 to 9 simulated unit-root observations), yet seldom giving false alarms. In addition, these indicator signals are easy to interpret. The most distinctive feature though is their ability to spot simulated unit root periods from the data, even when their indications are based on relatively modest sample sizes. Concerning the signaling power, both of the novel methods are able to signal correctly about 70–80% of the simulated unit root periods. These percentages compare very favorably with the other tested methods commonly in use.

In the fourth part, the aim is to apply these new indicators to real market data in order to see whether they are able to distinguish bubbles from real stock and housing market data during the times referred as 'consensus' bubbles in earlier academic research. The real data applications give promising results. In the case of US stock market data from as early as 1871 and covering the period up to September 2010, both of the new indicators are able to spot the major consensus booms and busts from the stock market data. The signals are accurate and arrive sufficiently early (in most cases, as early as 12 months prior to the peak) to have afforded regulators enough time to act. The results for the UK, Finnish and Chinese equity markets are relatively good as well, compared to the historical periods of booms and busts in the markets. A bit surprisingly, these indicators seem to work even in the real estate markets, as they are able to locate the periods which in earlier research have been cited as periods of severe overheating (or severe busts) in real estate prices.

2 Bubbles as a phenomena in economic series

Dictionaries define a bubble, in a general sense, as something that lacks firmness, is fragile and insubstantial. Kindleberger (1987) defines a bubble in Palgrave New Dictionary of Economics as ‘a sharp rise in the price of an asset or a range of assets in a continuous process, with the initial rise generating expectations of further rises and attracting new buyers – generally speculators – interested in profits from trading the asset rather than its use or earning capacity. The rise is usually followed by a reversal of expectations and a sharp decline in the price, often resulting in a financial crisis.’ In his book Manias, Panics and Crashes, Kindleberger (2000) adds that ‘In the technical language of some economists, a bubble is any deviation from “fundamentals”‘.

Concerning asset prices, the bubble concept is closely related to the basic pricing formula, which is used to represent the correct price of an asset: a price that is based on the values of fundamentals, fundamentals being those economic factors and variables that determine the prices of assets.

In its most common form, the pricing formula says that the price of an asset reflects all available information on the discounted future random payoffs associated with the asset. This is also the crux of the efficient market hypothesis (EMH), which says that asset prices in financial markets should always reflect all available information and hence that market prices should always be consistent with the ‘fundamentals’. Validity of EMH would therefore rule out the possibility of bubbles in asset prices. In this research, the adopted view is that the strong-version EMH cannot hold at all times. The concept of EMH is more thoroughly covered in the Appendix 1, which draws heavily on Taipalus (2006a).

2.1 Literature on asset price bubbles – classic examples

Taking as our starting point that the strong-form EMH does not always hold, we assume that bubbles can occur from time to time in asset markets. In the literature, as eg in Charles Kindleberger’s (2000) book, Peter Garber’s (1990) article, and Didier Sornette’s (2003) book, at least two of the three fascinating chains of stock market events are always mentioned under the heading 'stock market bubbles'. These three historical events are Tulipmania, Mississippi bubble and South Sea Bubble.

These three episodes entail some common features that have been linked to the classical bubble concept, the most important being extreme price appreciation. This is the necessary, but not the only sufficient characteristic of a bubble. The three periods have also been cited as good examples of pure speculative price appreciation without any reasonable economic foundation. This is another necessary symptom of a bubble: prices should become detached from their fundamentally justifiable levels.

The period of Tulipmania in the Netherlands was one of great prosperity in which the tulips became, most importantly, a 'must' for wealthy people to own. The prices of tulip bulbs rose over a long period, at a fairly steady pace. In connection with this episode, Sornette (2003) cites market players' increasing overconfidence as the basic reason for the speculation: 'people became too confident that this 'sure thing' would always make them money and, at the period's peak, the participants mortgaged their houses and businesses to trade tulips'.

The other two classic cases, the Mississippi and South Sea bubbles, were strikingly similar in terms of the financial dynamics. In both the South Sea and Mississippi bubbles, the actual period of price speculation was fairly brief. Continuation of the pronounced price rise was called into question when it became obvious that the values of the companies were not at all justified by the values of their tangible or intangible assets. Investors' confidence faded before the anticipated growth was ever realized.

2.2 Different types of bubbles in literature

The problem of determining which events to classify as bubbles relates to the concept of economic fundamentals. How can one separate a bubble, having no economic justification, from a price rise due to perceived potential for business expansion?

Several types of asset price bubbles have been specified in the academic literature, based primarily on how bubbles are thought to originate and develop. The first type is the speculative bubble. In this case, the asset is purchased under the belief that the price will appreciate further, but the belief is not based on objective changes in fundamentals. According to Shiller (2000) 'Initial price increases…lead to more price increases as the effects of the initial price increases feed back into yet higher prices through increased investor demand. This second round of price increases feeds back again into a third round, and then into a fourth, and so on'.

The underlying question in these feedback theories is what actually sets off the feedback process? One explanation relies on adaptive expectations, which means that past increases generate expectations of further price increases in the future. The second explanation emphasizes increased investor confidence, which increases as the price increases. But the real crux of a speculative bubble is the estimated probability of a price rise. The bubble can continue only as long as investors think the price will rise again in the next period. Another consideration is that investors' demand for a stock cannot increase forever because there are always resource limitations, and when the demand stops increasing the price rise comes to a halt. This can be seen as the reason for the bursting of the bubble in speculative bubble theories. But how sudden or sharp will the burst will be is not at all agreed among bubble theorists.

There is a great deal of literature relating to speculative bubbles. A few works that might be cited are Hamilton (1986), which deals with testing for self-fulfilling speculative price bubbles; Siegel (2003), which offers an operational definition of a bubble; Raines and Leathers (2000), which is a book on speculative theories of stock market fluctuations that examines eg the theories of Keynes and Galbraith.

Rational bubbles are often distinguished in the literature, one of the earliest mentions being in Blanchard and Watson (1982), which shows that there can be rational deviations from fundamental values in the asset markets. Rational bubbles are thought to be essentially much like speculative bubbles but with a small difference. Evans (2003) defines that, 'According to the rational bubble theory, as prices overshoot their fundamental values there is an increase in the probability the bubble will burst. In turn, the possibility of financial loss increases the risk associated with the ownership of bubbling stock, thereby justifying the acceleration of its price'. Rationality here refers to the idea that investors are supposed to know that there is a bubble component in prices, but prices are guided by self-fulfilling predictions causing prices to rise. But there is still an open question: Why would a rational investor be willing to pay for a bubble in a first place? The answer lies in investors' beliefs that they will be able to leave the market before the bubble bursts and that they regard the increases in a share's market price as sufficient compensation for the increased level of uncertainty and risk.

In the rational bubble models, the price comprises two components: the fundamental price and the bubble component. The bubble component solves the homogeneous expectations equation and the rational bubbles existence can be specified as follows (this part relies heavily on Campbell, Lo and McKinlay (1997) and Campbell and Shiller (1988a and b)).

The return rate $R_{(t+1)}$ of a stock can be written as the sum of the price change $(P_{(t+1)} - P_t)$ and the dividend $D_{(t+1)}$, adjusted to the price of a stock in period t, being

$$R_{t+1} = \frac{P_{t+1} - P_t + D_{t+1}}{P_t} \tag{2.1}$$

As the price change as well the dividends become known only in the period t+1 as they realise, one can take mathematical expectation of equation (2.1) based on available information on period t, this being

$$E_t(R_{t+1}) = \frac{E(P_{t+1} + D_{t+1}) - P_t}{P_t} = R \tag{2.2}$$

and where $E_t(P_t) - P_t + D_{(t+1)} = RP_t$. Rearranging this would result equation (2.3)

$$P_t = E_t\left(\frac{D_{t+1}}{1+R}\right) + E_t\left(\frac{P_{t+1}}{1+R}\right) \tag{2.3}$$

for multiple periods, this can be solved forward for j periods and written in following form (2.4)

$$P_t = E_t\left[\sum_{i=1}^{j}\left(\frac{1}{1+R_{t+i}}\right)^{i} D_{t+i}\right] + E_t\left[\left(\frac{1}{1+R_{t+j}}\right)^{j} P_{t+j}\right] \tag{2.4}$$

In order to get a unique solution for this equation, one must assume that the expected discounted value of a stock converges to zero (2.5) under assumption on indefinite amount future periods, reducing the forward solution of the stocks fundamental price (P_t^f) being the expected discounted value of future dividends, which is presented in equation (2.6)

$$\lim_{j\to\infty} E_t\left[\left(\frac{1}{1+R_{t+j}}\right)^j P_{t+j}\right]=0 \tag{2.5}$$

$$P_t^f = E_t\left[\sum_{i=1}^{\infty}\left(\frac{1}{1+R_{t+i}}\right)^i D_{t+i}\right] \tag{2.6}$$

If the equation (2.5) does not hold, this leads to infinite number of solutions, which all can be presented in the following form

$$P_t = P_t^f + B_t, \text{ where } B_t = E_t\left[\frac{B_{t+1}}{1+R_{t+1}}\right] \qquad (2.7)^2$$

In this equation the component B_t would present the 'rational bubble' as this components value would consist of the expected path of stock price returns.

Thus, in rational bubble models,[3] agents' current decisions depend on both the current market price and their expectations concerning the future price and value of the bubble: Agents who are buying must firmly believe that they will be able to exit before the bubble bursts, and they assume that the bubble will be present in the next period. Then, if bubbles are existent, they should produce unit root or even explosive characteristics in prices compared to fundamentals. By comparing the development of the SP500 index in 1871–2010 in the US (figure 2.1) and the three simulated series, where the AR(1)-coefficient is 0.6, 0.9 and 1.0 (the unit root) (figures 2.2, 2.3 and 2.4), the differences in trajectories are obvious. By looking at the quick appreciation in the price data, it also becomes obvious, that neither of the stationary processes isn't able to result such upswings or downward corrections as are evident in the real price index figure. Only the simulated unit root process (figure 2.4) is able to produce resembling trajectory.

[2] As mentioned by Evans (1991), rational bubbles can take the form of deterministic time trends, explosive AR(1) processes, or more complex stochastic processes.

[3] For example Blanchard and Watson (1982) define the rational bubble as the difference between the observed price on the market and its fundamental value.

Figure 2.1 **Development of the SP500 real price index 1871–2010**

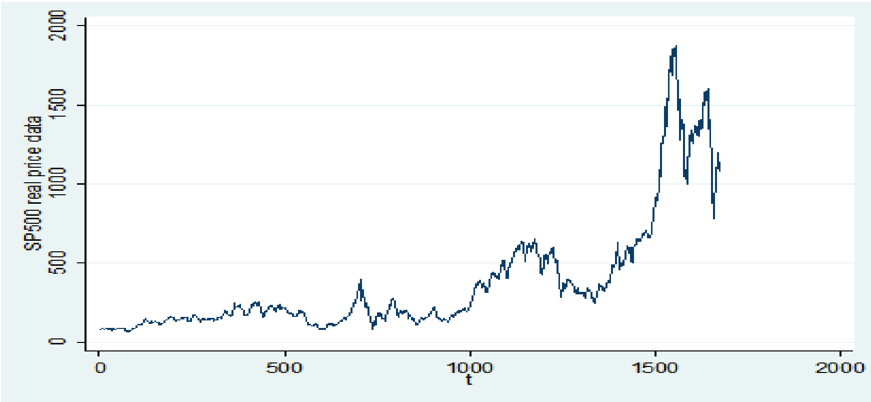


Figure 2.2 **Development of the simulated AR(1) process, where coefficient is 0.6**

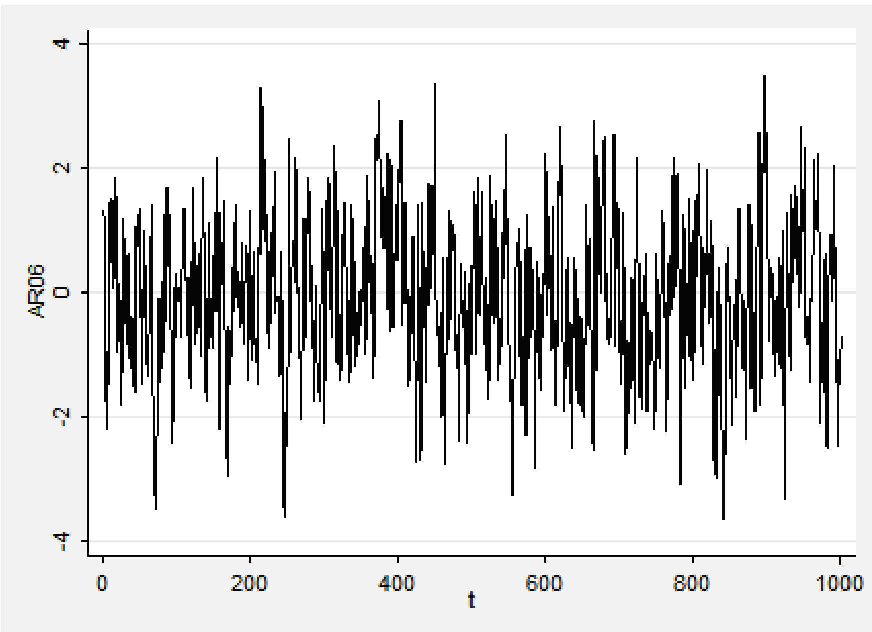


Figure 2.3 **Development of the simulated AR(1) process, where coefficient is 0.9**

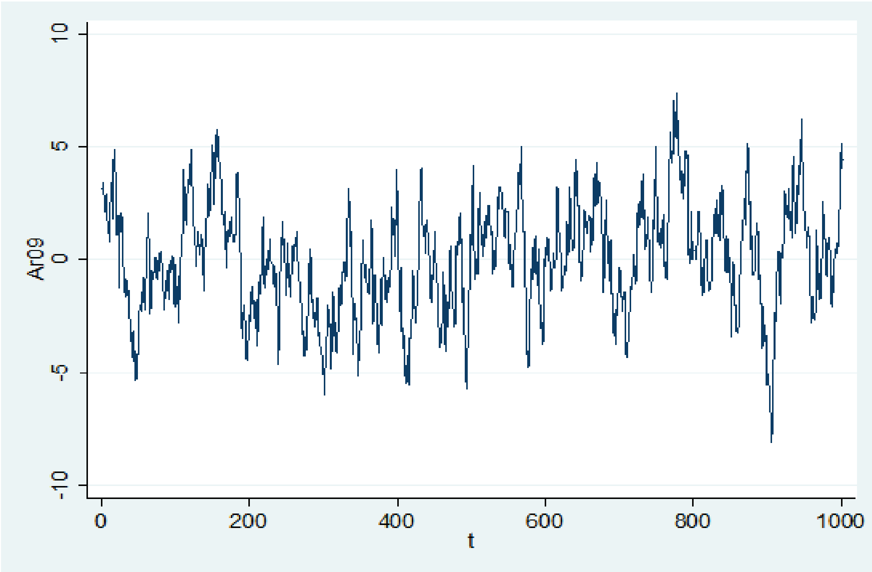
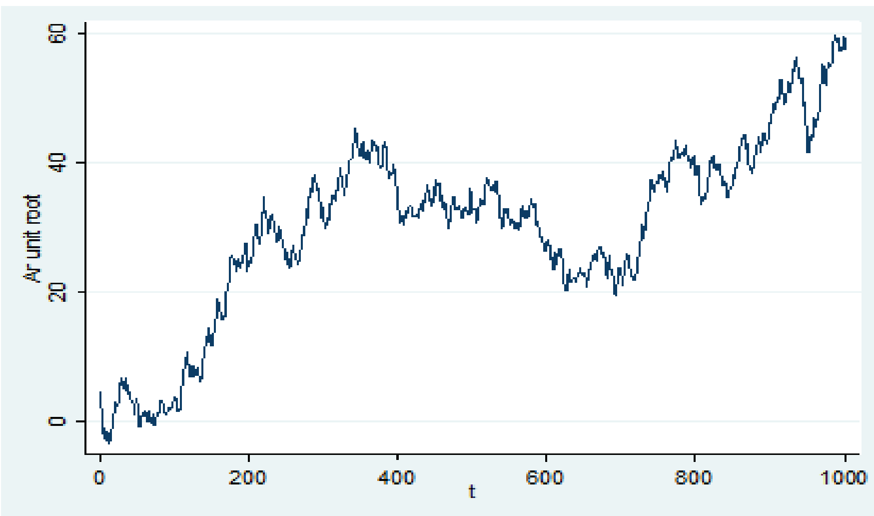
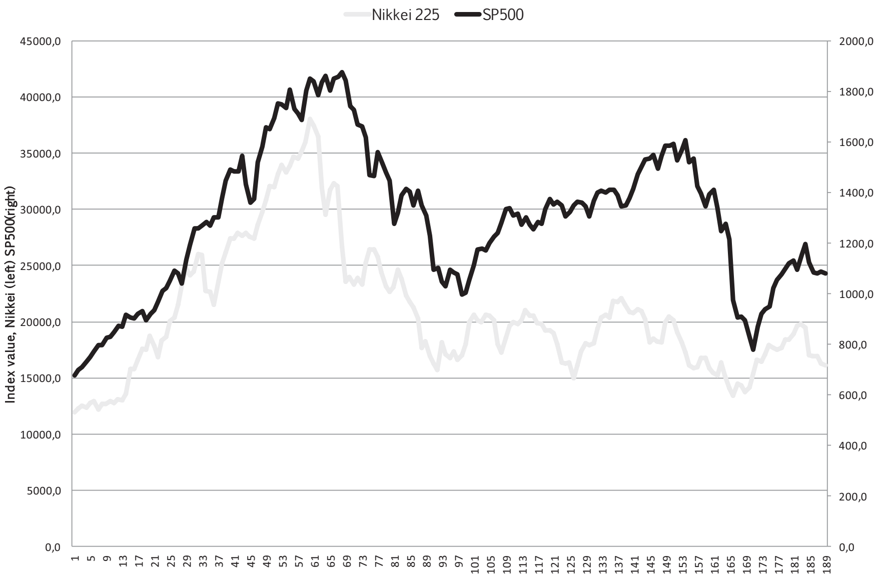


Figure 2.4 **Development of the simulated AR(1) process, where coefficient is 1.0**



In addition, when comparing for example two different markets and two different periods of time, it is striking how much the shape of the 'bubble' periods reminds one another (figure 2.5).[4] Based on these findings it would be interesting to explore common features appearing in asset prices during booms and try to identify these features developments by 'mechanically' quantifying their trends.

Figure 2.5 **Developments in the Nikkei 225 Jan. 1985 – Sept. 2000 and in the SP500 Jan. 1995 – Sept. 2010**



There is a large amount of literature on rational bubbles. Meltzer (2003) covers rational and nonrational bubbles; Adam and Szafarz (1992) studies speculative (actually rational expectations) bubbles and financial markets; Flood and Hodrick (1990) and Dezhbakhsh and Demirguc-Kunt (1990) focus on testing for speculative (again actually rational) bubbles, the latter being concerned with the presence of speculative bubbles in stock prices. Wu (1995) studies the existence of rational bubbles in the foreign exchange market, and Wu (1997) deals with rational bubbles in the US stock market. Diba and Grossman (1987a, b) attempt to determine the inception of a rational bubble and

[4] As well as for example Vogel (2010), who compared the technology stocks bubble (1995–2002) with housing market boom (2000–2007).

(Diba and Grossman 1988) studies explosive rational bubbles in stock prices as does Craine (1993). Santos and Woodford (1997) studies the general economic conditions under which rational asset pricing bubbles can form in an intertemporal competitive equilibrium framework.

In addition to speculative and rational bubbles, two other bubble types are also mentioned in the literature, churning bubbles and intrinsic bubbles. The churning bubble, which was mentioned in Allen and Gorton (1993), involves asymmetric information between investors and portfolio managers. This information asymmetry gives portfolio managers an incentive to churn; their trades are then motivated by the profits they earn at the expense of the investors who hire them, and as a result assets may trade at prices that do not reflect the fundamentals.

Intrinsic bubbles were first mentioned in an article by Froot and Obstfeld (1991).[5] These could be treated as a special type of rational bubble that depends exclusively on aggregate dividends and so derives all of its variability from exogenous economic fundamentals instead of extraneous factors. The striking feature of this type of bubble is that, when the fundamentals are stable and highly persistent, any over- or undervaluation in price can also be stable and persistent. Moreover, these bubbles can cause asset prices to overreact to changes in fundamentals.

So far we have been concerned only with positive bubbles, in which prices are constantly rising. But there are also negative asset price bubbles, which occur when market prices are undervalued compared to the fundamentals. As Shiller (2000) says, negative speculative bubbles may occur 'as initial price declines discourage some investors, causing further price declines and so on ... price continues to decline until further price decreases begin to seem unlikely, at which point there is no reason for people to want to stay away from the stock'.

2.3 Causes behind bubble-periods

Researchers, by no means unanimous as to the existence of bubbles in asset prices, have often voiced their doubts about it. One well-known critic is Jean Tirole (1982, 1985), who has argued that in a discrete-time finite-horizon setting stock prices cannot deviate from

[5] Also Ackert and Hunter (1999).

fundamentals unless traders are irrational or myopic. As Allen and Gorton (1993) mention, Tirole makes three important arguments for excluding the possibility of finite bubbles: 'First, with a discrete and finite number of points in time a bubble would never get started because it would 'unravel' … an agent would not buy the asset at a price above the discounted value of its payoff … because he would incur a loss if he did so … by backward induction it follows that a bubble cannot exist at any point in time. Secondly, if the probability of being able to sell the asset tends to zero as the horizon approaches then traders can only be induced to hold the stock by a price path that goes to infinity. Because there is finite wealth, there must be a date at which the (real) price path necessary to support the bubble would exceed the total available wealth in the economy … Finally, without insurance motives for trading not all of the finite number of traders can rationally expect to benefit since they know that the bubble is a zero-sum game. If traders are risk averse, some must be strictly worse off since they bear risk and not everybody can have a positive expected return.'

Tirole's critique is sufficiently weighty to make it difficult to construct a theory on the usual assumptions that is also consistent with the existence of bubbles. This has led some authors to abandon the traditional neoclassical assumptions of rational behaviour, as Allen and Gorton (1993) point out. They cite as examples Shiller (1984) and DeLong, Shleifer, Summers and Waldmann (1990). On the other hand, remaining within the world of rational behaviour but allowing for an infinite number of time periods, one can sidestep Tirole's first argument. The second and the third arguments are more problematic. Still assuming rational behaviour, one can take into account such things as shifts in growth opportunities (eg 'new era' productivity), which are difficult to evaluate and hence raise difficulties for valuing the amount of (expected) wealth to be allocated in the markets, as well as shifts in the degree of risk averseness. These topics have been covered in many recent books and articles (eg Evans, 2003, and Campbell and Cochrane, 1999).

Despite the criticisms of Tirole and others, the road chosen here is to proceed on the assumption that bubbles do exist. In current environment the stance and acceptance towards the existence of bubbles has changed compared to the earlier literature. Recent events in the global financial markets have changed attitudes towards the acceptance of the existence of price misalignments and bubbles have become one of the major research topics for example among central banks. The turmoil has also intensified the debate on whether central banks should use pre-emptive deeds to contain the build-up of financial imbalances. To be able to 'lean against the wind' would mean that central banks should be able to recognize the build-up of bubbles with sufficient certainty. First step to succeed with this aim requires one to recognize those portents which can lead to development of price misalignments.

In literature, there are several reasons which can lead to formation of bubbles in the markets. The following have been identified in the literature as driving forces for bubbles:

1) Breaks or major changes in regulatory environment

   History provides several examples of major changes in regulatory environment or easing of regulation that leads to rises in asset prices (Sornette, 2003, and Herrera with Perry, 2003). The main reason for this is that it is difficult to adjust to the new situation and correctly value all the underlying potential and effects of the changes. In such situations, asset prices are highly prone to overreaction and misjudgement. As an example one could mention the following examples: the breakdown of the Bretton Woods system, after which the speculative peak in prices was identified as occurring in 1973; and the deregulation and its effects on the markets in Mexico in 1994–1995 and in Thailand, Indonesia, Malaysia and Korea in 1997–1998.

2) Growth prospects

   Growth prospects and potential, within a sector or country, can be difficult to evaluate, especially when the pace of growth was previously slower and has subsequently accelerated sharply. This can happen especially through an innovation whose real pace of potential growth or impact to growth is hard to assess. This might easily lead to overestimation of potential, to overly optimistic expectations of future revenues and thus to overvaluation of asset prices. One good example of this is the technology bubble of the late 1990s. But history provides us with other similar examples. Rapid growth of industrial production led to the great bull markets of the 1920s and 1980s, both of which ended in stock market crashes (for 'new era' cases, see Shiller 2000 or Pastor and Veronesi 2004). Similarly, the development in Japan in the mid 1980s was filled with stories how the rising technical productivity justified rising stock valuations. In the case of Japan, appreciation was further fuelled by easy credit, which also boosted land prices. As Vogel (2010) mentions Japan was assumed to take over the US in chips and microprocessors, supercomputers, televisions and automobiles production. The boom ended finally to contraction of credit, slide of land prices and to recognition that the debt were overwhelmingly disproportionate to earning potential of the corporates. But not only impacts of technological innovations are hard to value, in addition some booms have been fuelled by financial innovation as presented for example by Rapp (2009). Financial innovation is of course in close relation also to policy changes as well as availability of credit. One of the most obvious examples of financial innovation as an engine to asset price overheating would be the latest real estate subprime boom in the US and securitization bubble in the US as well as in the Europe, which clearly were facilitated by financial innovation and various risk-shifting and financing techniques (boosting leveraging). Earlier examples of financial innovation would include the investment trusts and their operation in the 1920s US.

3) Policy changes

Changes in policies (being related also to regulatory changes), concerning taxation, monetary operations, pensions, etc can have far-reaching effects on asset prices (see eg Shiller, 2000). First, the monetary policies and other operations of central banks that are aimed at maintaining a stable environment and sound financial system, play key roles in restoring and maintaining confidence in the financial infrastructure. Overly lax lending policies, ie a surging credit expansion, can easily lead to soaring asset prices (see eg Kindleberger, 2000). Extension of credit facilities beyond what can be absorbed by the real economy tends to spill over to asset prices (Vogel, 2010). As known now, the recent financial crises that started in 2007 was one related to private and financial sector leverage growth, emergence of different risk transfer techniques as well as ample liquidity. For example in the US the debt as a percentage of GDP grew from 160% in the beginning of 1980s to 295% of GDP in 2002 and to nearly 400% in 2008. In many recent assessments especially the ‘too light’ monetary policy stance has been identified as one of the major factors leading to the overheating asset prices and finally to financial crises. Indeed, Allen and Gale (2000) identified credit growth as an important factor contributing to the build-up of asset price bubbles. In the first phase, financial liberalisation or a specific decision by the central bank enables a pronounced increase in lending, which leads to a rapid expansion of credit. This expansion is then accompanied by an extended rise in asset prices. As the bubble bursts some firms and agents that had borrowed to buy assets at inflated prices go under. The abundance (or even expected abundance) of available credit in the financial system can be connected, according to Allen and Gale (2000), to the asset price bubbles in Japan in the late 1980s, the Nordic countries in the late 1980s and early 1990s, and the emerging markets in the 1990s – to mention just a few of the latest incidents.

Tax laws that shelter contributions to assets can readily affect their demand and thus impact their prices. Concerning pension systems, an example is the 401(k) in the United States and its possible effects on developments in the US stock markets in the 1980s and 1990s. Concerning the developments in the US, the supply and demand factors contribution to bubble pressures were explored carefully, since from 1982 onwards the net share supply of corporate equities began to shrink due to repurchases, leveraged buyouts and mergers simultaneously with rising demand due to U.S. households equity investments increase through rising mutual fund purchases. This overdemand is thought to have assisted the overheating pressures to build-up further in the US equities prices.

4) Market infrastructure

In the early 1920s stock market practices were still fairly undeveloped. There was a lack of financial information about public corporations, no regulation against extensive market manipulation, etc. Since the crash of 1929, we have gotten for example (in the US) the Securities Acts of 1933 and 1934, and finally that of 1964, which focused on qualifications of investment advisers and due to recent crises many other regulations that will shape the structures of the markets.

In current global financial markets, the infrastructural issues are even more important due to wide interconnectedness among key operators and investors. In the globally interconnected system possible disturbances can spread quickly and widely causing extensive contagion in the financial system. Accumulating problems can lead to fire sales etc. causing dramatic changes in asset values. In the interconnected world, also reliable functioning of the market and clearing infrastructure becomes important. Infrastructural matters were integral for example to the stock market crash of 19 October 1987 (Black Monday). The official explanation provided by the Brady Commission identified the cause of the crash as the inability of market systems to handle the vast amounts of selling orders that were placed in the computerized trading system. The huge volume of orders to sell was connected with dynamic hedging strategies.

5) Overtrading

The crash of 1987 became a watershed for research on stock markets. Following the crash, more attention was paid to theories that explain investor behaviour and the possible price repercussions (eg Raines and Leathers, 2000). Kindleberger (2000) contains an excellent summary of financial crises, including stock market crises. The summary enables one to obtain information on the latest stock market booms and crashes and the factors deemed to be behind them. The speculation in each case has focused on specific countries, companies, or sectors such as trading companies, railroad companies, or technology stocks. This is evident, when examining for example the trading volumes. As Vogel mentions (2010), though the price changes are the most visible signs of emerging bubbles, no bubble would be identifiable without the dramatic rise in trade volumes. For a bubble to mature, rising volumes is one of the basic requirements and reflects buying investors' beliefs of continuing price appreciation. Interestingly, one of the factors that is cited in Kindleberger (2000) as being common to all of these crises is a period of over-trading. He says that 'As firms or households see others making profits from speculative purchases and resales, they tend to follow ...' Related to Kindleberger's ideas are those of Heaton and Lucas (2000), who list some likely reasons for the latest run-up in stock prices in the latter part of the 1990s. In general, reasons for overtrading are numerous, but majority of them can be classified under the stream of behavioral finance, especially under the topic of 'herding'. One core reason for overtrading is the tendency of people to be habitually overoptimistic and overconfident in their own abilities to handle risk and perform better then the markets on average. For example dynamic prospect theory says, that participants in a bubble become progressively bolder as time goes on. This can lead to overconfidence on one's own decisions and therefore to overtrading. Also 'anchoring' as mentioned by Vogel (2010) leads to outcome, where in absence of very reliable new information, the past prices do provide and 'anchor' where today's expectations are based on. Importantly, most of the features advancing build-up of bubbles are overlapping: for example increases in common knowledge have been identified to support formulation of overconfidence, especially so during strong economic growth. Herding on the other hand means that the individuals would suppress their own beliefs in favor of what is regarded as the market consensus during high uncertainty, stress and unusual market conditions.

As the above-cited reasons suggest, many different primary forces driving the bubbles in asset prices can be identified from the period preceding the emergence of bubbles. Search for early warning indications of emerging bubbles should utmost be a research focused on those common features which can be combined with every emerging bubble. In the behavioral sense, overtrading can be combined to every asset price bubble in the markets. Concerning other features, so does credit growth.

But why do we care about stock price bubbles? Are there some monetary, regulatory or broad economic reasons for seeking to identify those periods when stock prices have bubbled? The answer to this question is central to the motivation for this research.

2.4 Why is bubble identification important?

The importance of tracking bubbles in asset prices is due to the relationship between asset prices and overall functioning of the financial system and the overall performance of the economy. As commonly agreed, central banks have traditionally had two primary tasks: to promote a healthy economy and price stability, and to promote the stability of the financial system. Recent addition to this list is the task to promote (in co-ordination with national regulators) macrostability in the economy, where the core aim is to minimize economy's output losses through prevention of emergence of financial crises (for example Borio, 2010, and Melolinna and Vauhkonen, 2011). These core tasks indicate the causes why regulators and central banks should pay attention to asset price developments and to possible formation of bubbles.

2.4.1 Bubbles impact to overall economic growth and allocation of resources

The primary task of the central banks, is to promote price stability and a healthy economic developments. Concerning the relationship between asset price bubbles and economic growth, it has been shown that asset price bubbles can have long-lasting effects on the operationing of the financial sector and thus also on overall economic growth. As regards to stock market prices, their impact on the economy comes via five different channels: 1) stock market effects on investment, 2) firms' balance-sheet effects, 3) household wealth effects, 4) household's liquidity effects and 5) through reflecting the overall market 'sentiment' to intermediation of finance.

Regarding the causal relationship between stock market prices and investment, Mishkin (2001) and Herrera and Perry (2003) explain it using Tobin's q-theory. When the value of q is high, firms' market values are high compared to the replacement cost of capital, and new plant and equipment is cheap relative to firms' market values.

Firms' balance-sheet effects, as noted in Mishkin (2001), are based on easier access to credit as the valuation of the company rises through equity appreciation. When the price of a firm's stock rises, its net worth also increases, which simultaneously mitigates the adverse selection and moral hazard problems, which in turn leads to increased lending to finance the investment spending.

The crux of the matter as regards household wealth and liquidity effects is in the fact that agents' decisions depend on wealth, which is affected by movements in stock prices. At simplest form, appreciating asset prices generate wealth if one is assumed to be able to liquidate them at prevailing prices. Rapidly rising stock prices may be interpreted as a signal of brighter growth prospects, which will lead to higher levels of expected employment and labour income and thus to a higher level of private consumption. This can lead to an increase in consumption and even to overconsumption if the stock market run-up is robust, as mentioned in Dupor and Conley (2004). Brighter prospects in certain sectors of the economy also attract investment flows, as the growth potential raises investors' hopes of better returns on capital.

The liquidity effect relates not only to households but also to firms, as mentioned. Herrera and Perry (2003) and Bean (2004) describe the effect as follows: appreciating asset values raise the value of collateral, which facilitates the accumulation of debt. Especially during an upswing balance sheets will look healthy, as asset-value appreciation becomes widely apparent.

As seen above, there are several links between asset prices and economic activity. The strongest link being undeniably the intermediation of finance to real economy. These identified links apparently also affect the allocation of the capital, investment and demand. Because bubbles are based on misplaced expectations of the growth potential of certain sectors of the economy, they may cause inefficiencies in the allocation of resources in the economy. Financial resources may be used for capital investments in sectors where growth prospects are highly overstated. Indeed, Gilchrist, Himmelberg and Huberman (2004) show how stock market bubbles influence corporate investment by inducing firms to issue more shares and thus to raise new funding for investment. On a large scale, such a process would surely prove to be highly important, as the particular directions in which these new financial resources flow can affect the economy's future growth aspects and even the level of employment. It is clear that this is the sort of chain of events that occurred, at least on some scale, in the latter part of the 1990s. As Lansig (2003b) mentions, 'Firms vastly overspent in acquiring new technology and in building new productive capacity'. Another serious effect was that these booming sectors recruited lots of people who then lost their jobs in the course of the bust. Lansig (2003b) shows that the decline in business investment during the 2001 recession was much more pronounced than the average for the US economy, which is viewed as the result of the oversized investment boom in the late 1990s. In this respect, misallocation of capital can have long-run effects on economic growth.

2.4.2 Asset prices influence to inflation

Another important link between asset prices, central banks and their task to define monetary policy stance is that of inflation. Academic discussion on this field has focused on a couple of core issues. The first relates to the ability of asset prices to signal future changes in inflation and the second one relates to the actual measurement of inflation. Regarding the first issue, it has been suggested that a rise in stock prices could be interpreted as a signal of improving economic conditions. This could lead to a rise in consumption and investment, which in turn would lead to a further advance in inflation via growing demand pressures in the economy. Based on this argumentation, asset prices rise can be viewed as a leading indicator of inflation.

If the relationship were as straightforward as this, things would be relatively simple. But as Bernanke and Gertler (1999) put it, 'Changes in asset prices should affect monetary policy only to the extent that they affect the central bank's forecast of inflation'. The same message is repeated in Bernanke and Gertler (2001): 'an aggressive inflation targeting rule stabilizes output and inflation when asset prices are volatile, whether the volatility is due to the bubbles or to technological shocks; and that, given an aggressive response to inflation, there is no significant additional benefit to responding to asset price'. In this respect, it would not matter whether or not there was a price bubble, as monetary policy should be tightened if inflation was projected to accelerate. Bernanke and Gertler in fact anchor their argument on the idea that, as regards rises in stock prices, the central bank is unable to distinguish between those driven by bubbles and those driven by fundamentals. Moreover, since both types of shock ultimately affect real output and inflation, the central bank might just as well respond directly only to fluctuations in these variables – and not to fluctuations in asset prices (see eg Lansig, 2003a).

A somewhat different line of reasoning regarding the optimal policy response is found in a discussion paper by Kent and Lowe (1997), which argues that the negative impact of an asset price bubble could increase if it is deflated in time. The asset price bubble could burst in either the near or more-distant future. The further the bubble proceeds, the stronger the eventual impact it is likely to have on inflation and output. Therefore it would seem appropriate for the central bank to take action at an early stage by tightening monetary policy and thus rendering less likely the more extreme outcomes for inflation and output that might result from a prolonged bubble, even if such early action would drive inflation below target in the near future.

Cecchetti, Genberg, Lipsky and Wadhwani (2000) come to a similar conclusion: they propose that central banks should raise short-term nominal interest rates in response to bubbles so as to improve overall macroeconomic performance. Cecchetti, Genberg and Wadhwani (2002) confirm that conclusion: 'Monetary policy that pursues an inflation-targeting strategy should attempt to identify and respond to asset price misalignments'.

As we have seen, regarding inflation and output stability, there are two perspectives. On one hand, it is felt that since the central bank cannot distinguish between bubbles and fundamental shocks it is better to react only to observed developments in inflation and output. The other view asserts that economic performance would be improved if the central bank were to respond to bubble shocks. Regarding the two perspectives, two issues would seem essential. First, the central bank needs to know the extent to which asset prices contribute to overall inflation and, secondly, whether asset prices reflect the existence of a bubble. This knowledge would help the central bank perform its most demanding task, that of optimising the manner and timing of monetary policy actions. Though it is fair to note that, the picture between inflation and asset prices becomes even more complex if we take a look few years back. At that time inflation stayed low and monetary policy regime stayed light, but now it is obvious that in many economies asset prices were overheating.

Of course the measurement of expected inflation is central to monetary policy analysis, but even the measurement of actual inflation has come under serious debate. In academia, the debate has focused on two questions: What specific price index should a central bank target and should that index include prices of assets as well as prices of goods and services? Goodhart (1993) recommends that central banks replace the conventional inflation measures based on prices of goods and services with broader measures that include prices of housing and shares. This recommendation is clearly based on several historical events, including those in Japan in the late 1980s and early 1990s, the United Kingdom in the late 1980s and early 1990s, and the United States in the late 1990s. In the United Kingdom, as in Japan, the problem was that inflation remained low and stable for a long time even while the asset prices appreciated rapidly. As Mussa (2003) puts it, the problem in Japan was that 'the general inflation remained very low in 1988–1989, and it was difficult for the Bank of Japan to find a reason to begin to tighten monetary policy based on general inflationary pressures'. Prices of assets (land, buildings and shares), and hence their value as collateral, soared. The monetary tightening in Japan came too late. When consumer price inflation finally began to accelerate (peaking in 1991 at 4%), monetary policy was tightened. But this drove asset prices down, which in turn sharply reduced the value of collateral on banks' balance sheets and forced abundant write-offs (see eg Yamaguchi, 2003). The United Kingdom experienced a strong rise in asset prices in 1985-1987, but again inflation accelerated with a lag, starting in 1988, which then induced the central bank to tighten monetary policy. As Filardo (2000) mentions, inflation had already climbed to 6% pa by the end of 1989, and in 1990 it was still higher. What comes to one of the most recent asset price upheavals in the United States, around the end of the 1990s, it is noteworthy that once again the CPI remained subdued for a long time, giving only muted signals of a pickup during the years 1999–2000. The overheating of the market was not reflected in the rate of the inflation (eg Mussa, 2003).

If a central bank were to literally observe Goodhart's recommendations in its use of a broader measure of inflation, this would, as mentioned by Filardo (2000), mean that an increase in asset price inflation could prompt tighter monetary policy even if conventionally measured inflation remained low and stable. In the examples of the United Kingdom and Japan, this would have led to monetary policy tightening much earlier than happened in fact, and the subsequent inflationary pressures would have been mitigated.

Concerning the question of a broader measurement of inflation, there are several interesting findings. Bryan, Cecchetti and O'Sullivan (2002) examined whether asset prices should be incorporated into the aggregate price statistic, found that 'the failure to include asset prices in the aggregate price statistics has introduced a downward bias in the US Consumer Price Index on the order of magnitude of roughly ¼ percentage point annually'. This result implies that measured inflation lags behind actual inflation, which was higher than the inflation measured by the CPI. But as Filardo (2003) points out, 'If the increase in asset prices was due to higher expected goods prices, then the Bryan, Cecchetti, and O'Sullivan method would lead the monetary authority to tighten monetary policy and reduce the inflationary pressures. If, however, the increase in asset prices was due to an asset price bubble, then the Bryan, Cecchetti, and O'Sullivan method would generate an upward bias in their cost of life inflation measure and cause monetary authority to pursue an unnecessarily tighter monetary policy.' The key issue here is the extent to which an asset price rise passes through to inflation. The overall usefulness of including housing or stock prices directly in the inflation measure, as proposed by Goodhart, is not supported by Filardo (2000). His empirical analysis questions whether Goodhart's recommendation would lead to better economic outcomes. According to his results, housing price inflation does have some power in predicting future inflation, whereas share price inflation exhibits no power at all to predict future consumer price inflation. Question concerning the relation of asset price bubbles and inflation is still ongoing and currently there is no congruent way how policymakers should take this relationship into account.

2.4.3 Causality between financial stability and asset price bubbles

The second primary task of the central bank is to promote the overall stability of the financial markets. It is well documented that the link between asset price bubbles and financial stability can lead to highly adverse outcomes. Kent and Lowe (1997) mention that ‘A major fall in equity prices can create problems in the payment systems, with potentially large adverse consequences, … borrowers may find themselves unable to repay their loans’. One might well recall the major problems that emerged in the Japanese banking sector when collateral values suddenly plummeted. As Mishkin and White (2003) point out, the most important consequence for a policy-maker facing a stock market crash to consider is not the crash itself but rather the financial instability that may follow. The financial aftermath of a stock market crash is highly dependent on the strength of the balance sheets of financial and nonfinancial corporations. If balance sheets are in good condition, the crash will not necessarily lead to a large-scale bout of financial instability but will operate through the usual wealth and cost-of-capital channels to impact the level of aggregate demand. This argument is currently also one of the cornerstones in the macroprudential policies. Another case is that lost of confidence in the system can enlarge the impact beyond anything expected, as was seen during the latest crises.

Macroprudential supervision is one of the newest challenges confronting central banks, financial supervisors and regulators. The core aim of macroprudential supervision is to minimize systemic crises and their costs to the macroeconomy. The scope is wide: systemicity as a concept means an approach that transcends sectoral boundaries, market boundaries and international borders. The focus is on transmission channels, joint sensitivities and vulnerabilitites and also in procyclicalities in the financial system (Caruana, 2010, and Schauman and Taipalus, 2011). To accomplish the core task, the macroprudential analysis and surveillance of macrostability combines elements from both financial market stability as well as structural and cyclical policies. One of the key factors that link the financial markets and macroeconomic developments together is financial intermediation. Financial intermediation facilitates economic growth, but also contributes to exposure mechanisms trough its role in debt accumulation. Again, debt is the factor that links asset prices under macrostability to real economic performance via stabilisation mechanisms, wealth effects, demand and risk bearing (for example, Schauman and Taipalus, 2011). One of the key factors that facilitate the accumulation of the debt are abundant liquidity and a rise in the price of assets eligible as collateral. As known, growth in the level of debt relative to GDP or to disposable income unquestionably increases the vulnerability of the system and this is why large changes in these ratios are commonly considered to be signs of disturbances.

Considering the connection between bubbles and crashes and financial stability, it would seem appropriate to use several sets of indicators, one to indicate whether market prices are starting to bubble and another to indicate the unhealthy features in companies, households and financial firms balance sheets. The extreme cases of financial instability apparently emerge when asset price bubbles are combined with unhealthy balance sheets, as mentioned in Mishkin and White (2003). Especially dangerous seems to be the combination of ample liquidity, emergence of excessive indebtedness and overoptimistic expectations. Interesting result by Christiano et al (2008) suggests that, the ex-post overoptimistic expectations are not able to generate boom-bust cycles in a standard real business model, but a monetized version of the model which stresses sticky wages and a Taylor-rule based monetary policy, naturally generates a welfare reducing boom-bust cycle. In their model, asset price booms are correlated with strong credit growth. They are able to show that a modification to the Taylor rule in the direction of 'lean against the wind' ie. tightening when credit growth is strong, would raise welfare by reducing the magnitude of the boom-bust cycles. The combined information garnered from these sets of indicators could markedly improve the ability of policy-makers to respond to situations in which financial stability is jeopardised.

2.5 How to respond to bubbles; timing and tools of response

In light of the above discussion, one might well ask why a central bank shouldn't directly engage to pre-emptive policy actions in order to prevent possible misallocations? Such pre-emptive policy actions have been discussed a lot in recent literature concerning bubbles. Bernanke (2002) refers to these pre-emptive policies as 'leaning against the bubble' and 'aggressive bubble popping'. The first of these means that the central bank should take account of, and respond to, the effects of asset price changes on its macroeconomic target variables and should try to steer the asset prices away from the presumed bubble path. Aggressive bubble popping is even stricter: the central bank should sharply boost interest rates whenever it observes a potential bubble in asset prices. There are several problems connected with these proactive approaches though: First, they require identification of bubbles in real time, or preferably even earlier. The big problem here is that so far we haven't had any means of reliably forecasting the timing of a bubble, neither the beginning nor the end. As Alan Greenspan put it, 'There is a fundamental problem with market intervention to prick a bubble. It presumes that you know more than the market.' Another problem, mentioned in Bernanke (2002), is that besides deciding whether or not a bubble exists, the central bank should also measure the part of the price increase that is justified by fundamentals and the part that is not (see also Bean, 2004). Finally, it is important to mention the problem of timing the policy action. Even if the problems related to bubble and fundamental values are solved, the fact is that the instruments of monetary policy are very blunt. As Bean (2004) puts it, 'Once a bubble is large enough to be reliably identified, the presence of lags in the monetary transmission mechanism complicate the calibration of an appropriate policy. Raising official interest rates will be counterproductive if the bubble subsequently bursts, so that the economy is subject to the twin deflationary impulses of the asset price collapse and the effect of the policy tightening.' Cogley (1999) raises the same point: 'a deliberate attempt to puncture asset price bubbles may well turn out to be destabilizing … inability to identify speculative bubbles makes it difficult to take timely and well-measured countervailing actions.'

One of the core questions related to bubbles and responses to their appearance is, are some of the bubbles more problematic than others? In a matter of fact, there appear to be differences in the severity of outcomes related to bubbles and following asset price busts, which depend largely on asset class in question. As Helbling and Terrones (2003) showed in their article focused on search for common features in macroeconomic and financial developments, the equity price busts occurred on average every 13 years, lasted a couple of years and were associated with output losses around 4% of GDP. On the otherhand, the repercussions of a housing price boom followed by a bust were much less frequent in appearance, but when appeared, lasted nearly twice as long and were associated with output losses that were twice as large. The severity of housing price bust was being a reflection of greater impact on consumption as well as on banking system. This is due to the collateral and liquidity effects. In similar way, Zhu (2005) reported that increases in property prices were likely to have a positive impact on GDP in many of the countries included in his research, even though the magnitudes varied across sectors and countries. This strengthens for example the argument on wealth-effects, though the strength of these effects would be highly dependent on whether the house price gains are perceived to be permanent or temporary and how easily the appreciation in house prices can be taken advantage off. This last point was much facilitated by the introduction of home-equity instruments during the years preceding the current financial crises. In addition to Helbling and Terrones as well as Zhu, also Detken and Smets (2004) analysed various macroeconomic variables in a pre-boom, boom and post-boom phases in the economy and came into the conclusion that not all booms lead to large output losses. They were able to separate some of the features that led into economically higher cost booms than the others. According to their results ‘The booms that were followed by a large recession, and in some cases financial instability, are typically longer, give rise to significantly greater real and monetary imbalances, and, in particular, are characterized by a big boom and bust in real estate markets’. For a central bank this would mean that especially the housing market bubbles should be observed and contained in order to perform successful policies.

Tools with which the central bank can react to price misalignments are limited to three, as mentioned for example by Dudley (2010). The first one is to try to lean against the wind by speaking out in public the possibility of a bubble forming into the prices. In this option the policymaker could signal his concerns and question the accuracies of the underlying assumptions. The purpose would be to highlight the potential risks. The second option would be to use the macroprudential policy tools. These tools can include both rules-based as well as discretionary tools, which would target the operations of the sector that causes instabilities and channels that transmits them to the wider economy. The problem with these tools is that they are currently still under wide debate and there is little experience on the use of macroprudential tools. As mentioned by Vauhkonen and Melolinna (2011) one of the biggest challenges is to find tools that can target the key factors in the formation and realization of systemic risks, that impact quickly, and that can be swiftly implemented or even automatic. There are still large difficulties to use this kind of tools effectively in practice. Third option would be to use monetary policy. Compared to macroprudential tools, the monetary policy tool might approve to be too broad – the consequences from its usage would be felt widely in the economy and might approve to have unintended impacts. In addition, monetary policy is a tardy tool – in order to inflate bubbles, it should be used early in the cycle. Monetary policy is nonetheless a strong tool, if the bubbles are forming due to ample liquidity and leverage in the system. Stricter policy can reduce these both. Alessi and Detken (2009) point out, that even small increases of the policy rate could break the herding behavior of private investors, if the policy move is interpreted as credible signal of the central bank's information on the state of the economy (see also Loisel et al, 2008 and Hoerova et al, 2008).

As Dudley (2010) suggests, a proactive approach is appropriate when following three conditions are satisfied: If circumstances suggest that there is a meaningful risk that the crash in asset prices could threaten financial stability, if there are tools that might have a reasonable chance of success in averting such an outcome and if, with reasonable probability, the costs of using these tools would be outweighted by the benefits from averting the crash. But, instead of recognizing the emergence of bubbles, the regulators should also have policies ready to response to them. The next chapters focuses on those methods, which in earlier research have been used to signal the existence of bubbles in real market data. Before this, it might be good to shortly to sum up what has been said above concerning optimal policy actions and developments in the asset prices and how I see the order:

I. Asset prices and price stability. The guideline concentrates around two core questions: First, can developments in asset prices signal future acceleration of inflation and, secondly, should asset prices be included in the inflation measure? The second of these points has arisen because of historical experiences in which inflation has accelerated with a significant lag but then so rapidly that the monetary policy actions needed to tame it have been robust enough to abet the downfall of asset prices. Optimal policy responses in these cases would thus occur at an early stage, rather at the onset of the asset price boom. It should be noted that the wisdom of acting in this manner depends more on the magnitude of the price surge and not so much on whether a bubble is present. This complicates the task as the tools to measure the size of a bubble are not existent.

On the other hand, if one feels that asset price appreciation signals a future increase in inflation, the optimal policy action is either to tighten monetary policy immediately when the effects become apparent in either inflation or output, or already when asset prices begin to soar dangerously quickly. Concerning reactions to an asset price rise without observing a rise in the rate of inflation, there are two viewpoints. According to one viewpoint, monetary policy should be tightened also in those cases where prices are bubbling. The other viewpoint says that tightening in such cases should be extremely cautious, since a bubble left alone might burst in its own time and leave the future inflation rate lower than had been expected. An optimal policy response thus depends on the chosen manner of acting. If it is decided to react already to a surge in the price level, it might be important to know first whether there is a bubble, instead of reacting directly to the price increase. In either case the aim would be to know if asset prices are soaring too fast compared to their fundamentals as they could potentially endanger the stabile inflation development.

II. Asset prices and overall economic performance. Positive developments in asset prices increase wealth, companies' net worth, collateral values, etc. The latter developments boost investment and consumption. Positive developments in prices also indicate expectations of future growth and these expectations can affect investment. In such cases, if there is a market bubble developing, it may strengthen overly optimistic expectations, which can lead to overconsumption, overinvestment, overleveraging and misallocations of investment resources. Concerning the optimal policy response in these cases, it is recommendable to act as soon as when prices begin to bubble ie reach unjustified levels compared to their fundamentals. What to do is clearly a trickier question in case of investment misallocation and overly positive expectations. Tougher 'lean against the wind' policies would be again recommendable, but one perhaps weaker tool would be to increase public awareness of existence of bubbles. Unfortunately, in case of rational bubbles this might not be enough to control them.

III. Asset prices and overall financial stability. Positive developments in asset prices increases collateral values and strengthens companies' balance sheets, which makes it easier to borrow. Therefore, to sustain stabile developments in leveraging one should not overestimate the values of the collateral. If such valuations are overly optimistic, this may lead to sudden negative plunges in collateral values and, if financial institutions are not in good condition, to serious problems for overall financial stability as seen in previous crises. The optimal policy response would be to develop indicators of the condition of financial institutions and of bubble pressures, in order to be able to tame the overly positive developments in asset valuations in time.

These points serve to motivate and provide the basis for my research. They imply that Investors, as well as central banks and regulators would greatly benefit from information on the formulation of bubbles and bubble-pressures in asset prices, even though the chosen actions and appropriate policy responses could differ from case to case.

3 Identification of asset price bubbles – methods of testing for existence

Despite the fact that every bubble has had its own features, there are some symptoms, which precede every bubble as Dudley (2010), Vogel (2010) and Landau (2009) argue. As Landau (2009) points out, bubbles develop because investors have incentives to ignore the 'tail risks' which relate to burst of bubble. This relates to Reinhart and Rogoff (2009), where one of the core reasons for crises to appear are peoples beliefs to assume things to go differently this time: Crises are always believed to hit someone else at some other location. The overoptimistic expectations regarding emerging trends can be argued to be the seed of the new crises. To emerge, the overoptimistic expectations require period of long stability: Stable economic growth, low interest rates and ample liquidity. Expectations of investors are strengthened by upward surprises in companies' earnings, economic growth, asset prices etc. Problem with the overoptimistic expectations is that they lead to destabilizing allocation decisions in the economy. According to Dudley (2010) examination of some of the recent bubbles suggest that the asset bubbles often come through particular sequence of events. First, there usually is an innovation that changes the fundamental valuation in a meaningful way. As there is uncertainty about the true value of the innovation, there is also large divergence of expectations concerning its future growth potential. Second feature is the surge in the activity, particularly associated with the sector of the innovation. Dudley mentions as the third reason the positive feedback mechanism, which tends to reinforce beliefs that something of a regime-shift has truly occurred. Risk assessment of people becomes biased towards the permanent reduction of riskiness. The amount of market participants believing that market price appreciation is justified, increases. Bias towards optimism is clear and this actually is the cornerstone of building up of a rational bubble. As studies have found (for example Thaler, 2000), most people believe that they are above average in their terms of their acumen. Overconfidence can easily lead to the belief, that they can anticipate the end of the bubble and exit the market before the bubble bursts – just as the rational bubble theorem expects them to do.

As the two common symptoms in each bubble seem to be the overconfidence and overpositive price expectations, in order to formulate an early warning indicator of bubbles one should base the indicator on one of these symptoms. Since overconfidence is hard to detect with current tools and as it is partly reflected in prices, the focus in developing an early warning indicator of bubbles should at simplest be concentrated around prices. In light of the problems in measuring bubbles, it is no wonder that many econometric tests have been developed to detect asset price bubbles. Most of these tests have so far focused on detecting 'rational' bubbles.

As Gurkaynak (2005) mentions, the first econometric tests of rational bubbles were based on variance bounds (eg Shiller, 1981, LeRoy and Porter, 1981). The underlying idea is that it is possible to define bounds on the variance in asset price series under the assumption that prices are formed as the present value of dividends. When the variance bound is violated, this means that equity prices are not constructed as sums of expected discounted dividend flows. However, as Gurkaynak (2005) also pointed out, the underlying problem in all variance bound tests is that they are tests of present value models, and rejection can be due to a bubble or any other cause. Violations cannot be attributed solely to the presence of bubbles.

A clear step forward in this sense came with the test developed by West (1987), the main contribution of which was to test separately for the presence of bubbles and model misspecification. His main innovation was to observe in two different ways (Euler equation and AR representation) how dividends impacted on equity prices and, after model specification tests, to argue that the price estimates produced by these two methods should be the same unless there is a bubble present in the prices. Flood, Hodrick and Kaplan (1987) regarded West's test as a significant advance in bubble testing, but found some evidence of model misspecification. Dezbakhsh and Demirguc-Kunt (1990) also used a procedure similar to this procedure, but modified it because of what they saw as size distortions in small samples.

An approach slightly different from that of West was used by Diba and Grossman (1987, 1988). In their analysis, the basis is still the present value formula, but they focus on the cointegration of dividends and stockprices since, in the absence of bubbles, the stationarity of dividends should account for the stationarity of prices no matter how many differences are taken in the dataseries. In their 1987 article they came to the conclusion that rational bubbles cannot start if they do not already exist. This meant that if a bubble was found in a stock's price, it must have been present at the initial sale. Consistent with this, they showed that if an existing rational bubble bursts a new independent rational bubble cannot start. Campbell and Shiller (1987) tested the cointegration in stock prices and dividends and extended their approach (1988a, 1989) to allow for a stochastic discount factor and log linear approximation of the dividend/price ratio.

Evans (1991) strongly criticised Diba's and Grossman's argument, according to which bubbles cannot pop and restart. Evans showed by using Monte Carlo simulations that an important class of rational bubbles, so-called periodically collapsible bubbles (bubbles that erupt and start over again after collapsing close to zero value), could not be identified by using standard tests for unit roots and cointegration, even when such bubbles were present by construction. He demonstrated that it was possible to construct a situation where prices were more explosive than dividends, but which appeared to be stationary when unit-root tests were applied. The problem was that periodic collapses in series made the processes look like stationary processes.

Evans 'critique affected the bubble-testing literature. The subsequent literature focused on finding a way to test for bubbles in processes where the bubbles could erupt and start over again. One of the favourite methods was to treat bubble expansion and contraction as results of two different regimes, which could be tested via regime switch models. Related studies include Van Norden and Vigfusson (1996), Van Norden and Schaller (1997) as well as Hall and Sola (1993). Wu (1997) applied a slightly different approach in which he treated a bubble as an unobservable state vector and estimated it with a Kalman filter. His result was that estimated bubble components accounted for a substantial proportion of US stock prices. Bohl and Siklos (2004) used a momentum threshold autoregressive technique designed to detect asymmetric short run adjustments to the long run equilibrium and Wu and Xiao (2004) focused on testing periodically collapsible bubbles by introducing an alternative test that focused on the order of magnitude of fluctuations in the partial sum process of residuals from regressing asset prices on fundamentals. In something of a return to the roots, Koustas and Serletis (2005) analysed long US data series using traditional unit-root tests as well as performing tests for fractional integration in the log dividend yields. A summary of major bubble- tests can be found in Table A2.1 of Appendix 2.

It is troublesome that the results from these articles still do not give us a definite answer as to the existence of bubbles. As a consequence of this uncertainty, there is a growing branch of literature that seeks to determine whether the modelling of fundamentals in price formation should be different from the plain present value model. Among these works are Ackert and Hunter (1999), Pastor and Veronesi (2004), Balke and Wohar (2001) and Heaton and Lucas (2000).

In the search for the optimal indicators, the aim of the next chapter is to define the core features, which the optimal early warning indicators should possess.

3.1 Features of an optimal indicator

Concerning the desirable characteristics of an early warning indicator which is used for bubble-radar, it should be easy to update and give very up-to-date signals. In optimal situation, the indicators should also be able to reveal slow, but important changes in fundamental structures that could pose a risk to asset pricing. The primary function of an indicator is to serve as an alarm signal, after which the phenomenon should always need to be analysed in more depth. The well-functioning indicators should also be simple and easy to interpret.[6] The more complicated the indicators are, the more sensitive they are to various changes, for example in parameters. Often, even relatively simple indicators can yield the same information or good approxes, than their relatively complicated analogs.

Interpretation of the indicators' signals is rather a complicated task: first it must be decided when the indicator is thought to give an alarm or signal that necessitates a further action. Usually this is done through definition of threshold-values, which themselves includes several challenging issues. In setting the threshold values, it must be chosen, whether the aim is to minimize the chance that the emerging imbalances will be left unnoticed or to set the threshold too low leading to too easy alarms and thereby undermining confidence toward the launched warning signals. Concerning the indicators, it must also be examined, whether similar indicators and thresholds can be applied to various environments or are there such differences in country etc. -level that should be taken into account concerning the applicability of the indicator and related thresholds.

3.2 Unit root tests and persistence changes

In economic modelling there is a long tradition of using fixed-parameter autoregressive processes. In recent research growing evidence suggests that the parameters of autoregressive processes

[6] This section is in many ways based on Schauman and Taipalus (2011).

fitted to economic time series are not fixed over time, but instead display persistence changes,[7] once or even more frequently. Evidence of persistence changes in the stationarity of processes has also had a big impact on the evolution of unit-root testing procedures.

The traditional tests in the unit root literature, the Dickey-Fuller (DF, 1979, 1981) test and its augmented version (ADF) have both been shown to have severe limitations, especially in the case of changing persistence.[8]

As a result a number of testing procedures have appeared in the academic literature that is intended to deal with processes displaying persistence changes. Such procedures have been suggested for example by Kim(2000), Kim et al (2002), Busetti and Taylor (2001) and Busetti and Taylor (2004), Leybourne, Kim and Taylor (2004) and Harvey et al (2006) and more recently by Shin et al (2010a, b) as well as by Phillips et al (2011a, b). The procedures in Kim (2000) as well as in Busetti and Taylor (2001) were based on LBI (locally best invariant)- type stationarity tests rather than traditional unit-root tests. Concerning the methodologies offered as improvements on the conventional DF-testing methodology, one of the first was the procedure presented by Elliot et al (1996) and Elliot (1999), where the methodological improvement was based on detrending: the series was to be detrended before running a DF regression. Detrending was used later, for example, by Taylor (2002). Pantula et al (1994) and Leybourne (1995) used a slightly different approach that relied on OLS detrending. Leybourne et al (2003) used the traditional DF test as a starting point, but explored the power gains achieved by GLS-based detrending of the series. A good summary of those unit root tests, which have significantly more power than the traditional ADF and DF methods, can be found for example in Leybourne et al (2005).

Although the literature presents several methods for dealing with persistence changes, a number of challenges remain as regards their practical applications. One of the foremost challenges is to locate multiple starting and ending points of unit root periods from continuous data. This is an especially difficult problem because the times of occurance are not known in advance.

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[7] To name a few, Stock and Watson (1996), Garcia and Perron (1996), Kim(2000) and Busetti and Taylor (2004).

[8] Busetti and Taylor (2004) showed that the traditional ADF test is not consistent in the case of changing persistence, as the test does not converge to minus infinity with sample size when applied to series containing persistence breaks. This feature is due to the I(1) part's dominance in test results. Similar discrimination problems have been documented in Leybourne, Kim and Taylor (2006).

A new approach to deal with this problem has already been proposed by Banerjee, Lumsdaine and Stock (BLS) (1990). They treated the break date as unknown a priori, and their statistics were defined on the basis of recursive, rolling and sequential tests. The parameters that formed the basis for the BLS (1992) test were the minimal forward (reverse) recursive unit root test parameters. Leybourne, Kim and Taylor (2006) have later showed that this method did somewhat over-reject to constant I(0) series. The use of subsamples in unit root testing were later analysed further by Taylor (2005a), who examined the power of rolling and recursive augmented Dickey-Fuller tests. According to the results, the power of the tests depended heavily on the length of the subsample (window) and the warm-up parameter. Concerning the accuracy of the unit root tests, Choi and Chung (1995) explored the effects of sampling frequencies on the power of traditional unit-root tests (PP, Phillips-Perron and ADF). They found that using high-frequency data significantly improved the finite sample power, for example, of the ADF test. Even more recently, Shin et al (2010a, b) developed two testing methods based on the ADF test, which deal with multiple collapsing episodes within samples using a generalised sup ADF test.

Taking into account the previous research on the subject, the approach of this study is to create a new test setting by using traditional versions of unit root tests in a modified way in order to create a warning signal for an emerging bubble. The aim here is to study whether these simple modified applications of unit root tests can be used as easily applicable indicators of periods of persistence change and therefore as tools for early warning of emerging bubbles. Their reliability is analyzed via Monte Carlo simulations.

The theory underlying the construction of the test for rational bubbles in stock prices has been presented eg in five papers: Campbell, Lo and McKinlay (1997), Campbell and Shiller (1988a, b), Craine (1993) and Koustas and Serletis (2005). Theory is fundamental concerning the construction of the tests in this research. The analysis focuses on using dividend-price information, and the rationalization is simple: dividend yields provide a compact measure of how stocks are valued vis-à-vis their fundamentals. Low dividend yields are seen as evidence of overpriced stocks compared to their earning ability, represented by their dividends (or future dividends), and high dividend yields can be seen as evidence of underpriced stocks. Looking at the dividend yield time-series tells even more: constantly diminishing dividend-price ratios can accordingly be held as a sign of worsening overpricing, ie a bubble, because if prices are constantly rising, these rising expectations should at some point be realized as higher dividends. If price expectations keep rising, but higher dividends fail to materialize, the price rise is not due to fundamentals (ie earning ability). In other words, the price can be seen as a composite of fundamental value plus a rational bubble component, as described eg by Craine (1993). In more formal way, this above reasoning can be presented in a following way. As show, in case of rational bubbles, the price would include expected appreciation in the stock's price being besides just discounted flow of fundamentals (dividends)

$$P_t = P_t^f + B_t, \text{ where } B_t = E_t\left[\frac{B_{t+1}}{1+R_{t+1}}\right] \tag{3.1}$$

And the term B would represent the 'rational bubble' as it is consistent with rational expectations and the time path of expected returns.

As for example Koustas and Serletis (2005) argued, the time-varying expected stock returns has led to a nonlinear relation between prices and returns. As Campbell and Shiller (1988a) suggest, the traditional net simple return on a stock can be written by using a loglinear approximation into following form

$$\begin{aligned} r_{t+1} &= \log(1+R_{t+1}) = \log(P_{t+1}+D_{t+1}) - \log(P_t) \\ &= p_{t+1} - p_t + \log[1+\exp(d_{t+1}-p_{t+1})] \end{aligned} \tag{3.2}$$

where the lower letters represents natural logarithms of variables. Equation (3.2) is a nonlinear function of the log dividend-price ratio, which can be approximated around the mean by the first-order Taylor series expansion

$$r_{t+1} \approx \alpha + \rho p_{t+1} + (1-\rho)d_{t+1} - p_t \tag{3.3}$$

where α and ρ are parameters. This equation (3.3) is a linear difference equation for the log stock price. This equation can be solved forward and after imposing the no rational bubble condition (3.4), the equation can be written into following form (3.5)

$$\lim_{j\to\infty} \rho^j p_{t+j} = 0 \tag{3.4}$$

$$p_t = \frac{\alpha}{1-\rho} + \sum_{j=0}^{\infty} \rho^j[(1-\rho)d_{t+1+j} - r_{t+1+j}] \tag{3.5}$$

From (3.5) one can take mathematical expectation based on information available at time t and after some rearranging the equation can be written into following form (3.6)

$$d_t - p_t = -\frac{\alpha}{1-\rho} + E_t\left[\sum_{j=0}^{\infty}\rho^j\left[-\Delta d_{t+1+j} + r_{t+1+j}\right]\right] \tag{3.6}$$

This is the fundamental equation of this paper. Recalling what Craine (1993) and Koustas and Serletis (2005) have pointed out, 'if the dividend growth factor Δd_t and the log of stock returns r_t are stationary stochastic processes, then the log dividend yield, $d_t - p_t$, is a stationary stochastic process under the no-rational-bubble restriction' and on the contrary, *the presence of a unit root in the log dividend yield is consistent with rational bubbles in asset prices*. Accordingly, in their book Campbell, Lo and McKinlay (1997) develop a present-value approximating relation so that the traditional asset pricing model can be written in a form in which *the log dividend yield should follow stationary process in normal situations but to have a unit root where there is a bubble in asset prices*.

Craine (1993) writes: 'rational bubbles satisfy an equilibrium pricing restriction implying that agents expect them to grow fast enough to earn the expected rate of return. The explosive growth causes the stock's price to diverge from its fundamental value'. Luckily, it is easy to locate the point at which the construction of the dividend yield series changes to a unit root (or even explosive) series using time-the series methodology with slight modifications.

3.3 The new indicators

This study focuses on tools to detect changes in the time series patterns of asset returns. In econometric terms, such changes can best be analysed using changing-stationarity models that encompass changes from stationary process to unit root (or even to explosive process, as shown by Phillips et al 2011) and then back to stationary process.

Several problems arise when traditional unit-root tests are applied to a series that contains stationarity changes. As noted above, most of the traditional tests are unable to handle well persistence changes from I(0) to I(1) and back to I(0), as the tests suffer substantial losses of power in the presence of changing persistence.[9] Another limitation, especially as regards timely warnings, is that the tests are usually applied to long sets of data. This could easily lead to misjudgment as to the true nature of the process, since I(1) observations within the sample would dominate the rest of the sample.

3.3.1 Addressing the problem of stationarity change

The solution offered here for avoiding I(1) dominance is to use shorter and rolling samples. These samples would be fixed in length but would update and roll forward one step (observation) at a time, adding one observation to the end of the sample and dropping the first observation from the sample. This sampling procedure keeps the total sample size fixed. In case of a unit root, this procedure finally exits the unit root from the sample and therefore helps to avoid the I(1) dominance.

The idea of using subsamples in unit root testing has just recently gained more attention in the academic literature. For example, Shi et al (2010a, b) and Phillips (2011b) use fixed starting point windows in their SADF test, and moving windows in their GSADF and BSADF tests. But the idea of using subsamples and moving subsamples have been proposed before them. Taylor (2005) examined the use of rolling and recursive augmented Dickey-Fuller tests and Taipalus (2006a, b) analysed the use of ADF statistics to search for bubbles when using rolling windows to form subsamples.

Though the starting point and methodology for the tests presented in here and the ones presented in Shi et al (2010a) as well as in Phillips et al (2012) seem to be quite similar, there are some major differences between the chosen methodologies. First and foremost, the main difference relates to the construction of the sub sample. In Phillips et al (2011a) the SADF-test uses forward expanding sample sequence, where the window length changes, but starting point stays fixed. As has been shown (for example Phillips et al, 2012), constructing the sample in such a way, leaves the SADF test to suffer from reduced power and inconsistencies in case of multiple periods of excuberance and collapse. To overcome this weakness Phillips et al (2012) proposed method called the generalized sup ADF(GSADF),

[9] To name a few references related to this subject: Phillips and Xiao (1998), Stock (1994), Byrne and Perman (2007), Perron (1989, 1990), Banerjee, Lumsdaine and Stock (1990), Lee and Strazicich (2003), Lumsdaine and Papell (1997), Kapetanois (2005), Saikkonen and Lutkepohl (2002), Lanne et al (2002) and Lanne et al (2003), Elliot et al (1996).

where the main innovation relates to the construction of the subsamples. This innovation takes their approach quite close to the one used in here and previously presented in Taipalus (2006a, b). In GSADF they let the starting value as well as the end value to change, but they still use multiple forward expanding sequences as presented in SADF. Main difference being that the starting points are allowed to change but from that new starting point several different forward expanding sequences are used to form samples. This is clearly different way of constructing the subsamples compared to the approach used here: in this research sample is moving constantly forward by one step at time, its size stays fixes, but its starting value and ending values are allowed to change. This innovation gives each sample its own indication-value, which is then used to evaluate the signal. The way of constructing the samples impacts to the date stamping procedure, which clearly differentiates between this research and the previous work by Phillips et al and is an important feature concerning the timing of the signals.

Phillips et al (2011a) did use rolling regressions with 77 observations in the sample in their empirical application focused on locating bubbles in the Nasdaq stock index. Interestingly, they report that identification of a bubble appears to be robust over regression schemes, but the estimated collapse seems to be earlier dated in the rolling scheme. This result is in line with the argument presented here, that unit-root dominance occurs sooner in the sample in the rolling scheme. Another point in favor of using rolling samples is the sensitivity of the indicator, which is obvious if one looks at the results of Phillips et al: when they used forward recursive regressions the test ignored the 1987 bubble. When they used the rolling (albeit quite long) window they got a signal during the bubble of 1987. These results clearly argue in favor of using rolling windows to get greater accuracy in the timing of the received signals.

3.3.2 Construction of the new indicators

The basis for these new indicators is a novel and very simple use of traditional Dickey-Fuller and Augmented Dickey-Fuller tests. Though these tests were largely neglected for a time as regards the methodology for locating bubbles in asset price series, they have received more attention in the recent academic literature. Phillips et al (2011a) present techniques involving recursive implementation of a right-side unit root test and a sup test. These tests are based on ADF t-values. In Shi et al (2010a) a method called the SADF (forward recursive ADF test) was presented, the idea being to implement the right-tail ADF t- test repeatedly on a forward expanding sample sequence and make inferences based on corresponding ADF statistics. In the generalized sup ADF test, Phillips et al repeatedly implement the right-tail ADF t- test, but as mentioned, they change the sample sequence by letting the starting point of the sample change over a feasible range and superimpose expanding sample sequences onto each starting point. By using this structure, Phillips et al were able to show, via simulations, a considerable increase in power compared to their earlier version, the sup ADF test. They also presented a detailed proof for the asymptotic distribution for the GSADF. The major difference compared to this research's approach comes through the use of t-values in these methods (SADF abd GSADF), since the approach taken in this research does not require the use of t-statistics.

Even though these applications produced good results, simpler methods may yield yet more accurate empirical results and be able to signal both positive and negative bubbles. The methods of Shi et al (2010a, b) and Phillips et al (2011a, b and 2012) do not seem to be able to locate the negative bubbles at all.

The basic ideas of the two novel indicators offered here are very simple and are rooted in the theory underlying the basic features of the traditional Dickey-Fuller and Augmented Dickey-Fuller tests. The new interpretations are as follows:

Proposition 1. As is known, the Dickey-Fuller test scrutinizes the possible existence of a unit root in a simple AR model, which in its simplest form (without drift or trend) can be written as

$$y_t = \theta y_{t-1} + e_t \tag{3.7}$$

where y_t is the variable, t denotes time, e_t is the error term (iid) and θ is the coefficient of interest. A unit root is present whenever θ equals 1. The Dickey-Fuller test is based on the first-difference version of this equation, which can be written as

$$\Delta y_t = (\theta - 1) y_{t-1} + e_t \tag{3.8}$$

The DF tests the unit root hypothesis, H(0), ie whether the coefficient $\gamma = 0$, where $[\gamma = (\theta - 1)]$. The innovation suggested here is simply to use the AR equation and estimate it over rolling-data samples, such that for each period and each new sample a new least squares estimate for of the coefficient θ is obtained. An alarm is triggered when the least squares estimate of the AR coefficient is at least 1.0, which signals the presence of a unit root in the sample and thus warns of a possible bubble.

Interpreting an AR least squares estimate of at least 1.0 as a bubble warning seems justified. For example, Phillips et al (2011a) argue that if bubbles are present, it should be possible to detect explosive tendencies in the price data. As to the interpretation, unit-root or higher least squares estimate can, in terms of autoregressive behavior, cause such behavior in asset prices as are observed in the markets when bubbles are present.

One further point should be made concerning the coefficient least squared estimate of 1.0 as the limit value. As is known, the least squares regression produces downward biased estimates of coefficients, so that. In order to improve the indicator signals, critical values of even less than 1.0 could be used.

Concerning modification of the interpretation of the ADF coefficient, the suggested modification follows:

Proposition 2. The augmented Dickey-Fuller test is merely an extension of the original D-F test, to include lags in the autoregressive process. The testing procedure is the same, except that the ADF model now takes the form

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta y_{t-i} + e_t \tag{3.9}$$

where α and βt are the deterministic components (constant and linear time trend), y is the described variable and e_t is the error term, expected to be identically and independently distributed. As both of the deterministic components are restricted to zero, the process becomes a pure random walk.[10] In the case of ADF-model, the main interest focuses on the value of the coefficient γ. In the conventional form, the test is run to see whether this coefficient takes the value zero, consistent with the existence of a unit root; the alternative hypothesis is $\gamma < 0$. In the traditional testing procedure, the coefficient values per se are not examined; instead, they are used to calculate the test statistics (t-values), which are then compared with the critical values. This is also the way in which the more recent applications of right-side ADF tests are

[10] This holds only if $\gamma = 0$ and $p = 1$. When $\gamma = 0$ and $p > 1$, the process is I(1) as long as δ parameters fulfils requirements, which exclude I(d), $d > 1$.

performed. The modification suggested here is extremely simple: instead of using the t-values, one would use the coefficient values as such. The coefficients would be interpreted as signaling a unit root whenever the least squares estimate of γ is at least zero. It is important to notice, that the choice concerning the length of the lag in here as well as in case of the AR (proposition 1) is made through using the AIC. As the main interest is to identify unit root or explosive processes, the regression is run without trend component.

The regression is run over each period separately, using a rolling window of subsamples of a fixed size. New updated indicator values are obtained for each period, as the sample rolls forward by one step (observation) at a time.[11] The subsample over which the regression is run, the ϑ_t, is defined so that

$$\vartheta_t = y_t \dots y_{[(t+\pi)-1]} \tag{3.10}$$

where π denotes window length (36,48,60). As time advances by one period (t to t+1), so do the starting and ending points of the sample. (The sample rolls forward in such a way until the end-period reaches final period T).

Concerning the recent test-methods presented, there are major underlying differences between these methods and this indicator. The first difference relates to the use of a different construction of subsamples and to the ability of this method to provide period-by-period updates of the indicator. Another important difference lies in the use of actual coefficients in building the indicators presented here, as opposed to previous tests which focus on ADF t-values. Another difference surfaces in actual data applications: many recent research use only (real) stock price data, whereas here the methods are applied to dividend/yield data in order to get more depth to the analysis.

[11] Because the subsamples are overlapping, we could encounter a problem of correlation. To determine the seriousness of the situation, I compared, in MC simulations using similar datasets, the behavior of critical values in cases where the samples were overlapping versus simple one-off tests. The critical values simulated were quite similar, suggesting that, even though correla-tion might distort the results slightly, the overall impact should be relatively small.

3.3.3 Selecting the most informative window length

A key question relates to the choice of window length used in the rolling regressions. Concerning the properties and functionality of the indicator, the rolling windows should be wide enough to make the estimation of the parameters efficient. On the other hand, concerning the core features of the phenomenon under study, which this indicator is meant to capture (asset price booms and busts), the subsample data should not be too long, because booms often last only a few years. In order to provide an early warning indicator, able to provide reliable and timely signals, the rolling data windows are limited to lengths of 36, 48 and 60 observations (eg 3, 4 or 5 years) of monthly data. In several other studies in which subsamples have been used, the samples have been much longer and therefore also less amenable to the updating of information (here, unit root values) from the sample. This could be problematic, as reactions of such an indicator to information updates would be slow. The choice of the optimal window length to 36, 48 and 60 was done based on three facts: the usual duration of the bubble-phenomena, the need to have an efficient regression estimate and to extensive experiments with various window lengths done in previous research linked to the background material of Taipalus (2006a, b).

3.4 Numerical results

It is well documented, that the link between asset price bubbles and financial instability can lead to highly adverse outcomes. One of the newest challenges confronting central banks, financial supervisors and regulators is to minimize systemic crises and their costs to the macroeconomy. The scope of monitoring required to promote macro stability is indeed wide and so the required toolkit is also expansive. A major theme in the literature on early-warning tools is the need to develop an alarm system for a heightened probability of emerging bubbles in asset valuations. For meeting this challenge, a viable early warning tool should have several important qualifications. Foremost, it should have good power: it should give as few erroneous signals as possible but should still spot the majority of bubble observations. The type I and type II errors should be well balanced. The method should also identify emerging bubbles early enough to enable regulators to react. Further, the method should be robust. This means that, if bubble observations keep appearing in the data period after period, the method should signal bubbles repeatedly. Moreover, the indicator should be to be able to signal unit roots even where the persistence of a stationary process is already close to 1 (ie 0.9). This feature is especially important from the practical viewpoint: during normal market periods, the AR(1) regression coefficients in financial series are usually already close to 1.

3.4.1 Framework for Monte Carlo simulations

Monte Carlo simulations are used to explore the power and accuracy of the indicators introduced in section 3.[12] The aim is to search for optimal length of the rolling window used to develop the new indicator. In addition, we look at how well the indicators perform when the underlying stationary part itself has a long memory, as is usually the case for financial market series.

The data observations for the simulations were generated by a program in STATA. The creation of observations is based on an AR(1) process for which the initial value is generated by a random seed. The process is kept simple (no trend or constant, iid error terms). For each analysis a set of 1100 observations were replicated 5000 times, making the number observations in each run 1100*5000, and in each series the first 100 observations were omitted to avoid initialization effects.

Each of the 1100 series of simulated observations includes two breaks: from stationary period to unit root process and then back to stationary process. The break always occurs around the middle of the sample, since the first observation including a unit root is always observation no. 500.The first observation of the unit root is tied to the last stationary observation (traditional AR process with lag 1) to avoid sudden breaks in the process, which could invalidate the test results.[13] The coefficients used in data generation for the stationary part were varied from 0.6, 0.8 and 0.9, one coefficient being applied at a time.

The last observation including a unit root is dependent on the length of the simulated unit root, for which there are three options. The length of the simulated unit root process is 36, 48 or 60 observations, so that the last observation including a unit root is observation no. 536, 548 or 560.

[12] More about the construction of MC simulation in other comparable studies can be found from Appendix 3, table A3.1.

[13] Shape of the simulated bubbles compares well to those presented for example in Evans (1991).

The simulated unit roots were compared to real data bubbles appearing in the Shiller data. The simulated processes seem to be slightly more volatile than the real data bubbles.[14] A more volatile series means that the changes in stationarity should not be easier to spot in the simulated series and the ability of the method to signal stationarity changes is not likely to be overestimated.

The rolling OLS-regressions defining the least squares estimates to AR- and ADF- coefficient were run by using lag defined by the AIC. Lag was very short: in these results reported in this research lag is allways 1. Trend was not included, but constant was allowed. To provide timely warning signals to policymakers, the indicator should be fairly quick to flash warnings of developing misalignments. In the simulations, the AR- and ADF- based indicators should therefore start to launch warning signals shortly after the start (observation no. 500) of the simulated unit root period. This can be examined by looking at the shifts in the AR- and ADF- distributions. Shortly after observation no. 500, the coefficient distribution should start to shift towards 0 for the ADF and towards 1 for the AR. Concerning the length of the bubble and length of the rolling window, the shortest possible combination was chosen (36 periods for both). This is because if the signals emerge from short periods and narrow windows, they should work even better for longer periods and wider windows.

Clearly, the distributions in both cases show that the coefficient values start to change quite quickly to the right, towards the limits of 0 and 1 as the first unit-root observations are taken into the sample. After five observations, a definite change is already discernable in both distributions (see figures in Appendix 4) and already after 15 unit-root observations, there is a highly visible shift in the distributions. During the final phase, when all unit root-observations are included in the sample, the coefficient-distribution has already clearly shifted to the right.

As was seen, the first simulated unit-root observations entering the rolling window clearly starts to shift the distribution. A similar situation obtains when the unit-root period ends and stationary observations begin to enter the sample, ie the distribution starts to shift back. After all the unit-root observations have left the sample, the distribution returns to the form and place where it started. This is visible in the figures in Appendix 4. *This feature is a very essential piece of information concerning the clear advantage of using rolling*

[14] These bubbles are based on Shiller's data and seem to be relatively smooth for traditional stock market data. One contribution for data volatility comes through the way the dividends are taken into account when counting indexes.

samples in running the indicator regressions. In rolling samples the I(1) process does not continually dominate the samples; instead, the narrow rolling windows are quickly updated to bring new information into the samples, whether from I(0) to I(1) or the reverse. An enlargement of the memory of the stationary part does not affect the results since the coefficient distributions continue to react rather quickly to the start and end of the simulated unit-root period. This is a positive sign for the reliability of the indicator. The impact of the memory length of the stationary part on the indicator's ability to react can be illustrated by showing how the 5th percentile, the average, the 50th and the 95th percentiles of the coefficient distributions shift during the simulated bubble. This is illustrated also in the figures in Appendix 4.

In connection with the shape of the distribution of ADF estimator values a number of questions arise relating to the critical value. This becomes obvious where the sample includes only unit-root observations. In this case the majority of ADF-(coefficient) estimators should already be around zero (indicating the existence of a unit root). From the figures in Appendix 4 we see that the majority of observations are less than zero, rather than in the neighborhood. This suggests that, because of the distributional features, use of zero as the critical level might not be efficient, since it might result in too few alarms of unit-root processes. This may relate to the well known fact that least squares regression produces downward biased coefficient estimates in the first order autoregression.[15] One way to decide on an alternative critical value would be to use Monte Carlo simulation to find new critical limits for the coefficients. The table in Appendix 5 reports the 5% upper tail critical values for different window lengths. All the distributions are based on 5000 replications of datasets of 1000 observations.

The underlying process memory would be expected to be rather long in the real world during 'normal' times. It is therefore reasonable to choose critical values based on simulations in which the stationary process is 0.9. As all these 5% critical values lie around the value –0.05 (see Appendix 5) that is what we use here as the additional critical value for the warning signals, rather than zero.

[15] As mentioned earlier, in case of the AR-indicator this would therefore mean, that the correct level to launch warning signals could actually be slightly under 1 instead of being precisely 1 as interpreted here.

3.4.2 The power and accuracy of the AR- and ADF-signals

The performance of the ADF- and AR-based indicators are evaluated on the basis of three ratios that measure indicator performance in terms of the type I and type II errors. The indicators' sensitivity to changes in stationary-part persistence is studied in terms of the loss of power as the coefficient of the stationary process is increased from 0.6 to 0.9. A good indicator would not lose accuracy even if the stationary process is highly persistent. Based on the simulations, we examine the sensitivity of the indicators to the lengths of simulated unit root in the data and rolling window, which are the bases for the indicator coefficient regressions. *Because the bubbles may vary in length, it is important for an indicator to be able to give warnings even when the bubble is of relatively short duration.*

To evaluate the indicators, I studied the **number of false alarms given by the indicators, ie the number of signals of unit-roots triggered by the indicators in periods in which there were no unit-roots present**. The percentages of the false signals for the AR- and ADF- indicators are detailed in the tables in Appendix 6. The total number of false alarms seems to be very small, even where the stationary-period memory is long (0.9). The percentages of false alarms before and after a unit-root period can be analyzed separately. According to these results, the probability of false alarms increases slightly after a simulated unit-root, but remains very small. For example, when the simulated unit-root period length is 36 observations, the stationary period is simulated using relatively long memory (0.8) and the rolling subsample over which the ADF- and AR-regressions are counted is 36 observations. Here, the total number of false alarms is only 2782 in more 4.5 million observations, ie the false-alarm rate is just 0.06%.

As observed from the results shown in Appendix 6, the AR coefficient clearly produces the smallest number of false alarms. The difference in numbers of false alarms as between the AR and ADF indicators is even greater where the persistence of the stationary process is greater. For the ADF method, there is a clear difference between critical values (0 or –0.05) in terms of false alarms: using zero as the critical value clearly results in fewer false alarms than does –0.05.

Overall, the number of false alarms for both methods seems to depend on the stationarity of the 'normal' period: as the stationary-period persistence increases (from 0.6 to 0.8 to 0.9), the probability of false alarms increases for both methods. Increasing the length of the rolling window reduces the probability of a false alarm, especially for AR: the longer the rolling window, the less probable is a false alarm. In terms of indicator-specific features, lengthening the unit-root period does not seem to have a great impact on the number of false alarms given by the AR coefficient, in contrast to the ADF coefficient, for which the number of false alarms increases as the simulated unit root period gets longer. This can be explained by unit-root characteristics and by examining false alarms separately for the periods before and after a simulated unit root period. We know that a unit root will dominate a sample. In this regard, the AR coefficient seems to be more robust: the false alarms are clearly more frequent after long simulated unit-root periods for the ADF coefficient versus the AR coefficient.

Another important means of assessing indicator performance is to look at **the total number of simulated unit roots that the indicators are able to spot in the data**. This assessment can be done in two ways. First, the performance can be evaluated according to the indicator's *ability to mark correctly individual unit-root observations* in the simulated data. For example, in the case of 36 simulated unit root observations in the data, perfect performance means the indicator signals every one of these observations as a unit-root. Another performance metric (perhaps more relevant for practical applications) is to analyze *how many of the simulated unit-root periods are spotted* and signaled by the indicators. Here, it is sufficient that just one of the 36 simulated unit-root observations is signaled during the simulated unit root period. If none of the 36 observations is signaled, the indicator would be judged to have missed the unit-root period. Even a single signal would indicate the spotting of a unit-root period from the data. The AR and ADF indicators' ability to signal correctly individual unit roots or their periods is presented in the tables in Appendix 6.

In terms of correctly signaling single simulated unit-root observations, it is surprising that both methods perform the more accurately, the greater the persistence of the stationary process. The ADF coefficient produces quite different results depending on which critical value (0 or –0.05) is used. When the stationary process was simulated using the coefficient 0.6 and the rolling window as long as the simulated unit root period (36 observations), use of the zero critical value (ADF (0)) results in correct signals for only 5.32% of the single unit roots. In contrast, when –0.05 is the critical value, the ADF (–0.05) correctly signals 15.75% of the simulated single-unit-root observations. This is close to the level for the AR coefficient, which correspondingly correctly signals 16.20% of the single simulated unit roots. The performance of the indicators improves in most cases when either the rolling window or the simulated unit-root period is lengthened. For example, when the stationary period coefficient was set as 0.6 and the length of the rolling window was increased to 60 observations and the simulated unit-root period to 60 observations, the ADF (–0.05) was able to signal 23.39% of the single simulated unit-root observations correctly. This last result is not surprising since a longer unit-root period is always easier to extract from the data. If the previous example is changed so that the rolling window is reduced to 36 observations, other elements being the same, the ADF (–0.05) correctly signals 17.50% of the single-unit-root observations and the AR method 23.14%.

These indicators seem to retain power as the stationary-period simulation parameters get longer memories, from 0.6 to 0.8 to 0.9. When the stationary period was simulated using the coefficient 0.9, and the unit root period and the rolling window length were set at 36 observations, the ADF (0) was able to signal correctly 4.95%, whereas the ADF (-0.05) correctly identified 17.28% of the single-unit-root observations. The AR coefficient did even better, correctly identifying 20.76% of such observations.

When indicator performance was evaluated according to **ability to identify unit root periods instead of single observations**, the results were quite different. The percentages for each method are much higher when the focus shifts to finding periods instead of single observations. Concerning the ADF method, in a simulation framework where the stationary period was simulated using a shorter memory (0.6) and the unit root and rolling window were set at 36 observations, the ADF (0) signaled 37.54% of the simulated unit-root periods, whereas the ADF (–0.05) was able to indentify 59.70%. The rates were much higher than for the single observations. In the same setting, the AR method correctly signaled 55% of the unit-root periods.

Once again, the longer the simulated unit root period, the more easily it is identified from the data. In many cases as many as over 70% of the simulated unit-root periods were identified. For example, when the unit root period was set at 60 observations (other settings being the same), the ADF (–0.05) was able to correctly signal 79.04% of the simulated unit root periods. And in another option, when the stationary periods memory was increased (to 0.9), the rolling window being constant at 36 observations and the unit root period set at 60 periods, the ADF (–0.05) was able to correctly signal 81.36% of the unit-root periods. Simulation results and rejection frequencies along with correct signals are detailed in the tables in Appendix 6.

Summing up the core results, it seems that the optimal length of rolling window is quite short, as the shorter rolling windows clearly performed best, whether the method was the ADF or AR coefficient. Concerning the methods, the most robust and precise indicators seem to be the rolling ADF coefficient, with –0.05 as the critical value and the AR regression coefficient with 1.0 as the critical value. Even though the correct signals of individual unit-root periods remained at a rather modest level, they do not compare poorly to other such methods of signaling unit root observations from data. The most important finding though is the huge accuracy improvement as measured by the number of correct unit-root-period signals as opposed to finding individual unit-root observations. As both of the methods (AR and ADF) are able to signal up to 70–80% of the periods correctly, they are worthy of further study, especially as regards real data applications and the ability to produce early warning signals.

3.4.3 Are continuous-signal methods more accurate?

A consistent indicator would produce continuous warning signals during a simulated unit-root period. It is therefore important to investigate how the accuracy of the AR and ADF methods change if the bubble signal is given only after the unit-root indicator has identified five (or more) consecutive single observations as bubbles. The evaluation was done with more limited data, just to get an idea of how the criterion of continuous warning signals affects the results.

The analysis is based on MC simulations, where the total number of observations is limited to 100000 and the stationary period's simulation parameters vary from 0.6 to 0.9 (as previously, only one of the coefficients is used at a time). To evaluate the ADF coefficient's performance, the critical limit was set at –0.05 and for the AR coefficient the critical value was 1.

The simulation results are reassuring: It seems that the methods' sensitivity to changes in stationary-period coefficient is greatly reduced. The results and accuracies are much more alike as between the methods in the continuous-signals case than in the case of single observations: the coefficient (whether 0.6 or 0.9 during the stationary part of the regression) does not play such an important role in the case of multiple signals.

Concerning the number of false alarms, we note that the use of multiple (five or more) alarms further reduces the total number of false alarms. The total number of correctly signaled unit-root periods (meaning that at least one set of five continuous alarms is triggered during the simulated unit root period) is still around the 35% level, but the total number of correctly signaled single observations (meaning that each of the sets of five observations during the simulated unit-root period was correctly signaled as a bubble) is relatively low, approximately 10%. This can be seen from tables in Appendix 7, which includes the core results of the multiple alarm test.

The results of the continuous alarms can be compared to those of single alarms. The main difference between the use of single signals and multiple continuous signals is that the multiple continuous signals would reduce the total amount of false alarms but would reduce the total number of signaled bubble periods. In addition, the use of multiple continuous alarms makes both methods (AR and ADF coefficients) more robust to changes towards 'normal' period parameter changes. Therefore *it is seems prudent to use both methods – single and multiple alarms – in evaluating developments in a time-series, since it is found that the robustness of the alarm signal is greatly increased when five or more continuous bubble signals are received*. An especially important point is the small number of false alarms in these cases.

4 The power of conventional unit root tests in the case of rolling windows

To get an idea of whether the AR and ADF indicators really provide an improvement[16] to the already existing group of stationarity shift and unit root indicators, one might well compare the performance of the indicators to the conventional, and the so-far most powerful: unit root and stability tests.

Evaluation of performance is done by comparing the results of Monte Carlo simulations. The simulation setting provides a full replication of that of the previous section. First, each of the conventional tests was run using the same simulated series as the AR and ADF analyses. This is to avoid any differences resulting from newly simulated data. Each method was tested using similar lengths of rolling windows (36, 48 and 60) to define values for the test parameters. The dataset was again 1000*5000 observations for each test, since the first 100 observations were omitted to avoid initialization effects. The only exceptions were the rolling CUSUM and rolling variance ratio tests, where the total sample was limited to 100 000 an to 10 000, due to the core features of these tests, which are much more data-intensive and time consuming compared to the conventional unit root tests.

The simulated breaks in the data are similar to those in previous section: each of the simulated datasets includes two breaks – from stationary period to unit root process and back to stationary process. And as before, the break is always situated nearly in the middle of the sample. The chosen conventional tests were the R-test, MAX-test, CUSUM-test and the variance ratio test.[17]

[16] As proposed in the external evaluation, this chapter would greatly benefit from 'horse race test' between the new indicators pre-sented in this research and those methods presented in prior studies. As a proper set of horse race test would require a lot of relevant financial market series as underlying data as well as enough test methods to compare their relative strengths, it stays currently out of the scope of this research, but remains however a work to be done in order to properly evaluate different methods relative usefulness.

[17] One could have added also the Phillips et al (2011, 2012) tests to this group in order to be able to more properly compare their relative strengths and weaknesses compared to the methods presented in this research, but the most relevant version, Phillips et al (2012), came out relatively late compared to the performance of the simulations. This is a work to be done.

The R-test was presented by Leybourne, Kim and Taylor (LKT, 2006). Following Banerjee et al (1992), Leybourne, Kim and Taylor (2006) demonstrated that the forward recursions could be used for testing against persistence change from I(0) to I(1), and the reverse time series recursions can be used to test against change from I(1) to I(0). Forward and recursive tests, however, cannot adequately discriminate between change in persistence and constant I(0) behavior, as mentioned in Leybourne, Kim and Taylor (2006), this being the reason they proposed a new test statistic based on the ratio of forward to reverse statistics (the R) for use in unit root testing. The clear advantage of the R-test is that it remains consistent over changes from I(0) to I(1) and vice versa.

The t-test values associated with the forward and reverse recursion coefficients are the (Dickey-Fuller) $DF^f(\tau)$ for the forward-and the for the reversed series t-tests, τ being the true break fraction. As the precise date of the change in the series persistence is usually unknown, Leybourne, Kim and Taylor proposed using the minimum of the sequence of t-statistics over a set of subsamples (subsamples were constructed through using various break fractions). These minimum values were denoted by $DF^{f\,\inf} \equiv \inf_{\tau\in\Lambda} DF^f(\tau)$ and $DF^{r\,\inf} \equiv \inf_{\tau\in\Lambda} DF^r(\tau)$. The proposed R- statistic is constructed as the ratio

$$R \equiv \left|\frac{DF^{f\,\inf}}{DF^{r\,\inf}}\right| \tag{4.1}$$

Use of the minimum over a sequence of changing subsamples is problematic in our context. One of the main innovations here is to use rolling windows to define the subsamples that are always fixed in length. This is why I chose to calculate the R-statistic over subsamples of the same length and the selecting the minimum value in each sample.

For the second conventional test, the MAX-test, the starting point in Leybourne (1995) was to explore whether the unit root tests would improve in power if the conventional Dickey-Fuller and Augmented Dickey-Fuller tests were run not only in forward recursions but also with the reverse realizations of the data. The changes in definition of the new test-parameter was quite modest, since the MAX-test is transformed into a maximum of the t-test values of forward and reversed recursions over the chosen data sample.

Formally, the MAX- test by Leybourne (1995) can be simply defined using the standard Dickey-Fuller (DF) procedure. The forward regression t-value is denoted by DF_f and the t-value for the reversed series is denoted by DF_r. The MAX- statistic then being expressed as

$$MAX = \max(DF_f, DF_r) \tag{4.2}$$

and for the ADF,

$$MAX = \max(ADF_f, ADF_r) \tag{4.3}$$

The other two chosen tests, the variance ratio test and CUSUM-test use a slightly different testing approach. The focus in the Lo and MacKinlay variance ratio test is to analyze the random walk patterns in a time series. As is known, the random walk is closely related with unit root process, since the random walk possesses a unit root. Also, in random walk process the increments are required to be uncorrelated, which is also the feature in some traditional unit root tests (for example Dickey-Fuller). Due to these common features and despite the fact that the focus of random walk tests differs slightly from unit root tests, random walk tests have characteristics, which the traditional unit root tests lack and which actually could help finding to locate stationary changes in underlying time-series.

To put it short, in a random walk series the variance of a sample is linearly related to the length of the sampling interval. When a time series is split into n equal parts, the variance of the whole finite time series should be n times the variance of the first part, assuming the random walk hypothesis holds. The ratio between the sum of the n equal parts variance and the samples total variance should therefore equal 1. If the variance ratio stays under one, the series is mean reverting, ie. the series has a short memory and must include some negative correlation. When the variance ratio is greater than one, the series is persistent, meaning that the series has a long memory and positive serial correlation. Existence of a unit root in the series therefore indicates that the random walk hypothesis holds. The focus of the test is therefore to find out, whether the variance ratios deviate enough from unity in order to reject random walk hypothesis (Lo and MacKinlay, 1988).

The variance ratio test used here, can be described as follows: The test-values are defined by calculating the variance ratio by applying the Stata module *lomackinlay* to predefined subsample data. The major problem may be the likelihood of heteroskedasticity, as it is known that z(1) statistics may not have the usual asymptotic properties in case when the variance of innovations is unstable.

Variance ratio, homoskedastic errors:

$$z(1) = z_1(q) = \sqrt{nq}\,\overline{M_r}(q) \cdot \left[\frac{2(2q-1)(q-1)}{3q} \right]^{-1/2}, \ N(0,1) \tag{4.4}$$

where the number of periods q, over the which innovation parameter's effects on the values of the variable are screened. If the process is stationary, the innovation parameter should not have permanent effects, ie it should converge towards 0. In addition, in previous equations, nq is the sample size (n being the multiple for sampling frequency) and $\overline{M_r}(q) =$ the dimensionless centered variance ratio.

If the null hypothesis of random walk remains in force it can be interpreted to mean that the underlying series has a unit root. Evaluation of the hypothesis is accomplished by applying the critical values presented in Lo and MacKinlay (1989).[18]

Finally, regarding the CUSUM-test, the purpose here is to provide a completely different approach to testing for the existence of breaks. CUSUM is an old method that has been used mainly as a statistical process control tool, as originally designed by Page (1954). The underlying idea in CUSUM is to detect persistent changes or shifts in the underlying process.[19] In the traditional CUSUM analysis, there are three important values: the center line, which represents the target value, the upper control limit and the lower control limit. If the process is in control, it should stay between these two limits. Observations outside of the borders signal changes in the underlying process. Very large shifts result many observations outside the limits.

Li (2007) sees CUSUM as being among the most effective procedures for detecting small shifts in the mean process. For this reason it should be able to spot changing persistence also in series stationarity. CUSUM and its modified version's ability to signal changes in the time series persistence have been analyzed in many studies and the main outcome has been that the CUSUM-based tests have the big advantage of generally not spuriously over-rejecting a

[18] There are quite a few articles where the Lo-MacKinlay variance ratio test is applied to financial series (eg Whang and Kim (2003), Ayadi and Pyun (1994), Hoque, Kim and Pyun (2007), Ajayi and Karemers (1996)), but concerning unit root testing, the rolling application of the tests has been rare.

[19] As residual based cointegration test the CUSUM test has been applied for example by Phillips and Xiao (2002).

process that does not display a change in persistence. The CUSUM test used here is the traditional CUSUM test, with the innovation that it is calculated by using rolling subsamples of data. In traditional CUSUM-testing, an alarm means that one should return and 'nullify' the process before continuing. One advantage in using rolling tests instead is argued to be that the distortion caused by an alarm should be reduced due to the effect of overlapping 'clean' samples.

The formulation of the CUSUM test here follows closely Mellin (2009). The traditional CUSUM[20] test can be defined formally as follows.

Let there be n observations of variable x_i, $i = 1,...,n$ with the midvalue ω_0. Then the cumulative sum over n observations can be defined as

$$C_i = \sum_{j=1}^{i} (x_j - \omega_0), i = 1,\dots,n \tag{4.5}$$

The cumulative sum C can be defined so as to collect all the deviations exceeding the reference parameter. In the basic formulation, CUSUM is only able to trace the positive deviations. In a more advanced approach it is possible to track both positive and negative deviations. There, in addition to C+, which collects all the positive deviations, it is possible to define C– such that it collects all the deviations falling under the reference parameter. Calculation of cumulative sum over a certain set of variables $X = (x_{1\dots}x_n)$, with the expectation that the variables in the sample are normally distributed with parameters $(X) = \omega_0$, $D(X) = \sigma$, can be written as follows

starting values:

$$C_0^+ = 0 \text{ and } C_0^- = 0 \tag{4.6}$$

for $i = 1,\dots,n$, the values are defined as:

$$C_i^+ = \max[0, x_i - (\omega_0 + K) + C_{i-1}^+]$$

$$C_i^- = \max[0, (\omega_0 + K) - x_i + C_{i-1}^-]$$

[20] For further details on the change detection parameters and CUSUM-procedures, see eg Part I: Changes in the Scalar Parameter of an Independent Sequence, http://citeseerx.ist.psu.edu.

where ω denotes the target-value and K the reference value usually chosen to be situated halfway between the target-value and the value toward which the change in the process is hopefully leading. In the CUSUM-measure, the C_i^+ and C_i^- are presented as lines for values i=1,...,n, and they are expected to stay between the minimum and maximum control-borders. The limiting borders ie. the minimum and maximum control-borders for the cumulative sum-values, are dependent on the variance of the process and are defined in the basic model as the +H and –H, borders such that H = 5σ.

In this study the CUSUM is calculated by using the Stata-module cusum6, which calculates the recursive residuals from a time series regression in order to generate the CUSUM as well as the CUSUM squared tests of structural stability, which is more thoroughly presented in Brown-Durbin and Evans (1975). The approach by Brown-Durbin and Evans has been the basis for numerous pieces of academic research.

4.1 Monte Carlo simulations

4.1.1 The power of the rolling R- and $DF^{f\,inf}$-tests

For the R- and $DF^{f\,inf}$-tests the interpretation of results must be done carefully. Since the R- test statistic can be constructed only after defining the $DF^{f\,inf}$ test statistic, it is useful to analyze also the $DF^{f\,inf}$ test for the case of rolling windows, especially since Leybourne et al (2006) find that when one wants to test whether the series is characterized by unit root (ie H(0) of constant I(1) behavior against the alternative I(0)), they recommend using the $DF^{f\,inf}$ and $DF^{r\,inf}$ tests instead of the R-test.

The R-test and $DF^{f\,inf}$-test parameters are calculated by using rolling windows of lengths 36, 48 and 60. The critical values to evaluate the signals are again taken directly from Leybourne et al (2006), where the 5% critical level limits can be found for both tests for as small a sample size as 60. These critical values are used for estimates to evaluate the R- and $DF^{f\,inf}$-test statistics, though once again there might be a problem with the use of rolling windows instead of static samples for which these limits were originally created. As Shi et al (2010b) showed, the asymptotic behavior depends largely on the subsample size, distributions of smaller samples being leptokurtic.

In the case of the R-test, the major interest is to find out whether the test rejects the null hypothesis of constant persistence against the alternative of a change in persistence. In the case of rejection, attention is drawn to the tail of rejection, which may indicate the direction of the change, from I(0) to I(1) or from I(1) to I(0).

In the $DF^{f\ inf}$-tests the major interest is to examine how many times the rolling test correctly rejects the null hypothesis of I(1) during the stationary period, either before or after the simulated bubble and how many times it falsely rejects this hypotheses during the simulated unit root period. The power and accuracy of the $DF^{f\ inf}$-test are reported in the tables in Appendix 8.

Concerning the power of the test for different memory lengths in stationary period, the $DF^{f\ inf}$ performs clearly better when the stationary period is simulated with shorter persistence, 0.6. In this case it is able to correctly reject the unit root hypothesis in 52% of the cases, even with the very short window (36). As the window gets longer, the percentage of correct rejections increases. When the window includes 60 observations and the stationary period persistence is still 0.6, the test makes correct rejections in 88% of the cases.

The correct signals seem to be sensitive to changes in stationary-period persistence. This can be seen by comparing the results in the tables in Appendix 8. As the regression coefficient for the stationary period increases in size (to 0.8), the number of correct rejections of the unit root hypothesis decreases sharply. For the shortest window (36), the method correctly rejects the null hypothesis in just slightly over 20% of the cases, and although increasing the length of the window improves the results somewhat, the mehod correctly rejects in less than 40% of the cases. The $DF^{f\ inf}$ method seems to perform much better in environments of shorter memory.

On the other hand, during the unit-root simulation, false rejections of the unit root null hypothesis for single observations are quite rare when the persistence during the stationary period is high, 0.8. For the shortest window (36), false rejections occur only in slightly over 16% of the cases. Increasing the window length does not seem to improve the accuracy, as the number of false rejections increases as the window is extended.

The method's sensitivity to changes in stationary-period coefficient becomes visible once again when the false rejections during simulated unit root periods are compared for the series where the stationary period was simulated with shorter (0.6) versus longer (0.8) memory (see tables in Appendix 8). False rejections are quite numerous when the stationary-period coefficient is 0.8. The unit-root periods (rather than single unit root observations) that were rejected falsely during simulated unit root periods are presented in the tables in Appendix 8. From these tables we see that the test correctly identifies more periods when the stationary part has short persistence. When the stationary-period coefficient is 0.6, much fewer unit root periods are falsely rejected.

The R-test environment is slightly different. The null hypothesis here is a constant I(0)-period. Rejection of the hypothesis would be interpreted as a signal of persistence change in the process and, as mentioned in Leybourne et al (2006), when the rejection occurs in the upper tail, this suggests a change in persistence from I(0) to I(1). As the main interest in this study is to find methods that can reliably signal shifts from I(0) to I(1), the focus will be to examine how many upper tail rejections the R-test is able to produce for simulated unit roots when the data are run in rolling form. Critical values for the evaluation are from Leybourne et al (2006).

The core results are shown in tables in Appendix 8. The R tests rarely give false alarms of unit-roots during the stationary period, even when the stationary period is simulated by using higher persistence, ie when the coefficient is 0.8. On the other hand, the number of false alarms increases somewhat after the simulated unit root period, compared to the period before the simulated unit root.

Though it rarely gives false alarms, the method unfortunately is unable to signal unit-roots correctly. The test misses nearly all of the simulated bubbles. It seems that it is too rigid to react to relatively quick changes in process persistence. This can be seen from the results; the longer simulated unit roots are signaled much more often than the short ones. It also seems that the method finds breaks easier from the data where the underlying stationary process is already close to a unit root. This feature also confirms that the test is relatively rigid. If the method is very slow and rigid, this could mean that in short rolling samples and in short unit-root periods, the critical limits should be calibrated from a much narrower distribution. The results concerning the asymptotic behavior for different subsample sizes by Shi et al (2010b) support this interpretation.

Due to the problem of missing nearly all of the simulated unit-roots, I decided to experiment in order to find out whether the problem was the critical values. I simulated a new 5% critical value for the test and used it as a new critical level for the R-test, where the underlying data included one simulated unit-root period (48 observations), the rolling sample was also 48 observations, and the stationary period was created using of coefficient 0.8. After these changes, the results also changed: even though the number of false alarms increased, so did the number of signaled breakpoints. Though the method was able to spot only 2% of the single unit-root observations, after the changes in critical value it was able to signal approximately 10% of the unit root periods (compared to 0.6%). This clearly indicates that when the R-method is as an indicator in the case of short rolling samples, the critical values need to be calibrated and redefined.

4.1.2 The power of the MAX-test

In the case of MAX-test, the test setting is most similar to the conventional Dickey-Fuller test. The H(0) hypothesis is I(1), and the final test-statistic for evaluation purposes is the maximum of the forward and reverse realizations. The critical values for the hypothesis testing are from Leybourne (1995), which includes tables for 10%, 5% and 1% critical levels for sample sizes as small as 25 and 50. Of course, the use of critical limits from earlier research can be problematic especially since the samples here are rolling instead of static. Since no more appropriate limits were available, these must suffice as rough estimates. This is why the final results must be interpreted with caution.

Concerning the simulation results, the rejection of the null hypothesis H(0) = I(1) is difficult here. Therefore, though the MAX-test is able to signal most of the simulated unit-root observations in the data, it is unable to reject the unit root hypothesis in many cases during stationary periods. Another problem seems to be that the amount of false alarms increases sharply when the stationary period is simulated using higher persistence. When the stationary period was simulated with persistence of 0.8 instead of 0.6, the rejection of the null became even more difficult. The core results can be seen in tables in Appendix 9, where for a coefficient 0.8 the amount of false alarms reaches a fairly high level.

This rejection problem is nothing new. In case of the conventional Augmented Dickey-Fuller test with t-values, the results remind us in a sense of the MAX-results (ADF t-test results where the stationary period was simulated using the coefficient 0.6 are presented for reference in Appendix 10). There is, however, an important difference between the ADF t-test and the MAX test. The MAX-test seems to be much more accurate. This result is congruent with the results reported by Leybourne (1995).

An interesting feature of the MAX test in the case of rolling windows is that the amount of false alarms falls quite sharply when the window length is increased, ie more data are included in the sample (see tables in Appendix 9). This clearly means that the MAX-method works better with longer samples, but not so well with very modest sample sizes. Another core feature is that the simulated unit root clearly dominates the samples for a long time, even after the break from I(1) back to I(0). This feature explains why there are more false alarms after, versus before, the simulated unit-root period (see tables in Appendix 9).

When these features are compared with the rolling AR- and ADF-results, it clearly seems that, even though the ADF- and AR-methods do not correctly signal as many unit roots as the MAX- method, they are better as early warning indicators in two important respects. Firstly, they are more robust to persistence changes in the stationary period since they give far fewer false alarms, even when the stationary period is simulated using as high a persistence as 0.8. Secondly, the differences in accuracy between small- and larger sample results are modest. Therefore I endorse the use of rolling AR- and ADF-coefficients in the case of small sample size.

4.1.3 The power of the rolling CUSUM-test

For the rolling CUSUM-tests, the test-procedure is quite different than the other tests presented above. In all of the previous tests a single test-value was created. When the rolling CUSUM is constructed, this feature is impossible. The rolling sample of CUSUM-test consists of 36, 48 or 60 single data observations, but all of the sample observations are valued separately, since a structural-break alarm is set off if any single observations lies outside the upper or lower bound. One option is to create an indicator that takes the value one if any single observation in a sample breaches the upper or lower bounds. I decided that searching all observations separately would be more informative, since then it is possible to see how many single alarms are triggered in each window.

Concerning the interpretation of the results it must be kept in mind that the CUSUM test is primarily a stability test. It should trigger an alarm whenever the construction of the process changes. Therefore the major interest is to examine how this method reacts to the start and end of a simulated unit root period. In addition, we want to know how many false alarms of structural breaks it gives outside of the simulated unit root periods, ie during stationary periods. The results are shown in the tables in Appendix 11. In addition to these one can construct a graphical example of how the rolling CUSUM-values react to the simulated unit root where the stationary-period coefficient is 0.6, the bubble is 36 periods long and the rolling window consists of 36 observations. In graphs C1 to C4 in Appendix 11, the first figure illustrates the situation when the sample does not include any unit root observations. Figure C2 shows how the situation changes as 5 unit root observations are included in the sample, figure C3 shows the situation after 25 observations, and figure C4 shows the reaction when all unit root observations are included in the rolling window. Not all of the unit root observations breach the bounds, as is the case where only the first 25 unit root observations are included at the beginning of the sample. In this case the rolling CUSUM does give alarms during period 490 to 525, as the lower bound is broken in several occasions.

As the simulation results reveal, also the rolling CUSUM-test rarely gives false alarms of structural breaks. This result is in line with that reported in Leybourne, Kim and Taylor (2006b). A bit surprisingly, the test also misses many of the simulated unit roots in the data. Where the stationary period is already quite persistent, the method signals breaks more often. This could have something to do with the construction of the upper and lower bounds, as in the case where the stationary period is already quite persistent, the boundary values becomes narrower and are therefore easier to overrun.

Also the shortness of the samples seems to entail problems for the use of the rolling CUSUM. Since the underlying idea in this method is to detect shifts in the mean process, the construction of the mean process seems problematic in the context of a very short sample, as it becomes hard to recognize differences (especially when the majority of observations are already unit roots). Though not presented here, each of the simulations was reported in graphic form. From these rolling graphs it was easy to see that the rolling CUSUM seemed to react to the end of the simulated bubble more often than to the beginning. Therefore, the boundary was more often overrun when the process changed from unit root back to stationary. Instead of using only rolling samples, I also tested the whole samples (of size 1000 observations) using the conventional CUSUM test. According to these less extensive simulations and graphical analysis, it seemed that relatively often the whole-sample-based CUSUM was able to signal also the start of the unit root. This feature merely affirms that in order to operate with rolling samples the sample should be relatively large.

4.1.4 The power of the rolling Variance Ratio-test

Compared to the other tests presented here the number of total repetitions in the rolling variance ratio test was much smaller due to the test's time-consuming characteristics. The total amount of observations in each simulation was limited to 10 000.

The variance ratio test seems to be sensitive to two things: first to the underlying 'normal' stationary-period regression coefficient and secondly to the length of the rolling window. As the memory during the 'normal' period gets closer to 1 (ie moves from 0.6 to 0.8 and then to 0.9 in separate simulations), the number of correctly signaled bubbles increases, but so does the total number of false alarms. In each case the number of false alarms seems to increase after the simulated unit-root period. Unfortunately, at best only 6.4% of the single unit-root observations are signaled correctly from the simulated data, and in this case the false alarms already amount to 6.10%. A positive feature is that the number of unit-root periods spotted from the data is a quite high 30% this time.

From the table in Appendix 12 we see that the rolling variance ratio test seems to signal simulated unit roots correctly with higher probability when the window length is relatively short. On the contrary, it seems to less often signal stationary periods falsely as unit roots when the length of rolling window is increased. To reduce the probability of false alarms would therefore require that the rolling window be as long as possible; but to increase the probability of signaling unit roots correctly shorter rolling windows would be preferred.

Due to the sensitivity of the test to parameter change, it seems that this method might work well for what it was originally designed: to measure changes in long data series using shorter data samples. These data samples are separately constructed and they do not include overlapping observations, in contrast to rolling samples. Unfortunately, as the method is sensitive, the overlapping samples do not work well, as they share the common features. This might be one reason why the variance ratio test does not seem well suited for rolling samples.

5 AR- and ADF-based signals as leading indicators: evidence from equity and housing prices

In the last section I will study market developments in several countries to see how well the AR and ADF methods presented in section 3.3.2 are able to warn of emerging instabilities in prices in practice as they are applied to real market data. Reference periods for bubbles, which the indicators should be able to spot, were collected from several sources in order to truly represent the consensus view of 'troubled' periods. For example, as regards stock market bubbles in the US, the following sources were used: Raines and Leathers (2000), Kindleberger (2000), Mishkin and White (2003), Shiller (2000), Bordo (2003) and IMF (2003). These consensus periods are used for reference purposes when evaluating the timing of bubble-signals produced by the ADF and AR methods. The analysis in this section begins with the stock market and continues with application of the method to housing markets, each including an evaluation based on actual market data. Finally I will present a summary of the core results as well as a way forward in the search for early warning tools.

The rolling OLS-regressions defining the least squares estimates to AR- and ADF-coefficients were run by using the regressions presented in proposition 1 and 2. The lag was defined by the AIC, trend was not included, but constant was allowed. Window lengths used were varied, but the results presents here are all based on sample size 36. The series, where the regressions are applied to is always in a following form: log dividend/yield, in case of housing markets this being log rent/price.

5.1 Short history of consensus boom and bust cycles in US equity prices

The end of the 19th century could be described as a period of relatively volatile markets, there having been several periods of strong booms and sudden busts in US equities prices. Surprisingly many of the early equities booms in the US were related to the railways. In 1853 the railroad and public lands boom, which was connected with gold discoveries, reached its peak, and after a large negative correction stock prices ended 53.4% lower in 1859. In 1863–1865 the Civil War depressed stocks; and in 1875 the second railroad boom peaked and the stock prices, having appreciated by 50.5%, declined until 1877. As Kindleberger et al (2005) note, this boom was greatly supported by an increase in short term credit as well as an increase in capital inflows from Europe. The period also included a banking panic in 1873. The next railroad boom took place in 1881, as stock values had soared again by over 50% in value. The following bust lasted until 1885 and was accompanied by a banking panic in 1884. The boom that ended in 1892 was related to the silver agitation and the following depreciation of stock prices, which went on until 1894 and once again included a banking panic in 1893.

The beginning of the 20th century was hardly any more stable, as there were several periods of boom and bust in the markets. The first boom occurred already in the early years of the 20th century. Some of the references locate the price peak in the summer of 1901, but for example IMF(2003) and Bordo(2003) argue for 1902. This peak in prices was followed by a bust, which lasted until 1904 and has been labeled in history as the 'rich man's panic', as those who were hardest hit by declining stock values were the market insiders. The next boom, which took place only a few years later, was accompanied by monetary expansion via trust companies, reached its peak in 1907, and was followed by a banking panic and falling stock values. This period of negative correction was caused by a 'world' financial crisis, which undoubtedly was among the first ones[21] on such a scale and also included symptoms of contagion. The early 1910s experienced increases in war scares and international tensions, which finally broke out as the first World War. The US stock markets experienced a prolonged slump from 1916 onwards until 1918. Real stock prices depreciated during these years by 42.5%. A smaller downward correction in prices began in 1919 and lasted until 1921, as the disinflation and disarmament lowered stock prices by 24.5%. The true boom phase was short-lived, from summer 1920 until spring 1921. After this, we saw one of the major US booms in stocks as well as in land prices. During the years before the bust of 1929, stock prices appreciated by more than 200%. The price appreciation was extreme, particularly after 1926. This period of growth was accompanied by rapid macroeconomic growth and loose policies, as well as important technological innovations (automobiles and electrification). The crash

[21] The world-concept then was much narrower, being limited to the core countries suffering from the crisis: USA, Italy and France.

in October 1929 had devastating consequences: stock prices declined until 1932, losing 66.5% of their value. This period also included a banking panic and a huge contraction in GDP. But the volatile times were still not over. A new boom in stock prices soon followed; but it came into a halt already in 1936, after which there was a declining trend until 1938. The main cause of this sudden change of course was a tightening of monetary policy.

During World War II, from 1939 until 1942, real stock prices fell by 38.8%, and this period was followed by a post-war boom and bust, as prices peaked in the summer of 1946 and then sank in value until 1949.

The late 1940s through the 1950s was a period about there are conflicting views as to booms and busts: for example Bordo (2003) and IMF (2003) do not label any period during the decade as a boom or bust, yet Mishkin and White (2003) and Rea and Marcis (1996) name eg the period 1953–1955 as one of robust market expansion.

In the 1960s optimism increased as regards economic growth prospects, and by early 1966 P/E ratios had climbed to lofty levels. In 1968 the stock market peaked, and this was followed by negative correction in values, which lasted until 1970. The next two negative corrections in stock values were induced by the oil shocks of 1972 and in 1979. Kindleberger et al (2005) cite 1974–1975 as the winding down phase of a speculative period, in which pricing pressures were focused on stocks and commercial real estate. This speculation peaked in 1973 and was supported by a booming Eurodollar market in 1970-1971, at the end of the Bretton Woods system.

During the following decade there was a long and robust upsurge in stock prices as well as in commercial real estate, which were supported by large capital inflows. During 1982–1987 stock prices appreciated and a speculative peak occurred in1985–1987. The boom ended on ‘Black Monday’ (19 October 1987). It is well known that this period was followed by another long upward march in stock prices, and once again this period included technological innovations, which spurred inflated optimism for economic growth. The information technology bubble first generated concern over possibly overvalued markets already in 1995 and 1996, but the final bust did not come until 2000, after the Russian default and LTCM crises in 1998. Prices had by that time risen by more than 160%. The market bust ended in 2002.

The latest boom in the US markets was related to a worldwide leverage bubble, followed by global financial crises, which have not yet been fully resolved. US stock prices had been appreciating from 2003 onwards, reaching the top in autumn of 2007. The price appreciation got a boost in mid 2006 as the trend of appreciation became clearly steeper. Stocks reached their lowest values in early 2009 and have been sub-sequently on the rise, though not without interruptions related European sovereign debt fears and the repercussions for the global economic outlook.

5.2 Are AR and ADF indicators able to spot US stock market booms and busts?

As the main object of this research has been to develop an early warning indicator that can signal emerging pricing instabilities from asset price data, one acid test would be to run the AR and ADF indicators through historical dividend yield time series in order to discover whether they are able to signal any of the previously mentioned consensus booms (or busts) and most importantly, how early they are able to warn of growing instabilities (overheating) in pricing?

The time series used for testing was Shiller's real dividend yield and S&P500 price index data for Jan 1871 – Dec 2010.[22] Both indicators were run with several window lengths (36, 48 and 60) in rolling sub-samples, but the reported values are those based on window length 36, as this shortest length was found to be the most nearly optimal. But it is worth noting that most of the issued warnings were not affected by varying the length of the rolling window. Critical limits for warning signals were 0.0 in case of ADF36 and 1.0 in case of AR36.[23]

I denote the indicator values based on rolling samples of 36 observations as AR36 and ADF36. Concerning the main outcomes, both of these methods, based on AR36 and ADF36, are able to signal most of the previously mentioned major booms in stock prices. An interesting feature is that they also produce warnings during severe downturns, as stock prices have been receding for some years. This feature is clearly related to the appearance of negative bubbles, as stocks get undervalued compared to their fundamentals. Especially

[22] The data are those used eg in Shiller's book (2000, 2005) 'Irrational Exuberance', Princeton University Press.

[23] In case of housing markets, it must be noticed, that the reported results in this research use different critical limit for the ADF36, namely –0.05. The housing market results were counted by using both limits, namely 0.0 and –0.05 for the ADF36, but only the latter are reported later in this chapter. Periods signaled do not differ significantly.

interesting is that the cycle seems to turn shortly after these 'negative' bubble warnings are received.[24] From the methodological point of view this is not as bizarre as it might seem. Since the indicator is able to spot periods in which the underlying process changes from stationary to unit root, it is not surprising that it also spots the congruent negative changes in the time series.

Focusing on the precise timing of alarms compared to the actual historical events, it seems that both of these methods indeed have the potential to act as a leading indicator. Interestingly, they both signal warnings during the same periods, though the AR method produces more frequent alarms. Concerning the major stock market booms in the 1920s and late1980s and the technology boom at the end of the1990s, they are all spotted years in advance of the final crash. This is a useful feature, since it gives regulators and policymakers enough time to react to the overheating. Table 5.1 presents the precise timing of alarms given by the rolling AR36 indicators and rolling ADF36 indicators, as well as the timing of the consensus bubbles. Perhaps an even better view of the indicators' accuracy is given by the figures in which indicator warnings are compared to real price index movements and to the timing of consensus booms and their peaks. This information is presented in several figures (5.1 to 5.6), as the time period examined is relatively long. Figure 5.1 shows the locations of consensus bubbles compared to US stock market developments during 1871–1949, and figure 5.2 shows the location of the consensus bubbles during 1950–2010.

Figures 5.3, 5.4, 5.5 and 5.6 show the fit of the alarm signals by ADF36 and AR36 to these periods, which com-monly regarded as periods of price misalignments. In these four figures the consensus bubbles are marked as green bars and the AR36- and ADF36-signaled bubbles are represented by red lines. When the red line reaches the value 1, this signals a bubble. A bubble alarm continues as long as the value is 1.

[24] As Bordo and Wheelock (2007b) note, periods before and after the 1970s differ quite a lot, due to differences in regulation, mone-tary regimes and market developments.

Table 5.1 **Stock market booms, crashes and recessions in the USA, 1850–2010, precise bubble warnings given by 3-year ADF and AR indicators**

US Stock Market data Sub-sample length 36 AR-signals bubble	**ADF-signals bubble**	**Major cause of boom and bust***	**Identifies boom or bust**
12.1876, 02–06.1877, 12.1877–01.1878	–	Railroad boom and following bust	bust
04.1878–11.1879	–		
11.1885–04.1887	08.1886–11.1886	Railroad boom and following bust	bust
07. –09.1893	07.–08.1893	Silver agitation	bust
12.1893–01.1894	–	Silver agitation	bust
02.1899–04.1899	–		
08.1900–01.1900	–	Boom before rich mans's panic	boom
01.1903–02.1904	01.1903–03.1904	Rich mans's panic	bust
12.1905–01.1906	–	World financial crises	bust
08.1907–03.1908	08.1907–02.1908	World financial crises	
12.1915	–		
05.1917–05.1918	07.1917–12.1917	War	bust
11.1925–01.1926	–	Roaring 20's	boom
05.1928, 09.1928–09.1929	11.1928, 01.1929–03.1929, 07.1929–09.1929	Roaring 20's, Crash in Oct 1929	boom
09.1931–01.1932, 04.1932–06.1932	12.1931, 04.1932–06.1932	30's recession	bust following 1929 crash
01.1937–06.1938	–	Tight monetary policy	bust
05.1943–10.1943	–		
01.1946–07.1946	02.1946,04.–07.1946	Post war slump, prices peak in July	bust
02. –03.1948	–	Post war slump	
09.1954–03.1956	12.1954–04.1956	Strong market rise 1953–1955	
01.1959, 04.1959–08.1959	–		

US Stock Market data
Sub-sample length 36

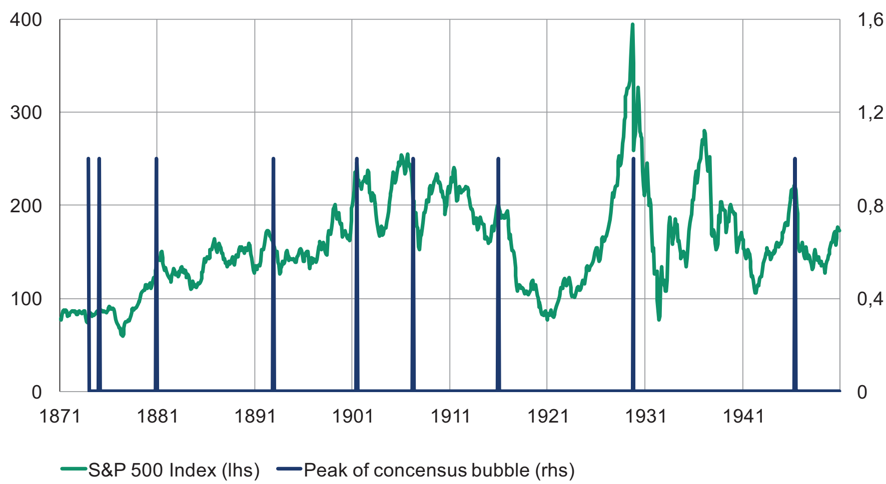
AR-signals bubble	ADF-signals bubble	Major cause of boom and bust*	Identifies boom or bust
08.1966–10.1966	08.1966–10.1966	September – October –25.2%	
05.1970–08.1970	05.1970–07.1970	Penn-Central, Bretton Woods	bust
04.1974–01.1975	04.1974–01.1975	Oil Shock	bust
02.1978–04.1978	03.1978	Oil Shock	bust
11.1978	–	Oil Shock	
03.1986–09.1987	04.1986–08.1986, 01.1987–04.1987, 08.1987	Sharp rise in stock prices 1984–1987, crasch in Oct. 1987	boom
07.1995–03.1997, 05.1997–10.1997	09.1995, 11.1995–06.1996, 09.1996–03.1997, 05.1997–10.1997	Information technology boom and crash in 2000	boom
02.1998–07.1998	03.1998–07.1998	Russian default and LTCM	
08.2002–11.2002, 02.2003	07.2002–10.2002, 02.2003	Information technology bust	bust
03.2008	03.2008	Leverage-bubble in the US housing markets and securitisation	bust
07.2008–04.2009	07.2008–03.2009		

For reference: IMF (2003), Shiller (2000), Raines-Leathers (2000), Mishkin-White (2003) and Bordo (2003)

The key message can be read from these four figures: the sudden and strong growth periods, where the slope of the curve clearly changes, are read as signals of stock-market bubbles. Interestingly, these periods match well with the timing of consensus bubbles, as the bubble alarms precede the consensus peaks. At best, they lead the peaks by years. This feature gives adds to the significance of the indicators, since they clearly give important warnings of excessive pricing far in advance of a crash that could have a devastating impact on the overall financial stability of the economy.

These indicators seem to work for the US stock market data, but to be good indicators they should yield equally good results when applied to stock market data for other countries. In order to ensure that the fit is not US-specific, I run the AR36 and ADF36 indicators also for UK and Finnish stock market data. The results are presented in later.

Figure 5.1 **Timing of concensus bubbles in US stock markets (SP500), 1871–1949, monthly data**[25]



[25] lhs = left hand scale, rhs = right hand scale

Figure 5.2 **Timing of concensus bubbles in US stock markets (SP500), 1950–2010, monthly data**

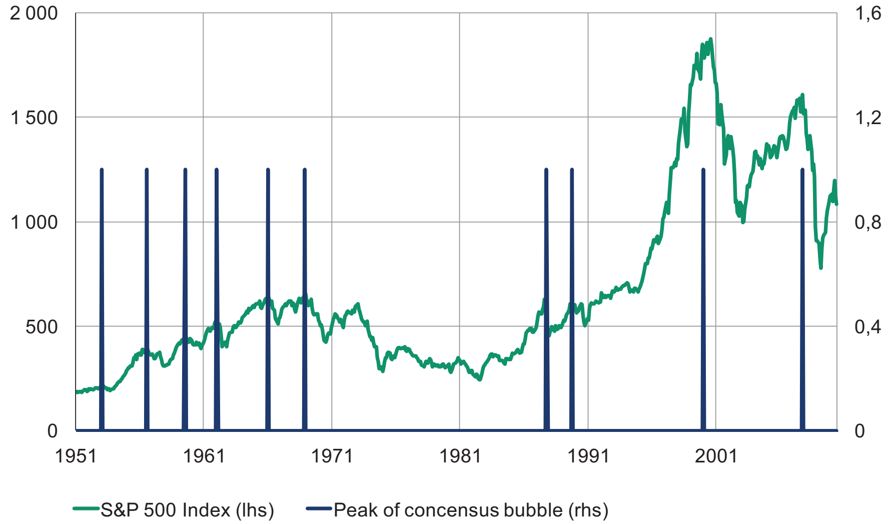


Figure 5.3 **S&P500 index, ADF36 bubble warnings and timing of concensus bubbles, 1871–1950, monthly data**

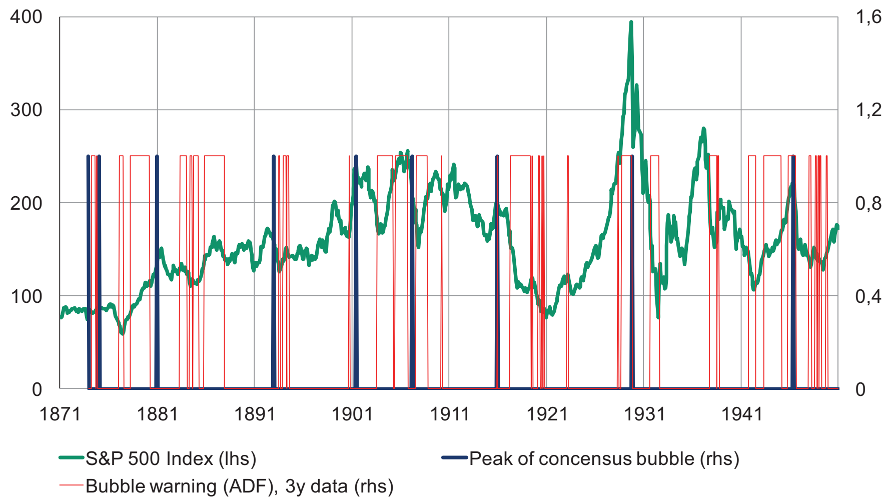


Figure 5.4 **S&P500 index, ADF36 bubble warnings and timing of concensus bubbles, 1951–2010, monthly data**

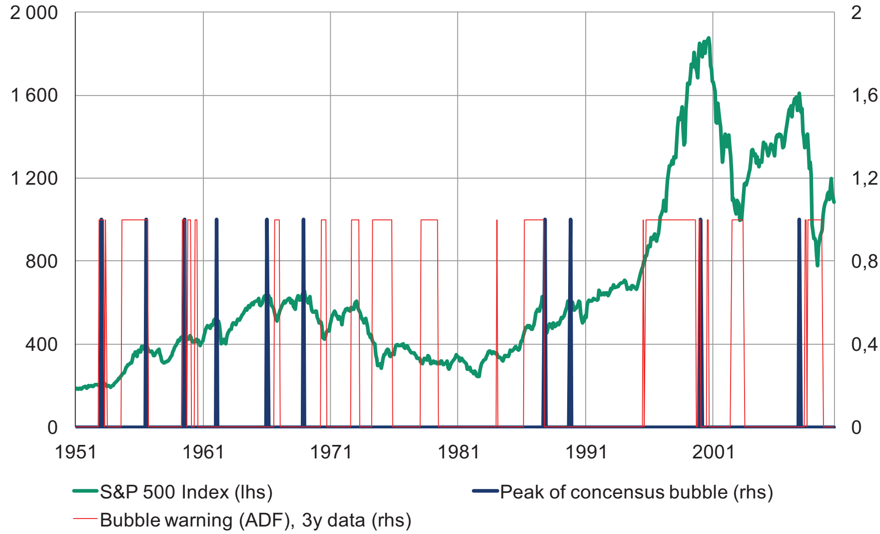


Figure 5.5 **S&P500 index, AR36 bubble warnings and timing of concensus bubbles, 1871–1950, monthly data**

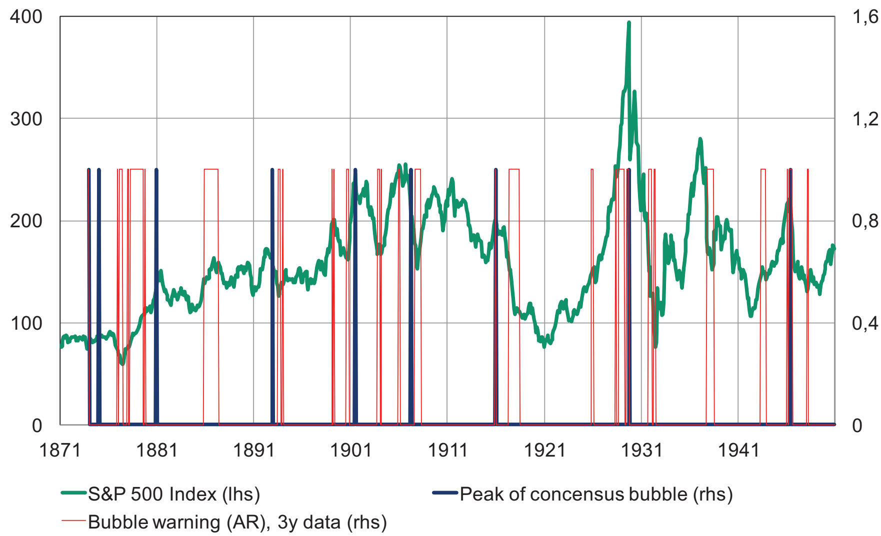
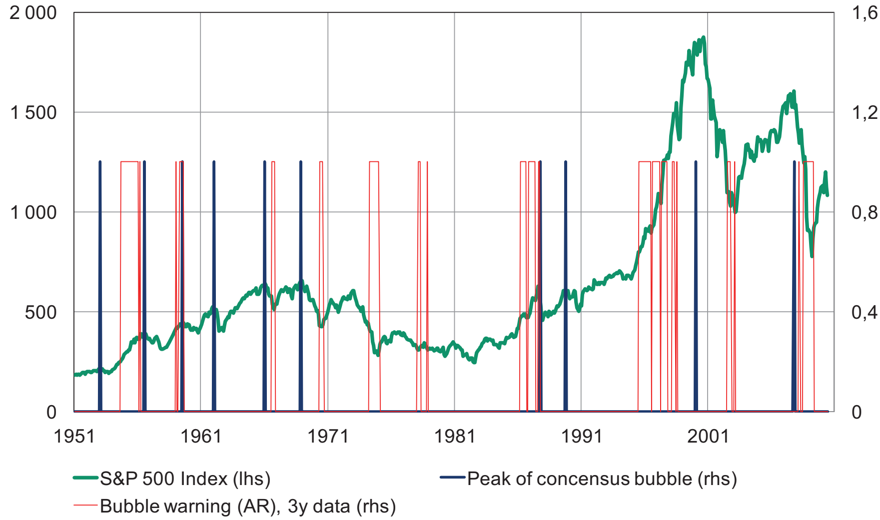


Figure 5.6 **S&P500 index, AR36 bubble warnings and timing of concensus bubbles, 1951–2010, monthly data**



5.3 AR and ADF indicators' ability to signal bubbles in UK and Finnish equity markets data

5.3.1 Historical perspective on UK stock market booms

The main purpose of this section is to specify the periods of consensus bubbles to be used as references for the AR and ADF indicators in evaluating their ability to signal the emerging threat of a price bubble. For this task I examined an ample body of literature, on which basis the periods of consensus bubbles are founded on the following sources, all of which identify the same periods as bubbles: Bordo in IMF's World Economic Outlook in 2003, Barclays (2010), Bordo et al (2007a, b) and Kaplan (2010).

The history of stock market booms and busts in the UK is long, starting with the early example of the 1720 South Street bubble. To sum up briefly the core periods of market booms and busts, the following years should be highlighted. Among the earliest booms was the export-led boom in 1810, where the growth was aided by credit expansion by banks. The first peak in stock prices occurred in 1809, and the downturn included a banking panic in 1810. The turbulent times continued, as the British economy enjoyed a period of rapid expansion supported by growing demand from newly independent Latin American states as well as domestic infrastructure projects. This boom, which was reinforced by Bank of England's easy monetary policy, ended in a crash of the stock markets in April 1825 (Clapham, 1945), and this included a banking panic that began in the same year.

Before the 1840s railroad boom, there emerged two boom periods in the UK stock markets, which peaked in 1829 and 1835.[26] The 1840s railroad boom was once again based on misplaced expectations of profit growth. The peak in stock prices was reached in 1844 after prices had appreciated by 51.9% during the boom. The price bust dragged on until 1847 and again included a baking panic, in 1847. The following booms peaked in 1865[27] and 1874, the latter being related to a web of European financial crises.

The first boom-phase in the UK stock markets in the 20th century peaked in 1909 and was followed by a period of weak economic performance, lasting until 1920. The weak performance was related to World War I. According to Barclays (2010), the real return on equity investments in 1909–1919 was –3.8%. The US was relatively unscathed by World War I and emerged as the world's leading economic power. On the other hand, the war was extremely costly for the United Kingdom. By the mid-20s the US and UK were both already on the road to recovery, and their stock prices were rising rapidly (Bordo et al, 2007a).The roaring 20s was felt also in the UK; in 1919–1929 equity investments yielded real returns of 7.8%, albeit the pace of the rise in stock prices remained much slower in the UK than in the US during the 20s boom. The rise in stock prices slowed and then came to a halt after the Bank of England raised interest rates in 1928. The boom finally cooled down in 1929. The timing of the boom and crash coincided closely with the what happened in the US, partly reflecting the high degree of capital mobility between the two countries.

The crash was followed by descending prices with the onset of the Great Depression. The trough was reached in 1931; by then, the prices had dropped 55.4%. A short period of positive developments followed, reaching a peak in 1936. As the housing boom ended and the threat of war became more obvious, stock prices began to descend, from 1936 to 1940 by 59.9%.

[26] Timing of these booms differs somewhat according to different sources, for example in Kindleberger et al (2005) the peaks are 1825 and 1836.
[27] According to Kindleberger et al (2005) also in 1857 due to break of a boom in railroad stocks.

The next boom in UK stocks was experienced in the early 1950s, as prices climbed during the summer of 1952 and on until July 1955. The climb resumed in 1958 and continued until spring 1961, as the indexes peaked in several European countries in real terms in 1960–1961. This period of growth was followed by a period of descending prices, which was relatively short; in the late 1960s stock prices were again on steep run-up. The next period of truly booming prices began already at the end of 1966 and lasted until 1968. This boom was followed by total returns of –35.80% (Kaplan, 2010), and the trough was reached in the spring of 1970. The next boom was relatively short, from spring 1970 to spring 1972, and was followed by one of the sharpest declines in UK stock market history. During the period from spring 1972 to the end of 1974, the total return on stocks was –73.81% (Kaplan, 2010). The reason for the negative performance was the oil shock. Stocks began to recover in value only in the 1980s, as the next boom started in 1981(according to some sources in spring 1984) and lasted until Black Monday (19 Oct. 1987), but it is noteworthy that UK stock prices began to decline already a bit earlier, in the summer of 1987. The last two periods of booming prices were the technology boom, which started in 1994, lasted until December 1999, and was followed by a bust that ran from December 1999 to the start of 2003; and the latest boom, which was fuelled by credit and securitization, and which came to an end in the autumn of 2007 due to the onset of a global financial crisis that remains unresolved.

5.3.2 Indicators' ability to signal stock market bubbles in the UK data

The stock index and dividend-yield data used to evaluate developments in the UK markets are the monthly Datastream and Barclays Capital data, covering the period from the start of 1965 to spring 2011.

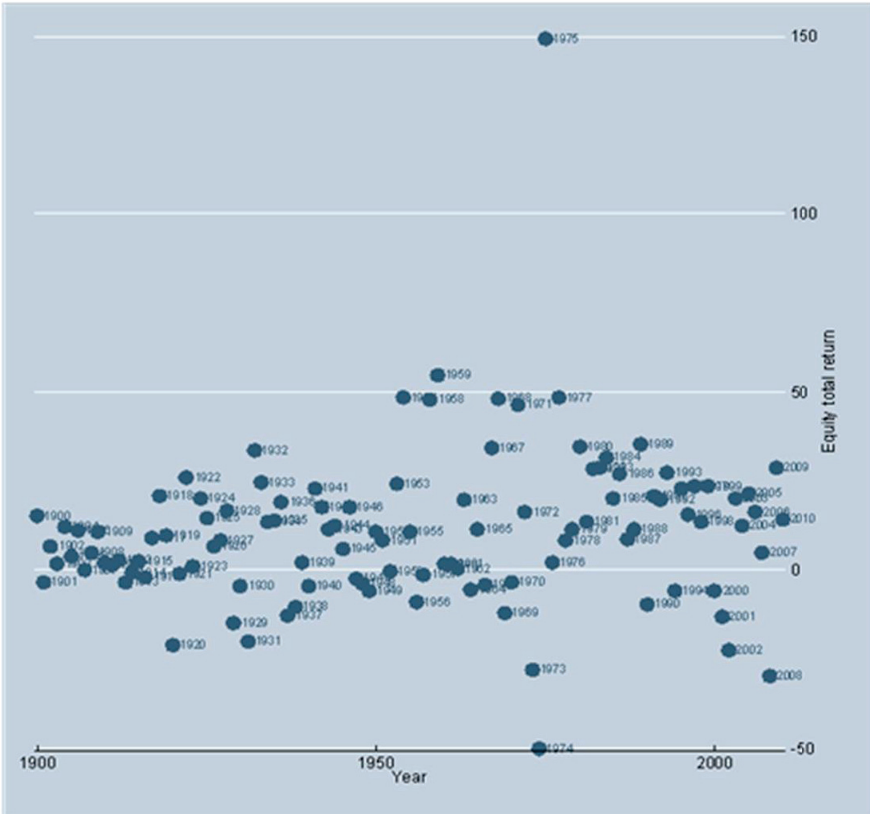
Concerning the bubble signals from the two indicators (AR36 and ADF36), the first observation again is that the timing of the signals is nearly congruent. Secondly, the AR36 method again performs better, as it produces warnings more frequently.

The ability of the warning signals to perform their core task – to signal price misalignments in the formative stage – is observable from figures A13.1–A13.4 in Appendix 13. Both methods seem to be able to signal oncoming major booms and busts over the period 1965–2011, but it also seems that they fail to identify as many of the consensus peaks and troughs as they did for the US data. Looking more closely at the warning signals, both methods are able to signal far in advance the boom that ended in 1968Q3. Similarly, bubble signals are received before the equities prices ended their decline in the mid 1970s. These signals are therefore to be seen as warnings of a negative bubble. The next boom was identified only by ADF36, which signaled a bubble warning during 1984–1985, before the consensus-boom peak. One of the major bubbles (1987) was identified again by both indicators, but the signals came only a half year ahead of the crash. This would have been too short notice to aid in decision making concerning the implementation of countercyclical policy tools. The next short boom in 1994 was identified only by ADF36 (in UK the boom ended with the Barings collapse). The following steep rise in equities prices at the end of the 1990s had its origins in the TMT stock boom. This was identified by both indicators as a bubble long before the peak: the first warnings of overheated prices came in 1997. Even though these warnings were received on time, they ended early, in 1998, as the Russian default, Asian turbulence (starting in 1997) and the LTCM default shook the markets and led to a brief downward correction in prices. This reaction also reveals one of the major flaws in our AR and ADF indicators. Even though they seem to be consistent in signaling continuous unit roots in time series, they are extremely sensitive to sudden negative price changes. Sizeable downward corrections, though short lived, seem to tell the indicators that the stationary change has occurred. In order to regenerate warnings of unit roots, enough unit root observations must be found to reach I(1) dominance in the sample. As seen in the case of year 1999, only ADF36 is able to regenerate warning signals before the TMT stock crash in early 2000. The more solid AR36 is unable to produce warnings before the final correction.

As is now known, the correction following the TMT crash was a large one, intensified by the Enron bank-ruptcy scandal. AR36 and ADF36 both give warnings of bubbles related to this period of descending prices, as the prices appear to have dipped too much in light of the fundamentals: warnings of ‘negative bubble’ begin before the signaled period of consensus trough.

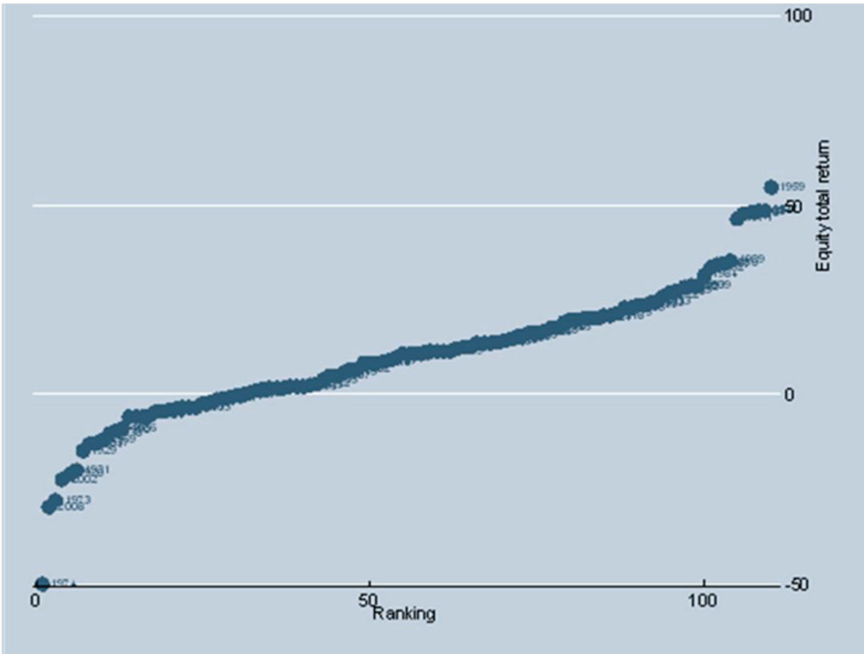
A bit mysterious is that neither indicator signals the existence of a bubble during the 2005–2007 phase, when stock prices were rapidly appreciating, but they signal do a bubble during the sharp price descent from mid 2008 to early 2009. This final warning once again came nine months before the global stock markets returned to a growth path in spring 2009.

Figure 5.7 **Yearly total returns on UK equities, 1900–2010**



One of the main reasons why identification of emerging overheating of the stock market is important can be seen in the long historical series of UK equities, their yearly total returns and their distribution. The yearly total returns series was obtained from Barclays Capital, and it has been published in their Equity Guild Study. The data covers 1900–2010. As can be observed from figures 5.7 and 5.8, the worst outcomes usually follow years of booming prices. The probability of a large negative correction following a bubble is much higher than that for a 'normal' market. One could say that the risk regime shifts to a fatter tailed distribution after bubble warnings are set off, since there may be negative correlation when there are warnings of excessively positive pricing in the markets, ie signals of positive bubbles. The tail risk of large negative correction in this regime is larger than in normal times and should perhaps be taken into account in risk models. the relation between risk modeling and bubbles is not new, having been analyzed from various perspectives for example by van Norden and Shaller (1999), Psaradakis et al (2004) as well as Kaliva and Koskinen (2008).

Figure 5.8 **Yearly total returns on uk equities by ranking, 1900-2010**



ten smallest yearly returns: 1974, 2008, 1973, 2002, 1920, 1931, 1929, 2001, 1937, 1969

5.3.3 Historical perspective on Finnish stock market booms

Examination of the Finnish data provides a valuable input on how the signaling methods work in a smaller, less liquid market for which the available reliable historical data is relatively short. The raw market data from Finland consists of dividend yields for Finnish stocks, in the period 1971 to December 2010. The sources for the data are Global Financial Data and Bloomberg. The index used for the evaluation is the HEX all-share index and its predecessors.

As the available historical data is rather short, the number of periods that include booms and possible bubbles is rather small. Still, it is possible to use consensus bubbles as reference points, since the Finnish markets have been analyzed in several studies on the boom-bust cycles in the equities markets. During the 1960s and 1970s for example IMF(2003) cites several periods of boom and bust in the Finnish equities markets.

In the late 1960s and the 1970s there were several peak-to-trough cycles in Finland. The first one began in autumn 1962 and lasted until the trough at the start of 1968. After this, equities prices rose to a peak at the start of 1971. The oil price shock impacted Finland and, as was the case elsewhere, stock prices started to descend from autumn 1973 onwards. The next definite peak in stock prices occurred in autumn 1979, after the boom.

After this, the stock market was relatively free of turbulence until the mid 1980s when the big boom began. At this time, there was a surge in borrowing, which fuelled rises in property and other asset prices. IMF (2003), for example, signals two boom-peaks for this era: one in mid 1984 and another in autumn 1987, the latter coinciding with 'Black Monday'. After October 1987 stock prices still rose for a while, until the rapid descent began in autumn 1988. During the early years of the 1990s Finland experienced a banking crisis accompanied by an economic recession. The bottom in stock prices was reached in autumn 1992, after which valuations began to recover quickly. According to IMF (2003), a new peak after a brief boom was reached already in the autumn of 1995, and prices surged up until the Russian default in 1998Q2. After a brief correction, stocks resumed their upward march. One driving force for the rise was the technology-sector, which played a large role in the Finnish stock markets. This worldwide technology bubble finally burst in the mid 2000s. After that, equity prices descended sharply until shifting into a sustained rise only in 2003. This rise lasted until the beginning of the global financial crises in 2007.

5.3.4 Indicators' ability to signal emerging bubbles in the Finnish data

All bubble signals produced by ADF36 and AR36 for the Finnish stock markets over the period 1971 to May2011 are reported in table A4.1 in Appendix 14. Once again, the main result is that both indicators signal nearly the same periods as bubbles. Comparing these warning signals to those cited in the literature as periods of boom or bust in equities prices, we find that the AR36 and ADF36 warnings seem to be able to signal some of the consensus booms or busts. Unfortunately, it seems the indicators are unable to signal as many consensus booms as bubbles, in contrast to UK and US cases.

From the table and figures A14.1–A14.4 (figures start at 1983), we see that the first warning signals are flashed by AR36 in the late spring of 1976, the second warnings come just prior to the 1979 peak of the consensus boom in stock prices. The next warning signals, given by both AR36 and ADF36, occur simultaneously starting in 1983 and running until spring 1984. These warnings come just before the peak of the consensus boom, in summer 1984. At the end of the 1980s Finland experienced a stock market boom, which was strengthened by profuse borrowing and a congruent real estate boom. The late 1980s stock market boom started to overheat in early 1987, according to the two indicators: by April both indicators were flashing warning signals of bubbles in stock prices. AR36 reacted faster, giving the signals already in January 1987. As the US stock bubble busted in October 1987, stock prices reacted globally and plunged. So did also Finnish stocks, which depreciated until spring 1988. The bubble signals given by AR36 and ADF36 end in October and November 1987.

In the early 1990s Finland experienced a severe economic recession along with a banking crisis and a decline in stock valuations. Both indicators signal a price bubble in 1990–1991, but this should be interpreted as a warning of a negative bubble, as the stock markets were undergoing a sharp downward correction. In March 1990 the stock market index was still at 1576, but by January 1991 it had dropped to 909.

It is a bit mysterious that both indicators nearly missed the peak of the next consensus bubble, a ‘technology bubble’, which was particularly strong in Finland. AR36 and ADF36 do give warnings of the bubble, but not until the start of 2000, prior to the consensus peak dated at summer 2000. The reason for the rather late warnings might be twofold: the first relates to the timing of the Russian default and the second to the dividend policy of the major technology companies in Finland. The Russian default occurred in 1998 and had a strong negative impact on Finnish stocks. This correction could have affected the regression results based on rolling samples. Concerning dividends, it is noteworthy that the boom in Finland focused strongly on one company, Nokia, which actually grew very fast during this period and also paid good dividends. Similarly, during the full period from mid 1990s onwards, overall economic growth in Finland was robust and so might have been enabled dividend flows sufficient to justify the strong growth in the value of Finnish equities. But one can certainly question this, especially as regards the technology-bubble.

5.4 Evaluation of overheating fears in the emerging stock markets

The recent crises created a long period of low interest rates as monetary policies in developed countries were kept, as expected, at reflationary levels. Low interest rates had an impact on the behavior of investors, especially to those with fixed payout targets (eg insurance companies). Those investors became yield seekers and began to invest in securities promising high returns. One consequence was that the capital in search of yield was channeled increasingly into countries experiencing rapid growth, which strengthened their exchange rates as well as asset values. The risk of overheating became apparent, as most of the effervescent foreign capital flowed into the capital markets – not into fixed investment. Asset price pressures were slightly eased by an increase in new issuance of debt and equity, but this also led to increased leverage, which could itself lead to a build-up of financial imbalances.

As was seen in the UK and US cases, one of the lessons to be learned from this history is that capital inflows can contribute to a build-up of asset price pressures and thus to exaggerated prices. Even in connection with the recent run-up in US asset prices capital inflows were identified as a key factor, or even a more important factor than loose monetary policy, in the housing price buble (Bernanke, 2010 and Sa and Wieladek, 2010). Therefore, concerning the current situation, a page could be devoted to analysing in greater depth the situation in emerging economies that have experienced heavy capital inflows during the last couple of years.

Directions and destinations of the heaviest foreign capital flows can be found for example in IMF’s interna-tional financial statistics since the end of 1980s. Data on net capital inflows show that, compared to levels seen in the late 1990s and early 2000, the share of foreign direct investment has declined in each of the main economic areas in EMEA, Asia, Asia ex-China and Latin America, being largely replaced by portfolio flows.

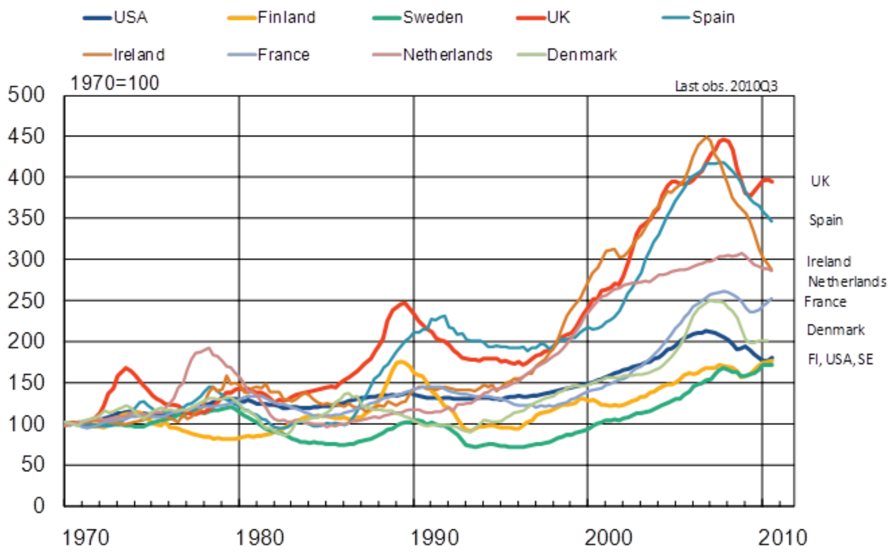
When foreign net capital inflows are compared for the economies in each area, China seems to have been one of the main recipients in Asia. as to the overheating of the markets, I thus focus on testing the AR36 and ADF36 on Chinese stock market data, to determine whether the indicators produce signals of overheating in the Chinese stock markets.

The results are shown in figures A15.1–A15.2 in Appendix 15. For testing, I chose the most liquid stock price indices and their dividend yields (smoothened over 12 months to avoid concentration of dividend payment peaks), both of which are from Bloomberg. For the Chinese stock markets, our representative index is the Shanghai Composite Index, which was developed in December 1990. Unfortunately the dividend information is available only from the end of 1997, so that the indicator's values for 3-year rolling data do not begin until the start of 2000. As seen from figures A15.1 and A15.2 in Appendix 15, both the ADF and AR based indicators flash several warnings of a bubble in the Chinese equities markets. Even though the signaled periods in a sense are the same, ADF36 definitely gives more frequent warnings. The first two periods of warnings for both indicators are related to the price descent in late 2001 and in 2002. Here the bubble is clearly a 'negative' one since the warnings end with an upward revision in prices. This can be seen for AR36 in spring 2002 and for ADF36 in autumn 2003 – summer 2004. The same 'negative bubble' is signaled in autumn 2005, which is perhaps more clearly observable for the AR36, for which the signal of 'too negative prices compared to fundamentals' occurs just before the turning point. The latest signals are related in the period of rapidly rising after spring 2007, which clearly could be interpreted as a signal of a positive bubble. This period was spotted by both indicators and was characterized by fairly large foreign capital inflows. Concerning the current period of large foreign capital inflows and related fears of overheating, neither indicator sees current price levels a being at too high compared to fundamentals.

5.5 Indicators' ability to signal bubbles in real estate prices

The existence of bubbles in the housing, and more widely for real estate prices, was heavily debated in the years preceding the financial crises that broke out in 2007. Among others, Case and Shiller (2003) argued pro existence, whereas there were as many arguments against misalignments in prices (for example Quigley (2003), Himmelberg et al (2005)). Looking at the speed of the rise in real house price indices in several OECD countries from year 2000 onwards, it seems clear that some of the real estate markets might have experienced a bubble during the last decade (Figure 5.9).

Figure 5.9 **Real house price indices in some OECD countries, 1970–2010**



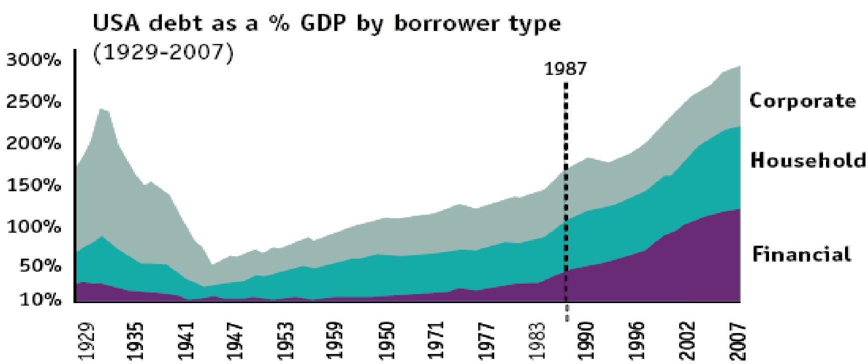
Source: OECD.

Central banks, G20, IMF, and eg OECD have collected data on the developments that led to the global financial market crisis that broke in mid-2007. The situation worsened with the Lehman Brothers bankruptcy in autumn 2008, all of which contributed to the emergence of the European sovereign debt problems in 2010 and 2011. The channels of financial contagion through which the problems began to accumulate in the financial markets were several, but these can be broadly divided into two parts: the channels of direct contagion (via balance sheets) and indirect contagion (via market behavior). The housing markets had an impact via both channels. First, the problems started to accumulate because of the negative valuation corrections of investment objects backed by US mortgages. Uncertainties as to the true owners of risky assets and investor's true exposures added to the mistrust and thereby to the malfunctioning of the financial system. After the normal operation of the financial system became aggravated due to the growing mistrust, real economic developments turned for the worse, which led to an increase in the amount of non-performing loans in many countries. As banks' balance sheets came under pressure and their market funding became impaired due to the distrust, governments were forced to provide financial support for the banking systems. In some countries this forced the government into a deeply troubling situation. As regards Europe, Ireland affords a good example.

Researchers have subsequently been able to identify several phenomena that could have served as warning signals of overheating housing prices and progressing instabilities in the markets. On the global scale, the economic system went through a period of greater openness of operations and increasing interlinkages, which exposed the whole system to idiosyncratic shocks. Inflation was stable in many developed countries and economic growth in many countries seemed to be on a steady path: prior to the crisis cyclical fluctuations in both activity and inflation had trended down (eg Dalsgaard et al, 2002 and Elmeskov, 2009). The sense of a stable environment had generally reduced risk premia. Monetary policy in many regions was accommodative following the 2001 economic downturn and interest rates were left at low levels for an extended period in many developed countries. In the low interest rate environment, the development of financial innovation led to a surge of credit growth. In many countries the credit growth rate was very high compared eg to GDP growth, which should provide a kind of reference for productivity growth and therefore a reference for the long-term sustainable rate of growth in indebtedness.

The boosting effect of financial innovation and securitization on financial and household sector indebtedness became apparent eg in the case of the US, where the trend of the debt-to-GDP ratio clearly changed in the financial sector after the introduction of securitized instruments in the mid 1980s (figure 5.10).

Figure 5.10 **US debt-to-GDP ratio by borrower type, %, 1929–2007, source: IMF**



Leverage and liquidity creation occurred outside the banking sector but had an impact on banks' business models and exposed them to risks they thought had been transferred out of their balance sheets. Investors searched for yield from securitized products, as these new products offered better yields compared to traditional investment products with similar ratings, which is one of the factors behind the emergence of the latest bubbles. Especially in the case of the US, overly accommodative monetary policy is cited as one of the main reasons for the emergence of bubbles. Such criticism has been presented for example by Taylor (2007), Gordon (2009), Calomiris (2009) and Allen and Carletti (2009). However, this view is not a unanimous one. Dokko et al (2010) argue that US monetary policy was well aligned with the goals of policymakers and that the monetary policy stance was not the primary contributor to the robust housing market. Dokko et al came to the conclusion that developments in housing finance and the mortgage market more broadly were among the factors that contributed to the rapid housing price growth. They name as the main contributors the securitization, the rise of cheap and readily available credit[28] and investors' appetite for novel mortgage backed instruments.

The linkage between securitization activity and access to credit is clear: securitization contributed especially to greater access to mortgage credit for subprime borrowers (Nadauld and Sherlund (2009), Gabriel and Rosenthal (2007), Mian and Sufi (2009), Goetzman et al (2009) and Keys et al (2010)). The US was not the only country where securitization grew at spectacular pace. For example in Spain securitization grew synchronously with the increases of bank credit to the private sector. In the early 1990s the securitization volumes were still insignificant, but already in 2006 securitised issuance totaled 90 billion euros in Spain. Growth in bank credit was followed by a large increase in private sector debt (Carbo-Valvedere et al, 2011).

Glaeser et al (2010) examined whether the low interest rates, high LTV (loan-to-value) levels and permissive mortgage approvals were able to explain the boom in house prices in the US. Their analysis showed that low interest rates were able to explain only a fifth of the rise in prices during the years 1996–2006. Moreover, they did not find convincing evidence that changes in approval rates or LTV levels could explain the bulk of the price changes. Though they did not find convincing evidence of a strong relationship between housing prices

[28] Though this had a direct link to too loose monetary policy.

growth and low interest rates, several other studies that find such evidence. For example Eickmeier and Hofman (2010), using a factor-augmented vector autoregressive model, found that monetary policy shocks do have a highly significant and persistent effect on house prices, real estate wealth as well as private sector debt, and a brief but strong effect on risk spreads. In addition, according to their results, monetary policy shocks contributed discernibly, but at a late stage, to the unsustainable developments in the US house and credit markets in 2001–2006.[29] The role of money aggregates, credit markets and investment dynamics were cited eg by Borio and Lowe (2002, 2004) as reasons for the build-up of bubbles and therefore as factors in the increased the probability of a negative correction in asset prices.

Even though financial liberalization and mortgage innovations increased the access to loans in the housing market, lowering the costs of loans, the deregulation also posed a macroeconomic stability risk due to the significant relaxation of lending standards. For example in the US, the credit standards were significantly relaxed during the booming years: in 2001 only 8% of home purchases occurred without a down payment, but by 2007 the figure was already 22% (OECD, 2011). Concerning developments in the housing markets before the prices started to descend in 2008, real home prices appreciated in 2001–2007 at annual rates of 4.5% in USA, 10.5% in Spain, 8.6% in UK, 7.9% in Denmark, 5.4% in Ireland and 7.6% in Sweden. Although in many developed countries prices were rising, there were at the same time several countries that were experiencing minor increases or even declines in housing prices in 2001–2007. Among these countries were Japan (–3.4%) and Germany (–2.5%).[30]

Although the main contributors to the rise in housing prices is debatable, it is clear that the prices did boom in many of the OECD countries during the last decade. Since the purpose of this study is to test our new indicators' ability to signal the emergence of price misalignments, ie detachments from fundamentals, the rest of the analysis is devoted to evaluating the developments in the housing prices in several countries that have experienced housing booms and to examine whether the AR36 and ADF36 indicators are able to warn of misplaced prices in advance of the costly price declines. Before this, I look briefly at how the fundamentals concerning stocks (ie

[29] There are several other academic studies on the role of the monetary policy shocks in the build-up of the recent housing price bubble, eg Taylor (2007), Iacoviello and Neri (2008), Jarocinski and Smets (2008) and Del Negro and Otrok (2007).
[30] Source: OECD Economic outlook, 2010/2.

dividends) and real estate are parallel and why similar evaluation methods can be applied to the pricing of both asset types.

5.5.1 Measurement of 'fundamentals' in real estate markets and price bubbles

The key question is how to identify a bubble in real estate prices. When have prices detached from their fundamentally justified level? Determining whether prices are detached from the fundamentally justified level is not a simple task, as there is not unanimous agreement on what factors actually establish the fundamental price in the real estate market. The pricing process in the real estate markets is regarded as a relatively complex one where expectations as well as real economic variables together determine the final market price. Among the core variables which are seen to affect the pricing of the real estate are the following: household incomes, interest rates, supply (especially in the short-run), financial market institutions, demographic variables, availability of credit, taxes, public policies directed at housing etc. (see eg ECB 2003, Lamont and Stein 1999, Burch et al (1986), Tsatsaronis and Zhu 2004 and IMF's WEO 2004). Most importantly, the movements in asset prices are not exogenous fluctuations; they should foremostly reflect the purchasing power of current and future homeowners and therefore be tightly bound to overall macroeconomic developments (Carroll et al, 2010).

Badly designed housing policies are among the factors argued to have played an important role in triggering the recent crisis. OECD mentions the responsive housing supply as one of the main factors in avoiding bottlenecks in the housing market that could drive prices to bubbles. Indeed, it has recently been shown that very large price increases usually take place in countries where the responsiveness of the housing supply to housing prices has been very weak (OECD, 2011). A similar result was reached by Glaeser et al (2008) who were able to show that the price run-ups eg during 1980 were experienced in cities where the housing supply was more inelastic. Concerning other policies, it has been shown that tax policies favouring housing can lead to excessive housing investment and crowd out more productive investment (OECD, 2009).

It is true that the housing markets are very vulnerable to possible mispricing. As Krainer and Wei (2004) mention: 'Most market participants have little experience, making transactions only infrequently. Asym-metric or incomplete information between buyers and sellers about demand and prices is acute…matching of buyers with sellers is cumbersome and slow. And unlike other markets, there are no good ways to 'short' the housing markets if prices get too high'. According to Burnside et al (2011), agents at first have heterogeneous expectations about long-run fundamentals defining the prices in housing, but that they are prone to change their views because of 'social dynamics': those with stronger priors are converting others to their beliefs. Beliefs of ongoing price growth can easily become implanted, as people are prone to accept 'good news'. Such behavior clearly promotes the development of rational bubble dynamics in price formation.

One way to approach the fundamental value in the real estate market would be to examine the rent-price ratios. As is known, the rent-price ratio can in a sense be seen as corresponding to the dividend-yield ratio in the stock market, as dividends and rents both represent the underlying capital component, ie the uncertain future capital flows associated with the asset in question. In the financial literature an asset's fundamental value always equals the sum of its future payoffs, each discounted to its present value at rates that reflect investors' preferences (see eg Krainer and Wei, 2004). Whereas in the stock market this relationship is between discounted dividends and stock prices, it could be between rents and house prices in the housing market, as argued by Krainer and Wei (2004): 'The fundamental value of a house is the present value of the future housing service flows that it provides to the marginal buyer.[31] In a well-functioning market, the value of the housing service flow should be approximated by the rental value of the house.' This idea is that the price of a home can be approximately the discounted future flow of rents that it would generate if it were rented. Earlier for example Himmelberg, Mayer and Sinai (2005) as well as McCarthy and Peach (2004) have worked with rent-price ratios.

Using rent-price ratios, the bubble-concept also becomes easier to define: the developments in house prices or rents should not differ greatly from each other; otherwise this would mean that a bubble is developing in the housing markets, presented in the case of equities in section 3.2.

This seems tempting and easy, but it should be noted that there are some important differences between rents and dividends, which can greatly affect the way they actually relate to each other. The first difference is in the way dividends and rents are dependent on

[31] It should be noted that this argument ignores the potential effects of taxation.

underlying price-developments. In the stock market, a rise in the price level signals higher expected earnings and therefore higher dividends. In the housing markets the chain of events is somewhat different: price-level rises actually precede rises in rents. Another important difference is in the way decisions are made on dividends and rents: dividends are decided by the firm's board (possibly relating to a variety of motives) whereas actual rents are an outcome of a negotiation process. A further obstacle to the use of rent-price ratios might be rent controls, which can greatly impact the way the rents are able to adjust to pricing pressures inherent in a system of controls: landlords cannot exploit their market power on their current tenants. Rental markets in various countries are influenced by a range of regulations. The most stringent controls are in countries with relative large rental sectors, such as Czech Republic, Germany, the Netherlands and Sweden (OECD, 2011). On the other hand, according to OECD, rent control is lax in Finland, New Zealand, Slovenia, UK and the US. One of the effects of strict controls is reduced residential mobility, as shown by Lind (2001), Nagy (1997) and Ball (2009).[32] There is however no clear evidence that rent levels are lower in countries with stricter rent control (OECD, 2011). According to OECD (2011), the reason for this is that in an environment of strict rent controls, landlords tend to inflate rents for new tenants in order to compensate for the rental losses suffered during occupancy. In the case of rent controls it should be noted that in most countries rents have been less restricted only since the mid 1990s; before this, rent levels could have been too sticky compared to the changes in the price-level. The second important matter is that in working with raw data I am not able to take into account the impact of taxes or interest rates in rent-price ratios, which could bias the results of the unit-root tests. Interest rates in particular affect dividend-price ratios. Lower rates justify higher prices, as the discount factor gets smaller in the present value pricing model. To get an idea of how large an impact this can be, I analyze the US markets using historical housing market data, which have been cleared of the impact of both interest rates and taxation. The data were obtained from the Federal Reserve.

[32] A similar phenomenon relates to a house-price decline if prices fall enough to produce negative equity for leveraged household (Ferreira et al, 2008). Such is apparent already in several US states that experienced larger rises in the share of households with negative equity.

5.5.2 Search for real estate bubbles motivated by their large costs to the economy

Though real estate booms occur less frequently than equity market booms, their busts are associated with larger GDP losses. In addition, the duration of the busts are documented to be twice as long as those related to the equities markets. Macroeconomic and systemic risks are further accentuated if the cycles become synchronized. Besides being synchronized within an asset class across borders, the developments seem to be synchronized across asset classes. This increases the overall fragilities in the financial system, as the different investment instruments move in same direction.

Helbling and Terrones (2003) analysed several stock marketand housing price booms and busts in 19 industrial countries from the 1950s onwards and confirmed that asset price crashes were often associated with declining economic activity, increasing financial instability as well as sometimes larger budgetary costs due to recapitalization of the banking system. An eye-catching result was that though the stock market busts were followed by economic slowdowns, they were seldom especially severe. Looking at the average crash in stock markets, the price decline seemed to be approximately 45% from peak to trough, a period of 10 quarters. In the case of housing price busts, the average negative correction after a boom was approximately 30%, but declining prices lasted some 1.5 years longer than for stocks. In addition, the implied probability of a boom being followed by a bust was much larger in the case of housing prices than for equities. Most importantly, the housing booms were associated with much larger output losses: on average, the loss was 8 per cent three years after the crash compared to the pre-crisis growth. For equities, the comparable output loss was only 4 per cent (Helbling and Terrones, 2003). As the impact of real estate booms and busts are much more severe in terms of overall economic impact, this clearly provides motivation for trying to find methods of identifying real estate booms early enough to counteract them.

The reason for the heavier losses from housing price booms that these have larger impacts on consumption and on the banking system, both of which are heavily exposed to real-estate risks. The wealth effect from real estate prices has a huge impact on the build-up of debt: as the real-estate share of households total wealth is large,[33]

[33] In Italy, for example, over the forty years the share has fluctuated between 51% and 66% (Cannari et al, 2006).

fluctuations in real-estate valuations affect the value of households' potential collateral. Changes in collateral values relaxes and ties up liquidity constraints for them. In addition, Case, Quigley and Shiller (2003) found that the marginal propensity to consume with respect to housing wealth is much higher than with respect to stock holdings.

The strength of the housing-wealth effects are highly dependent on whether the house-price gains are perceived to be permanent or temporary and moreover the strength of the wealth effect seems to differ across countries. This is easy to understand, as the sophistication of the financial markets and the tools that can be used to take advantage of house-price appreciation influence the size of the wealth effect. New tools that came with the development of securitization techniques, especially the use of home equity, served to link consumption and personal wealth more tightly to house-price developments. Carroll, Otsuka and Slacalek (2010) reported that, at least in the US, housing price movements have typically been followed by highly positively correlated movements in consumer spending. Besides these new tools, an important consideration is the liquidity situation in the housing finance system, since this affects households' ability to take advantage of the capital gains in house prices (Zhu, 2005).

Besides consumption, real estate booms also impact investment flows. In several studies a connection has been found between higher house prices and housing investment, which in turn impacts course of the business cycle (Cannari et al, 2006). For example Ferrara and Vigna (2009) and Alvarez and Cabrero (2009) find that for France and Spain the current housing sector cycles are highly correlated with future GDP cycles, which should not come as a surprise considering eg the role of real-estate business and construction in the latest construction-led boom in Spain.

Concerning the effects of real-estate price booms and busts on the banking sector, the real estate busts were associated with swifter and more powerful adverse effects on the banking system than eg were the equity price busts (Helbling and Terrones, 2003). Following a real estate bust, banks face rapid increases in provisioning costs as the amount of non-performing loans increases. Moreover, the capital-to-asset ratio falls as real estate prices plunge. These events lead to a reduced willingness or ability on the part of banks to provide financing for economic activity. Especially for bank-dominated financial systems, the impact can be severe, as nonbank sources of finance are not readily at hand. Further, as real-estate holdings comprise a significant part of collateral in the banking system, their values impact the build-up of debt in the system. Strong appreciation of collateral prices can affect loan policies and increase the procyclicality of the financial system.

In the following section the main focus will be to examine whether the AR and ADF indicator methodology (presented in section 3.3.2) can be applied to the housing markets and how well do these indicators work in the context of actual housing market data. In the housing markets, the rolling OLS-regressions are applied to log rent/price series to get the least squares estimates to AR- and ADF-coefficients (presented in proposition 1 and 2). In regressions the lag was defined by the AIC (here 1), trend was not included, but constant was allowed. Window lengths used were varied, but the results presents here are all based on sample size 36.

Evaluation is based on the indicators' ability to flash warnings before and during historical consensus bubbles. Although the bubble model presented in section 2 was originally developed for stock markets, it can be made applicable to housing markets via the assumption that dividends and rents are congruent by definition, ie both represent the uncertain future cash flows associated with an asset. One can then apply the same AR- and ADF-based tests to log dividend-yield ratios so as to assess the presence of unit-roots (bubbles) in housing prices.

5.5.3 Practical application of AR36 and ADF36 indicators to housing prices[34]

The group of countries chosen for the more thorough analysis was based on developments in the housing markets, the focus being on those countries where house-price growth rates have been the highest over the last 10 or more years. Data limitations meant that in order to count the indicator values we had to have both monthly house prices and rental prices. Quarterly prices were available for several countries for rather long time periods, but monthly data were harder to find and the available time series were much shorter. The main source for the housing prices used here is the BIS (Bank for International Settlements) property prices databank, for which the data are originally provided and compiled by local authorities and providers and then collected by the BIS. Unfortunately, this means that the statistics are complied differently and the quality of the underlying

[34] Appendix 17 presents summary table of country-level data; the consensus booms and the precise timing of the AR36 and ADF36 warning signals.

series can vary. Much analysis has been devoted to examining features of different house price indexes and the problems related to their construction and representativeness. More information on these documented problems is available eg in McCarthy and Peach (2004), ECB (2003) and RICS's European housing reviews. One of the main consequences of these quality problems is that the country-level results are not comparable across countries, so that any findings based on them should be interpreted with some caution. I take this into consideration in analyzing the test results. The rental data is simpler to interpret, as regards the cross-country quality differences, as these data are constructed in a similar way in all of the countries included in the sample. The source for the rent series is the OECD. The rent data from OECD is the housing component from the CPI-data, which actually is not the pure rent data. This shortcoming must be taken into account when interpreting the results. On the otherhand, it seems to formulate good proxy for the rent series as when compared in some countries pure rent-series data, the differences seem to be relatively small.

5.5.4 Bubble signals for the Spanish housing markets

The house-price data used to analyze the Spanish housing market are from Bloomberg the BIS databank and the rental data are from the OECD. A complicating factor concerning the house-price data is that the official price indexes in Spain have often been criticised for not reflecting the actual cycles in housing prices. By comparing data from different sources, we found that the negative correction in housing prices is smaller in some of the official indexes than in those provided by commercial sources. Finding a representative, good quality price index was therefore a rather complicated task. A further problem was the quarterly frequency of the official data. Because of the lack of official sources for monthly housing price data, I had to such data from a valuation company called TINSA. It is widely felt that these data accurately describe the trends in housing, and they exclude subsidized housing. The data go back to 2001 and can therefore be used to singularly evaluate developments during the latest boom in Spanish housing prices. Due to the relative shortness of the data, I collected the quarterly residential property prices from the National Statistics Office, which provided the data starting with 1995. The quarterly figures were then transformed to monthly figures via a statistical program.[35]

As for rental data, there are serious problems regards the Spanish housing market: the rental share of housing markets is strikingly low compared for example to the EU as a whole. In 2007 the rental share in Spain was only 11% compared to 29% in the EU as a whole. As the rental markets are very small, there is a question about the reliability of the rent-index figures for Spain.

Developments in the Spanish housing markets during recent decades have not been smooth. From 1987 to 1991 real-estate prices went through an expansionary phase which peaked in 1991Q4 (IMF, 2003). The period from 1992 until 1996 was characterized with flat growth, but it was followed by one of the premier real estate booms in Europe. From 1997 until 2007, housing prices in Spain rose on average by nearly 200% – in some coastal areas by even more. The price rise was fastest in 2002–2006 when the annual growth rate was over 10%, according to Bank of Spain statistics. As prices continued to climb, the construction industry also expanded, and this fuelled a boom in real economic development and raised the GDP-share of housing investment and construction.

The strength of the housing boom was intensified by two factors. First, mortgage interest rates fell from 17% in 1991 to below 3.5% in 2004–2005, making mortgages extremely cheap. Secondly, securitisation provided banks with a means to 'transfer' risk out of their books and with a cheap source of finance. Securitisation increased, and by 2008 Spain had the most 'securitised' mortgage market in Europe. The mortgage heap grew in step: by 2008 the ratio of mortgage debt to GDP was 62% compared to only 14% in 1990.

Then the boom in housing prices came to a sudden halt as the global crisis hit the markets and credit dried up around the world. As the real economy slumped, the property developers were left with thousands of unsold and even unfinished properties and a huge amount of debt. Spain's banks were hit by a flood of problem loans. By the start of 2011, over 6% of banks' aggregate portfolio was in bad loans. Real-estate and housing prices had plummeted, so that by the end of 2010 they were down 17% from their peak values.[36]

[35] The statistical program used in disaggregation was Ecotrim. The results were cross-checked with country level data from Datastream in cases where monthly prices (but short series) were available.

[36] According to other sources, TINSA 14%, Fotocasa 22%, Housing Ministry data 16% (RICS, 2011).

Against these developments one can evaluate the signals produced by the AR36 and ADF36 indicators. The indicators were tested by using the log rent/price index data for the periods 1995–2010 (official sources) and 2001–2010 (commercial sources).[37] The results reported here are those obtained using critical limits of –0.05 for ADF36 and 1.0 for AR36. The surge in housing prices is visible from figure 5.11, and the warning signals are shown in figures 5.12 and 5.13, where the shaded areas describe the timing of the warnings. Overall, concerning bubble signals given by AR36 and ADF36, they occur in the period of the greatest price rises, 2002–2006. AR36 clearly gives fewer warnings than ADF36, which flashes bubble warnings nearly throughout the period of robust price growth (figures 5.12 and 5.13). It is hard to tell which is the more accurate signaller and whether ADF36 gives too many signals. Looking at the individual signals, it becomes apparent that the two indicators actually spot roughly the same periods as bubbles, though it seems that AR36 is the more solid indicator, which surely derives partly from the lower critical limit (–0.05) used in the ADF36 testing.

Comparing the yearly changes in the house price index with the timing of AR36 bubble signals (figure 5.14) one sees that the AR36 signals are clustered around the largest yearly changes – positive or negative. Reason for focusing on yearly price changes instead of focusing just on price level developments is that the changes more clearly visualize the periods of continuous strong positive growth, especially if prices at some stage are booming expansively. Expansive growth can be enormous compared to previous historical developments, making it harder to spot any other local booms than the only expansive growth period. Concerning the use of indicators as early warning tools, we note that it might be useful to have one that reacts quickly to signs of overheating and that in sizing up a situation, warning signals flashed simultaneously by both indicators could be given more weight than other signals.

It is noteworthy that both indicators give warning signals also during periods when housing prices are descending. This might seem questionable, as prices should be corrected downwards in order to reach a reasonable level in light of fundamentals. This result highlights the problem of using these methods with housing data. Rents being generally sticky, they do not correct downward very quickly. As prices undergo sizeable negative corrections while rents are stuck at their old previous levels, our indicators readily signal

[37] Signals based on shorter time periods can be found in Appendix 16.

problems in the log rent/price relationship. The problem of rigid rents is not limited to downward correction but obtains also when housing prices are surging. Therefore the indicators' very earliest signals of (positive) bubbles should be interpreted with caution.

Concerning the differences between the signals given by the ADF36 (which seem to give warning signals relatively often) and the signals given by the AR36 there is a principal reason for this. In the case of Spain, only those results were reported, which were obtained when using –0.05 as the ADF36 critical limit. Later, in the case of UK (figures 5.20 and 5.21) it is easy to spot that when the limit 0.0 was used in ADF36 instead of –0.05, the amount of warning signals was reduced and the periods were nearly the same as received through AR36 warnings.

Figure 5.11 **Housing price cycle in Spain, 1995–2010**

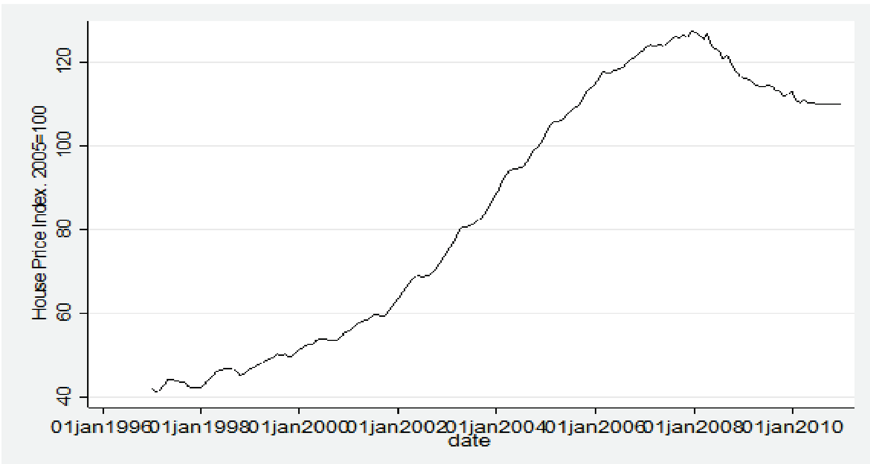


Figure 5.12 **Bubble signals in the Spanish housing market, ADF36**

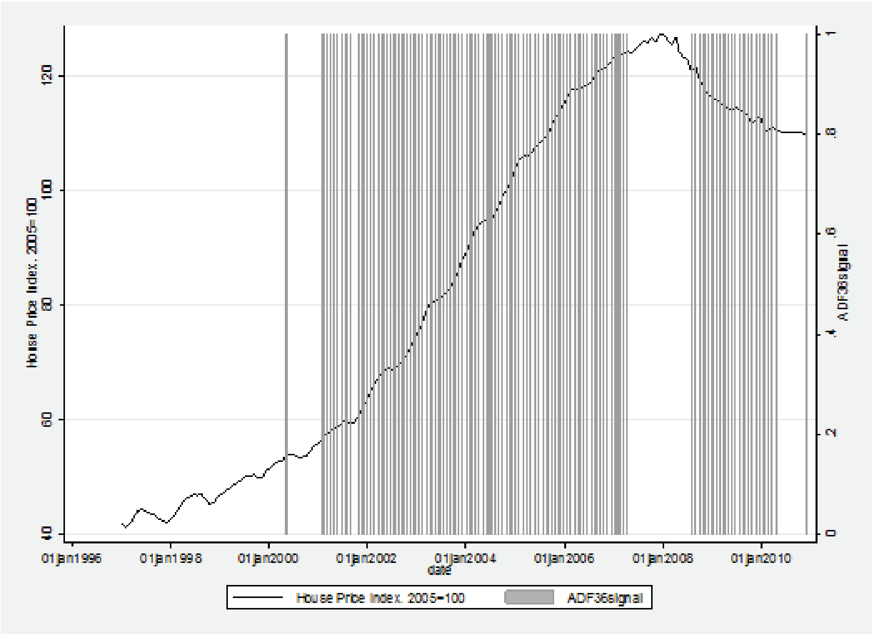


Figure 5.13 **Bubble signals in the Spanish housing market, AR36**

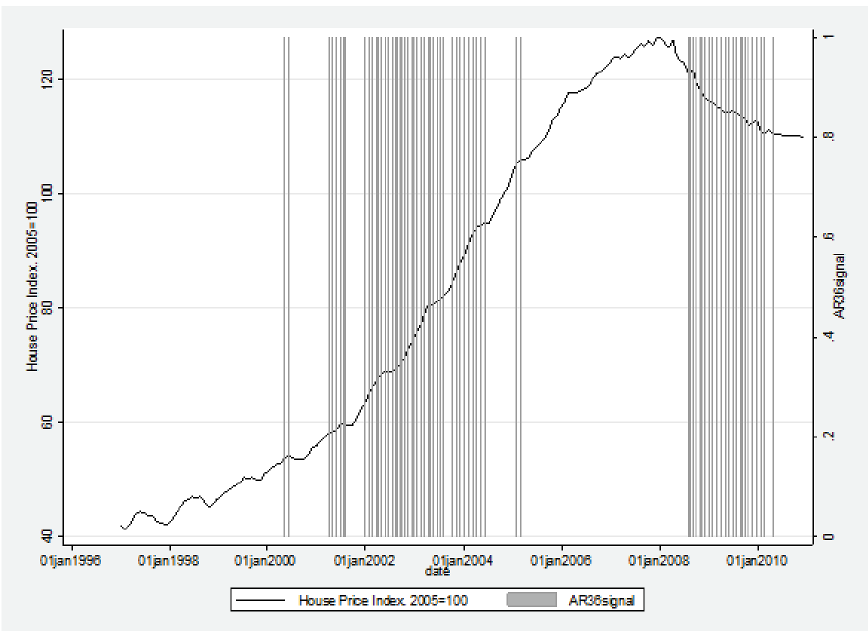
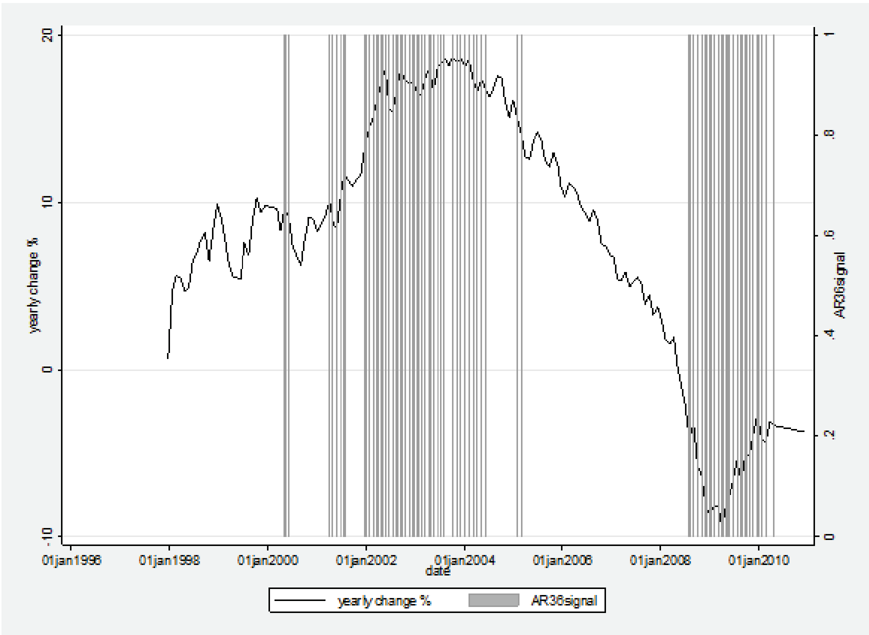


Figure 5.14 **Yearly change in housing price index, %, and AR36 bubble signals**



5.5.5 Bubble signals for the Irish housing markets

The case of Ireland reminds one of Spain, as Ireland too experienced a relatively long and robust housing price boom. The permanent tsb House Price Index,[38] compiled by the ESRI (Economic and Social Research Institute) and widely held as the most authoritative measure of house price movements in Ireland, rose on average by 14.9% yearly during the 10 years from 1996 to 2006. During the same period national total house-price appreciation was 270%. On a yearly basis, one of the biggest price booms occurred in 1998 when housing prices rose 30% in a single year. As in Spain, financial innovation and securitization were important factors in the rise in housing prices and mortgage loans in Ireland. Booming prices had a boosting impact on building activity in Ireland and this can be seen in the number of new houses: a third of the current housing stock was built during recent 15-year period (ESRI, 2006).

[38] The tsb relates to the company name as the index is 'permanent tsb/ESRI House Price Index'.

The boom in prices finally came to an end in 2006, and currently Ireland stands out as one of the countries with the most sustained price declines. In the aggregate, housing prices have fallen by 38% since the peaked at the end of 2006 (RICS, 2011).

AR36 and ADF36 indicators were studied using log dividend-yield data for the period 1977–2010.[39] The house-price data are from the BIS databank, but were originally constructed by the Department of the Environment, Heritage and Local Government. Price data included in this series cover existing house and apartment prices for the whole country. The rental data are again from the OECD.

Figure 5.15 shows the overall rapid growth of the Irish housing markets. From the figure, the growth speed-up since the mid 1990s is clearly visible. Figures 5.16 and 5.17 show the timing of AR36 and ADF36 warning signals for Irish housing prices. As seen from the figures, a clear difference between the indicators is once again seen in the frequency of warnings: ADF36 gives warning signals much more frequently than does AR36. Concerning the timing of the warnings compared to the known history of the housing markets, ADF36 gives its first warning already in 1985, as housing prices long appreciated by 6% to 7% on average. The first simultaneous warning by both indicators occurs in 1987 and is clearly related to the sudden negative correction in the housing prices. The second common warning occurs in 1992, as the indicators give send signals during a short but fairly pronounced negative correction in housing prices. After this, the two indicators flash warnings related to housing prices from the spring of 1996 all the way until 2001. By then, the Irish housing markets were experiencing extremely rapid price appreciation, 20% yearly on average. These prices dipped in 2001, which is also visible in the price index series. The drop also caused the rolling warning signals to cease for a while, as it changed the nature of the data in the sample, so that instead of generating a unit-root, a sample included a pronounced downward revision in prices, which was interpreted instead as deriving from the re-emergence of a stationary process. As housing prices again began to appreciate, warning signals were flashed in 2003 and continued all the way until 2005. It is a bit mystifying that the signals did not cover the rest of the strong boom up to 2007 when the prices turned downward. One possible reason for this is the rather volatile development of prices: while still on an upward trend, these prices had frequent dips during a period of a couple months. The last

[39] Due to the rolling window the first 36 monthly observations are always used for generating the first signal and this limits the data included in the figures to the years 1980–2010.

warning is related to the sudden strong negative price correction, which is quite visible, especially if compared to the timing of warning signals among the yearly price changes in figure 5.18. As mentioned in the case of the Spanish data, the rent levels do not adjust quickly, so that the sinking prices are able to trigger warning signals in the log rent/price data. As rents adjust, the warning signals stop, even though prices continue in to slide.

Figure 5.15 **Housing price cycles in Ireland, 1977–2010**

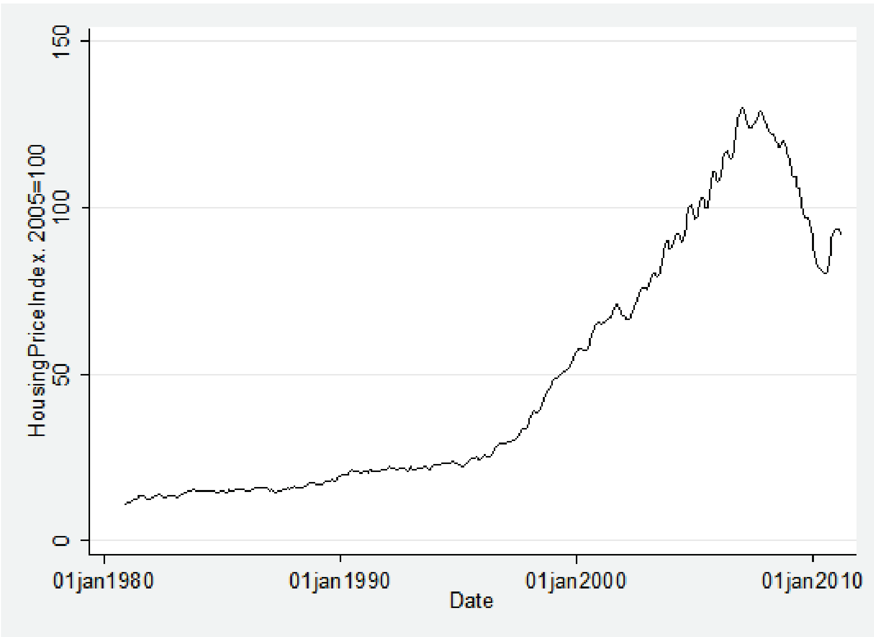


Figure 5.16 **Bubble signals in the Irish housing market, ADF36**

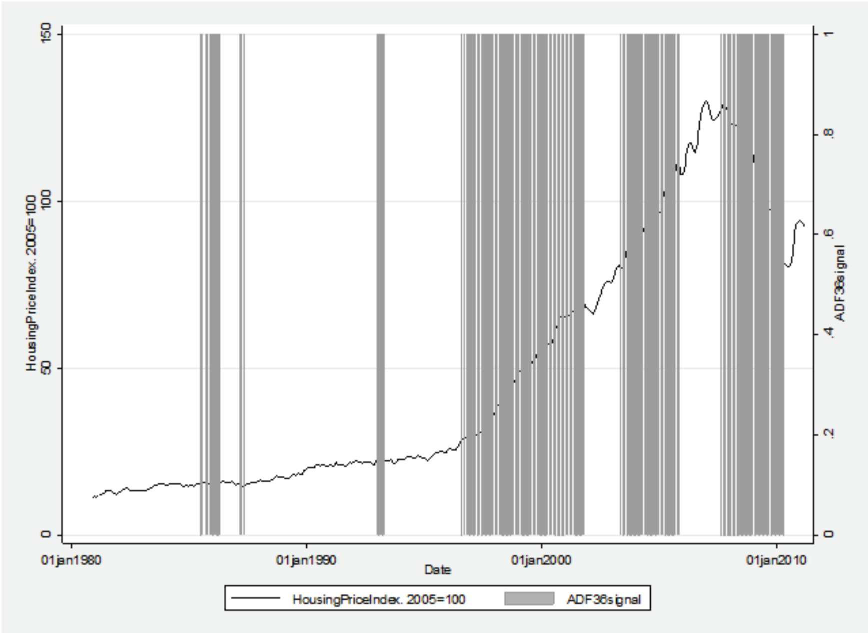


Figure 5.17 **Bubble signals in the Irish housing market, AR36**

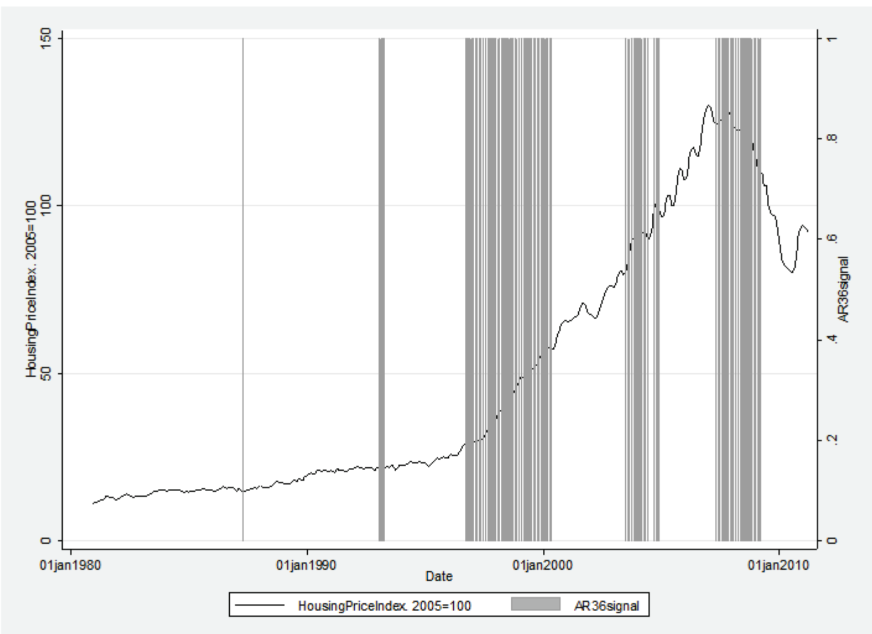
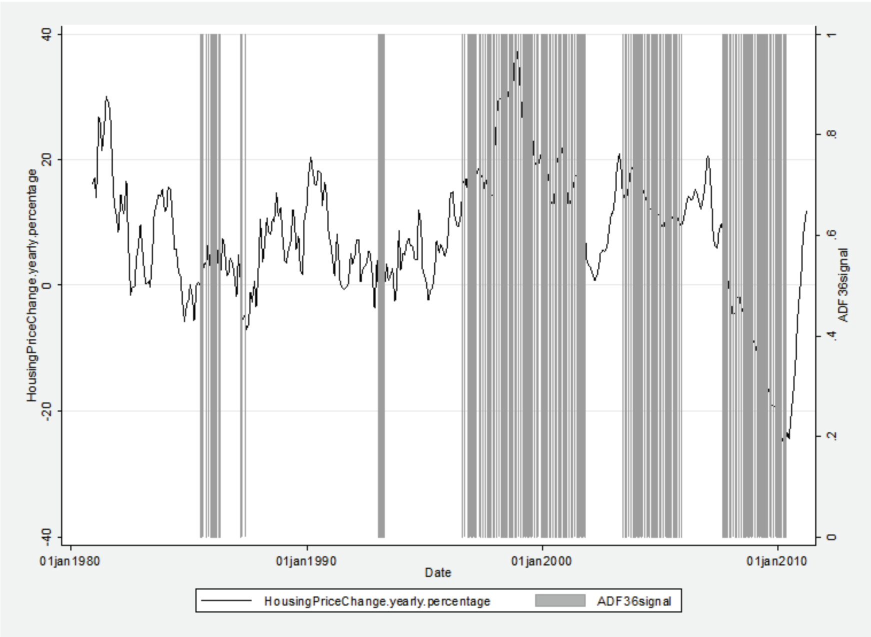


Figure 5.18 **Yearly change in housing price index, %, and ADF36 bubble signals**



5.5.6 Bubble signals in the UK housing market

There were several cycles in the UK housing market during the 1970s and 1980s. One of the factors producing housing price volatility in the late 1980s was a series of major institutional and legislative changes that have affected the structures of retail financial markets in the UK since 1979. Especially important here was the abandonment of direct control over bank lending in 1980. At the same time restrictions on building societies were lifted in a series of measures that allowed them to fund their operations partly via wholesale deposits and so to compete with banks (Aoki et al, 2001, 2002 a and b). This period of regulatory change brought in new entities to provide loans and liquidity to the housing markets, which greatly extended the availability of housing credit. According to Bayoumi (1993), the share of liquidity-constrained consumers in the UK fell from 60 to 30 percent in 1974–1987. These developments boosted the demand for housing and made the prices more buoyant. In this respect the evolution of the market reminds one of the onset of the recent crisis, which was preceded by intensified competition and product innovation in retail banking. The emergence of securitisation increased liquidity in the financial system and brought in new players.

Developments in both periods led to the formation of bubbles in the real estate markets. For the 1970s and 1980s IMF (2003) identified all together five periods of housing price booms in the UK, the first reaching its peak in 1970Q3 and the second already in 1973Q3. During years from 1977 until 1979 the prices rose 72% and finally peaked in 1980Q3. In the early 1980s a short boom occurred which, according to the IMF, peaked in 1983Q3. In the late 1980s prices rose between 1987Q1 and 1989Q3 by 69% (Chamberlin, 2009). These price peaks are clearly identifiable eg in the time series of price-to-income ratios from 1953 until 1995 (Muellbauer et al, 1997).

Developments in the UK housing market are illustrated in figures 5.19–5.23. The overall housing price index cycles are captured in figure 5.19, where the index used is the monthly Halifax House Price Index covering all dwellings (new and existing). The warning signals given by the AR36 and ADF36 indicators are marked by shaded areas in figures 5.20–5.22. For the UK and US (as seen later), the use of the critical limit –0.05 for ADF36 leads to very long and persistent bubble signals. Though these long-running warnings can be rationalized, their persistency does raise some doubts. For this reason I ran the ADF36 test also using zero as the signal-limit; the signals are reported in figure 5.21. These results do not differ widely from those from those for AR36.

Looking at the warnings given by the two indicators, the main observation is that both of them produce signals during the periods of sharpest rises in prices. The first signals for both indicators occur during the booming years from spring 1987 until autumn 1989, a period that coincides nicely with the boom cited eg by Chamberlin (2009). The second period of alarms began in 1991, lasted until 1993, and was clearly related to a decline in prices. In the housing markets the years 1990–1994 were characterized by negative rates of return in housing and rising rates of repossession. Perhaps in log rent/prices, the price correction was excessive during this period, which set off the warning signals. The third period of warning signals was related to the short but pronounced negative correction in prices, running from 1995 to 1996. Looking at the history, we see that the latest UK housing boom, which ended in the financial crisis, began already in 1998. The rise in UK housing prices was dramatic during the years 1998–2007, and it increased the availability of home equity, which in turn fuelled higher consumption. Households' indebtedness increased. A Bank of England report of 2001 noted that competition in retail credit markets had intensified significantly and, along with product innovation, may have widened the availability of credit and lowered its price. The availability and size of loans provided further support to the housing markets. No wonder that the next bubble signals came in the period 2002–2004 and then again in 2007. All of these periods relate to the peaks of persistent price paths, as can be seen in figure 5.23, where the yearly price changes are compared to the timing of warning signals. The latest signal in figure 5.23 is clearly related to a negative bubble, as it concerns the housing price bust, which a came after a fairly elongated descent.

Figure 5.19 **Housing price cycles in UK, 1983–2010**

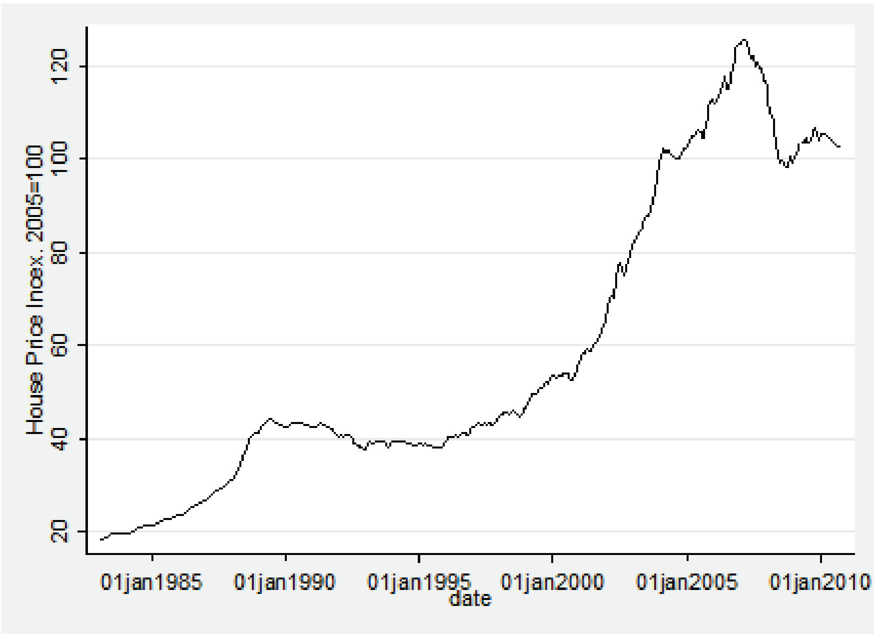


Figure 5.20 **Bubble signals in the UK housing market, ADF36**

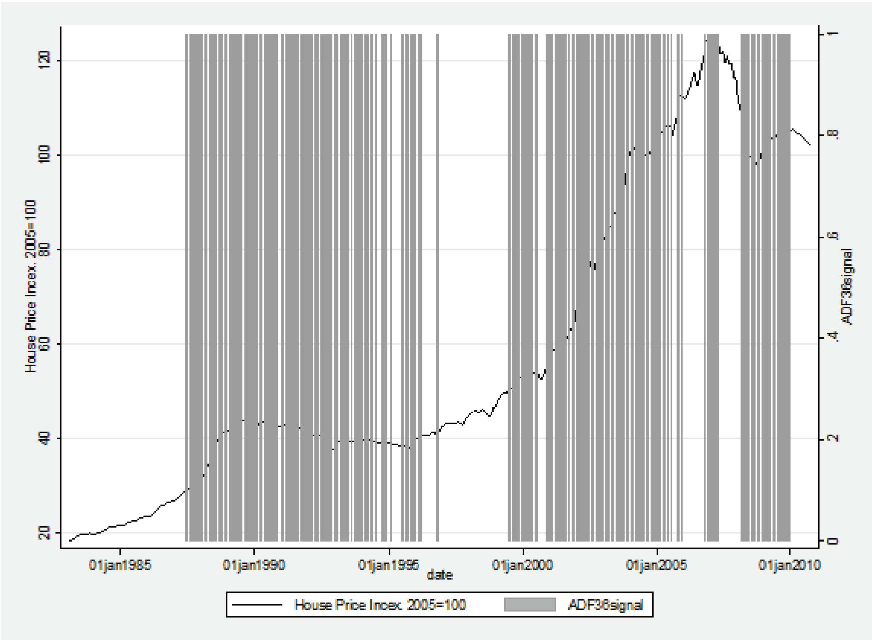


Figure 5.21 **Bubble signals in the UK housing market, ADF36 (zero)**

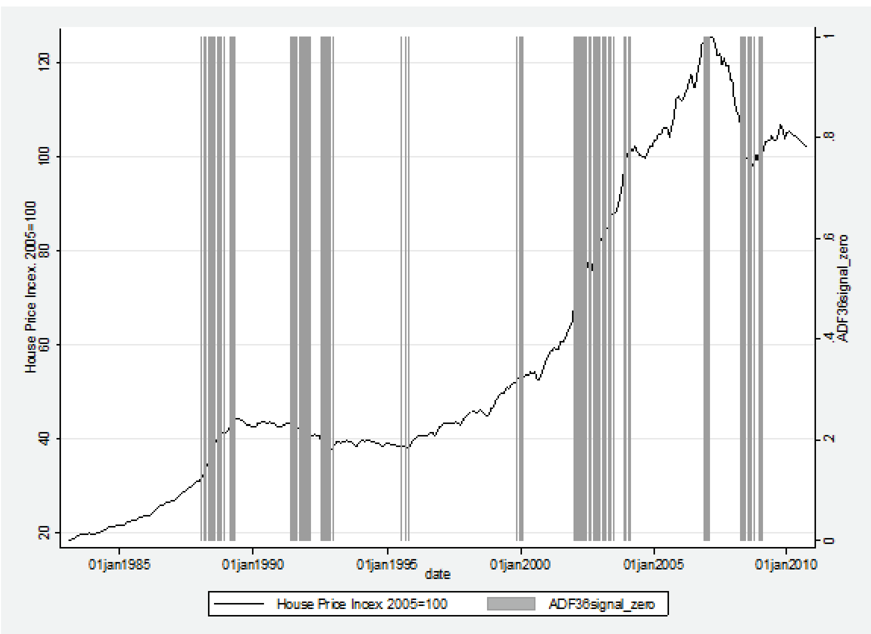


Figure 5.22 **Bubble signals in the UK housing market, AR36**

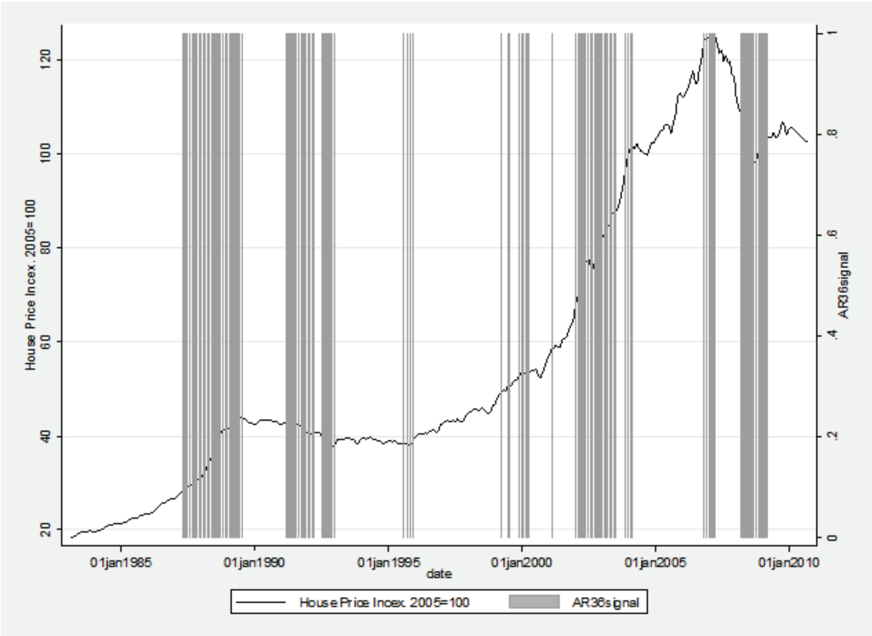
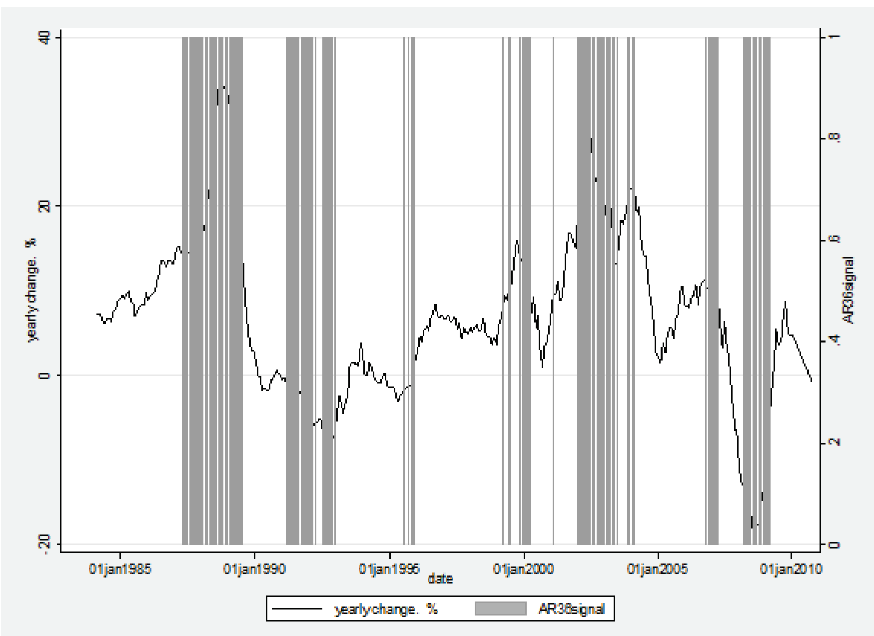


Figure 5.23 **Yearly change in housing price index, %, and AR36 bubble signals**



5.5.7 Bubble signals in the US housing market

In the US large house-price booms occurred in the late 1970s and late 1980s. For the 1970s and 1980s the IMF(2003) cites three periods as boom peaks: 1973Q3, 1979Q2 and 1989Q4. Concerning to these periods, there have been several studies that describe price developments prior to these events and explore the factors that led to overheating in the markets. Such analysis can be found eg in Himmelberg et al (2005), Mankiw et al (1989), Shiller (1993), Case (2004) and Shiller (2006).

Unfortunately, since monthly data were only available for a rather a short period (from 1991), the analysis here is constrained to focus on the developments that preceded the latest housing boom and the bust in 2008. To gain a more extensive view of the indicators' functionality, I once again made use of quarterly data on housing prices, since quarterly data was available from 1975 onwards and could be adjusted to monthly level using a statistical program. The rent-index data used to analyse the US housing markets is from the OECD, as in all previous country analyses, and the monthly housing price index-information was obtained from the Federal Housing Finance Agency, which provides monthly (purchase only) housing price indexes for the whole country as well as by census divisions. The quarterly data were obtained from the BIS databank, having been originally constructed by the Federal Housing Finance Agency. These data included all the census divisions and were based on all transactions data on existing houses.

The current economic crisis is undeniably a correlative of the collapse of the speculative bubble in the US real estate markets. According to Shiller (2009) the main cause of the bubble was the widespread misunderstanding of the factors that influence the prices. Concerning the core features of the rational bubble it seems that both the 1988 house-price boom and the recent one were preceded by several of the symptoms that are typical of a rational bubble build-up. These symptoms are documented in Case et al (2003) on the basis of survey results for home buyers. During both of these boom periods many buyers were motivated by future price developments, as in surveys approximately 90% of the respondents expected the house-price ascent to continue. The expected growth rate itself was a clear symptom of a bubble: at the aggregate level, the respondents expected housing prices to rise 12% yearly. Expectations of continuous strong growth in prices are a typical symptom of a rational bubble.

In the recent boom the house-price appreciation even intensified towards the end. On one hand, this is not surprising, since this was also the period during which the growth of subprime lending and securitisations of the loans contributed to the overheating of the mortgage markets and boosted the supply of credit. During period 2001Q1–2007Q1 the purchase-only housing price index appreciated 58.1% in the whole country compared to earlier period from 1996Q1 to 2001Q1, when the growth was only 29.3% and even less (12.3%) in 1991Q1–1996Q1. Another feature of the house-price appreciation in the US was that there were large regional differences, as some of the census divisions experienced even larger upswings in the housing prices. One such example is the Pacific division, where housing prices rose by 97% during the period 2001–2007.

US housing market developments are illustrated in figure 5.24, which presents the housing market price index over the period 1977–2010. In figures 5.25, 5.26 and 5.27, the shaded areas once mark the bubble signals given by AR36 and ADF36 (–0.05) as well as ADF36 (zero). As is clear from these figures, the ADF36 (zero) gives warning only rarely, and they are concentrated round the latest housing price boom from1998 onwards. AR36 produces signals for several different bubble periods, some relating to rapidly descending prices, ie not always to long periods of robust increase. This is visible via the yearly percentage changes in the timing of AR36 warning signals (figure 5.28). Finally, as seen from figure 5.26, the ADF36 (–0.05) signals are very steady and long-lasting.

Comparing these three signals, we find it interesting that, even though in some cases the warnings are much longer, the core periods around which these warnings concentrate are the same in each case. The earliest warnings by AR36 occur in 1977–1979, just prior to the 1979 housing price crash (Dreiman, 2011). After that, warnings are flashed in 1980–1981, in connection with a steep price descent that finally ends in 1982(figure 5.28). The next warnings cluster around the boom in the end of 1980s, as the first warnings occur in 1985, though the more persistent bubble signals are related to the period 1986 to 1987 and, after a short brake, to spring 1988. This period matches closely the timing of the economic and asset market boom. As eg Case and Shiller report (2003), the prices in some of the census areas began to rise rapidly already in 1984 and 1985, but by the time they topped out in 1988, they had risen by 140%. This boom in real estate prices in the US was followed by a negative correction, which ended in the early years of the 1990s. The end of this period of falling prices coincides quite well with the next bubble warning given by AR36 in 1990–1991. This period was followed by a period of soaring real estate prices. From 1999Q2 onwards, the price appreciation was very pronounced, as it was again in 2004Q1–2005Q1. These periods are signalled as dangerously rapid price growth also by the AR36 indicator, which flashes warnings in 1998–2001 and again in the period from 2003 until the spring of 2006. The final signals given by AR36 are related to the strong negative correction in prices, as can be seen in figure 5.28.

Figure 5.24 **Housing price cycles in US, 1975–2010**

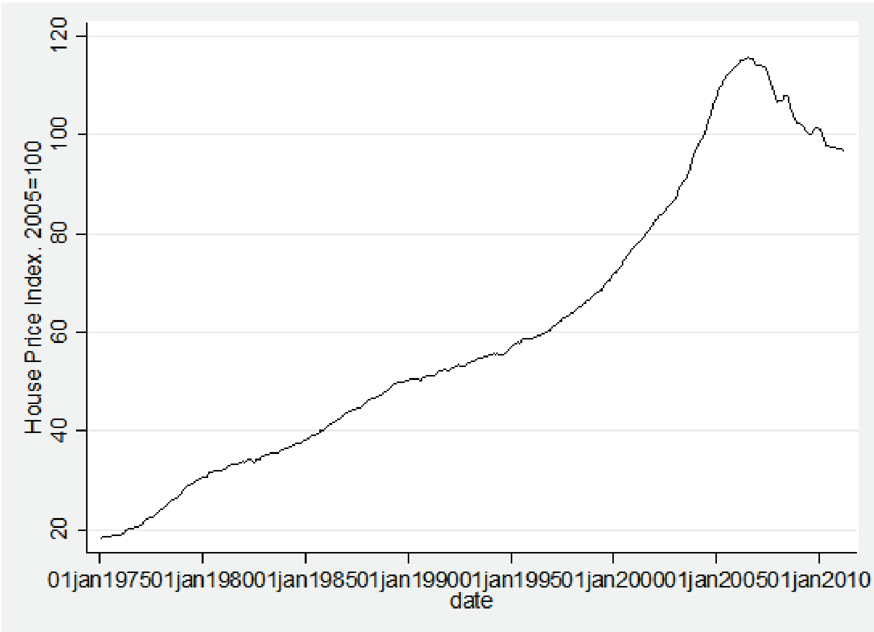


Figure 5.25 **Bubble signals in the US housing market, AR36**

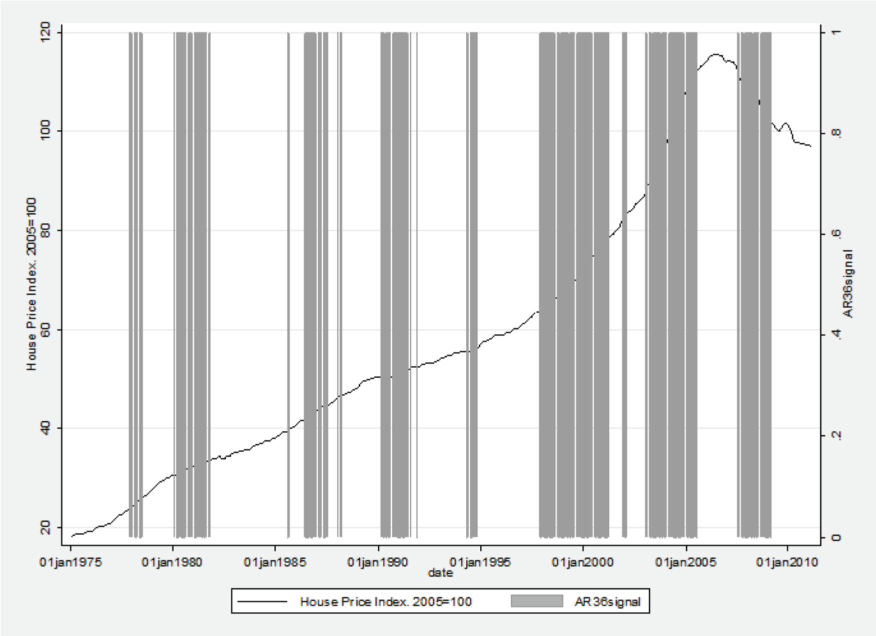


Figure 5.26 **Bubble signals in the US housing market, ADF36**

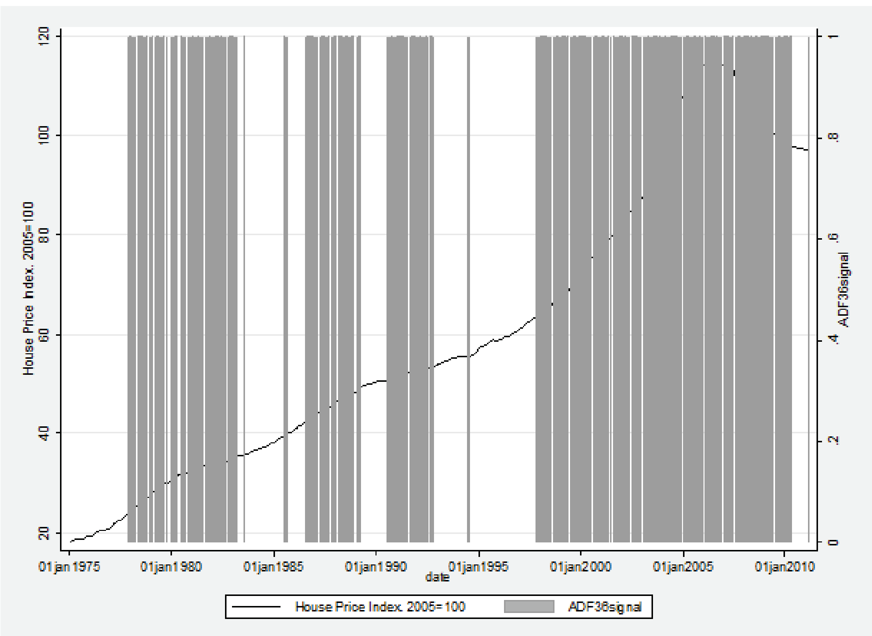


Figure 5.27 **Bubble signals in the US housing market, ADF36 (zero)**

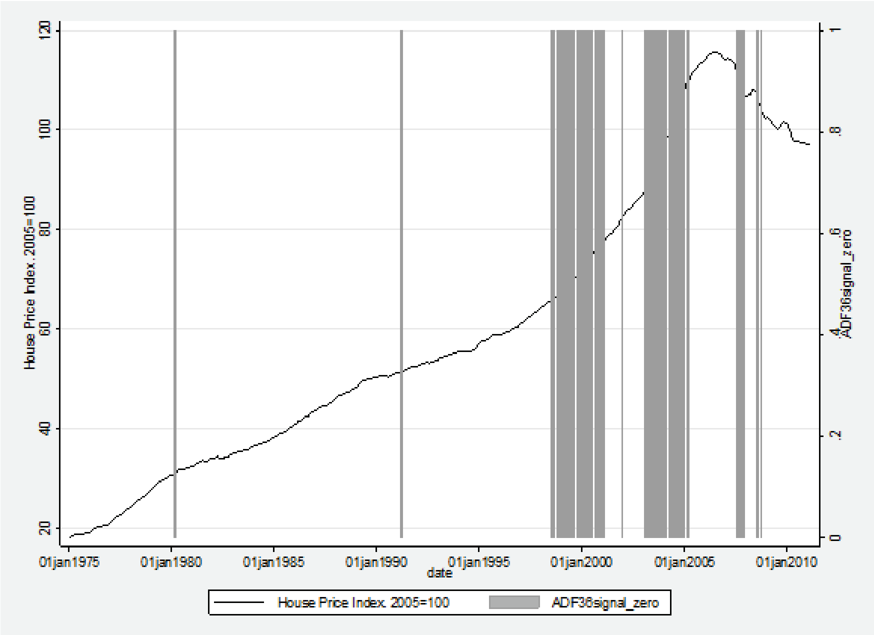
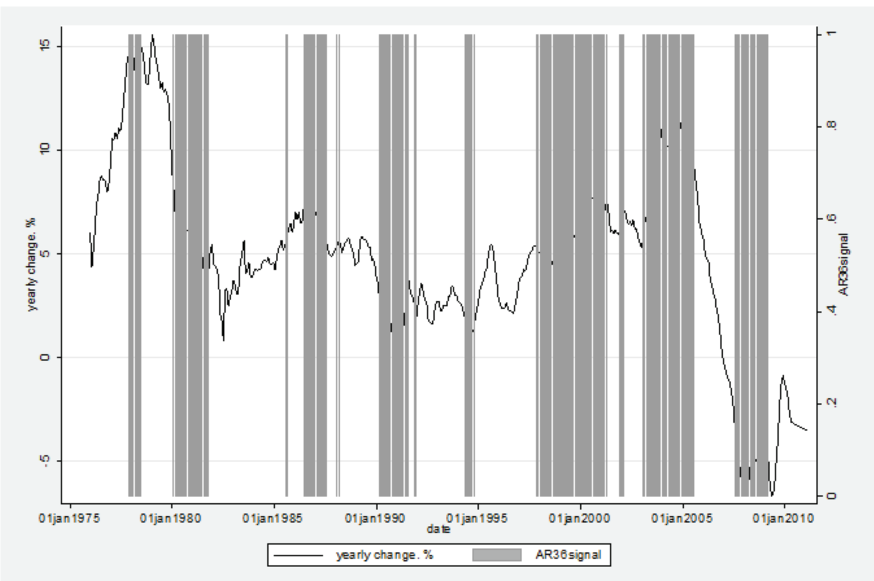


Figure 5.28 **Yearly changes in housing price index, %, and AR36 bubble signals**



It is true that prior to the bust in the US, many academics had criticised housing price levels and devel-opments in housing finance. On the other hand, there were also studies that found no reason for such concerns. For example, McCarthy and Peach (2004) came to the conclusion that the upturn in home prices was largely attributable to strong market fundamentals.

One of the major sources of criticism for the use of rent/price ratios has been that this measure does not take into account the impacts of interest rates or taxation. For example, McCarthy and Peach (2004) argued that interest rates do matter since they influence home ownership affordability and also represent a yield on competing assets in a household's portfolio. McCarthy and Peach thus made an adjustment in the US rent-to-price ratios that took account of interest rates (mortgage rates) as well as income taxation. The novel indicators were run with a revised version of the data used by Jonathan McCarthy. The data unfortunately end at summer 2005. The AR36 and ADF36 indicators still flash warnings, despite the interest rate and taxation adjustments to the data. The only clear differences are that the indicators do not signal any negative bubbles and that the positive bubbles signals end already in 2001, and do not reoccur.

5.6 Evaluation of real data applications

It seems that both indicators deliver valuable early warning signals of emerging bubbles in asset prices in the stock markets and even in housing prices. In this regard, it important to keep in mind that, in serving as a tool for giving early warnings, an indicator should be able to deliver timely signals of possible mispricing. The signals should be of course by at least fairly reliable. The primary use to be made of such an indicator is not to immediately set off counteractive action as such, but to function as an alarm mechanism that will draw sufficient attention to the possible future problems and to act as a spur to deeper analysis of the phenomena and its driving powers. In this respect both the AR36 and the ADF36 seem to be able to produce valuable signals.

Of course, one open question is: could the information from these early-warning indicators be combined with other indicators to signal other kinds emerging instabilities in the financial system or in the real economy. As seen in section 2, several common symptoms characterize the periods preceding asset price bubbles and financial crises. Based on these common symptoms, a set of indicators could be assembled to warn of dangerous developments and trends emerging in these core areas. The two indicators presented here could be included in the set, for the purpose of giving warnings as to asset price evaluations.

6 Conclusions

Although financial asset-price bubbles have unique features each time they appear, this study attempts to put the spotlight on those features that are common to all of them for the purpose of constructing early warning indicators that are able to signal emerging bubbles in asset prices. The basis of the indicators is simple and focuses on distinguishing bubbles from increases in asset prices that are driven by fundamentals by focusing on the rational bubble component in prices.

The main contribution of this study is to present two easy-to-use indicators that, due to use of short rolling windows in subsample construction and repeated regressions, are able to accurately detect simulated bubbles from the data in Monte Carlo simulations. In simulated data, the methods found up to 70–80% of the simulated unit root periods. As was shown in the third section, this accuracy compares very favorably with the power of the other conventional unit-root and stability tests in similar simulations.

A clear advantage of the indicators presented here is their ability to perform accurately even with relatively modest sample sizes, as was shown in Monte Carlo simulations. Small sample sizes enable the use of these indicators in various real time-series, and the indicators are able to detect even relatively short booms in prices. In addition, to my knowledge, these indicators are among the few that are able to signal also negative bubbles, ie overly-negative corrections in asset prices compared to their fundamentals. Signals of negative bubbles usually arrive just before the turning point in prices. This analyses focuses on an examination of how the two indicators are able to flash warnings before the major asset price booms in the US, UK, Finnish and Chinese equities markets, as well as in several countries' real estate markets, especially bringing attention to those periods that in the earlier academic research have been identified as bubbles and causes of financial instability. The ADF and AR indicators were run with the real market data series and were in most cases able to signal major booms from the data, often as early as 12 months prior to the crash.

Because these indicators seem to provide accurate and timely warning signals of exuberant prices, their potential use would seem to be extensive. For central banks they could provide valuable information for two types of pre-emptive policy: promoting financial stability and achieving the goals of macro-stability. As the tools now available to regulators require considerable time to take effect, it is crucial to find means of detecting bubbles sufficiently early – at best just when bubbles are just starting to emerge. Therefore, it is especially interesting to consider the possibility of using these indicators together with other stability indicators, such as credit growth, as signaling devises for regulators, to tell them when to start to ‘lean against the wind’ in order to restrain any dangerous developments or prevent the development of unsustainable trends.

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Appendix 1

Efficient markets hypothesis

I. Theoretical background

There is a close relationship between EMH, according to which prices reflect fundamental values, and the basic pricing formula. As mentioned in Shleifer (2000), the theoretical foundations of EMH depend heavily on following three considerations:

- First, investors are assumed to be rational and to value securities rationally. This implies that all news concerning fundamentals is immediately evaluated and passed through to market prices. Therefore asset prices always fully reflect all available information. But people differ on the meaning of 'all available information', and the different interpretations have led to three different forms of EMH:[40] weak form, semi-strong form, and strong form.
- Second, trades carried out by nonrational investors are assumed to be random and hence likely to have mutually offsetting effects. For this reason, these trades should have no net effect on market prices. The crucial aspect of this assumption is that such trades are not correlated with each other.
- Even for the case of correlated trades there is a rationale for EMH. To the extent that there are nonrational investors, there must also be rational arbitrageurs who act to eliminate the price effects of nonrational traders and their correlated trades (Shleifer 2000 and Raines and Leathers 2000).

[40] Fama (1970) describes the differences in information that is incorporated in prices in the three forms of EMH. *In the weak form*, the information incorporated in prices is simply historical prices. Thus it is impossible to earn superior risk-adjusted profits based on knowledge of past prices, since all such information is already incorporated into prices. *In the semi-strong form*, the information incorporated in prices is all publicly available information on fundamentals, ie information that affects a company's ability to generate profits and dividend flows. Under this form of EMH it is impossible to earn superior risk-adjusted profits based on knowledge of any publicly available information such as announcements of annual earnings, since all such information is already incorporated into prices. *In the strong form*, the information set contains all information available, even insider information. This is an extremely strong assumption, as it means that it would even be impossible to earn superior risk-adjusted profits based on insider information, as all of it is already incorporated into prices.

There is a great deal of literature on anomalies and how they relate to the above three considerations and to the three forms of EMH mentioned in the footnote. These observed and documented anomalies call into question the reality of efficient markets. A key issue is whether these documented anomalies are sufficiently strong to prove that there are indeed inefficiencies in the markets or are they merely mildly inconsistent with efficient market theory.

II. Inconsistencies in EMH

The main documented anomalies in connection with the assumptions of the EMH include the following:

I. EMH assumption concerning investor rationality: Can investors be considered rational and do they value securities rationally?

Overall rationality of capital markets: According to Mishkin (1981), 'The theory of rational expectations, introduced by John Muth, asserts that both firms and individuals, as rational agents, have expectations that are optimal forecasts using all available information'. In the stock market context, this means that the difference between the one-period-ahead price forecast and today's price, ie the forecast error conditioned on information available at the end of the current period, is not correlated with any information or linear combination of information available at the end of the current period.

The financial models of the 1970s incorporated rational expectations. Among the noteworthy studies of the decade are Merton (1973), An Intertemporal Capital Asset Pricing Model, and Lucas (1978), Asset Prices in an Exchange Economy. Since the 1970s, many academic papers have raised considerable doubt about the rationality of financial markets. In the 1980s the focus turned to econometric evidence on time series properties of prices, dividends and earnings, as noted by Shiller (2003). In the 1990s behavioural finance introduced psychological factors into the discussion of financial markets, which allowed one to relax the assumption of pure investor rationality.

An excellent summary of the development of the rationality concept over time is available in Doukas (2002), which is a collection of panellists' views from a meeting of the European Financial Management Association. The discussion sheds much light on the different viewpoints on rationality and summarises the course of development over time. As we know, full rationality per se is a very strong assumption. In the context of economic models that incorporate rational expectations, it implies that agents process all information perfectly (Doukas, 2002). But a rationality shortfall does not immediately prove that markets are inefficient. A market can be efficient even though the participants make random errors, and errors are by no means systematic. It is not necessary that all market participants be rational in a market that incorporates rational expectations, if there are enough arbitrageurs to immediately take advantage of any unexploited profit opportunities. In this respect, Shiller's survey (1987) is of interest because it documents the fact that prior to the crash of 1987 there was widespread belief among investors – buyers and sellers – that the market was overvalued.

My own view of rationality is that it holds most of the time in the markets. One can usually explain market participants' behaviour on the basis rationality. The real problem is that spells of overoptimism do occur from time to time. The issue is then whether these spells of overoptimism should be considered signs of irrationality. The answer seems to be two-fold: overoptimism that obtains because of a lack of information should not be considered a sign of irrationality, whereas overoptimism based on exuberance that is not founded in available data should certainly be taken as a symptom of irrationality. In practice, it may be very difficult to distinguish between the two cases.

II a) EMH assumption that asset prices fully reflect all available information on fundamentals: Is all relevant new information immediately incorporated into market prices?

Speed of incorporating new information into prices: According to EMH, prices should adjust immediately to new information. As mentioned in Fama (1991), many event studies indicate that prices do adjust quickly and efficiently to firm-specific information. On the other hand, Chan, Jegadeesh and Lakonishok (1996) present evidence that documented momentum in stock returns could be partially accounted for by the slow adjustment of the market to past profit surprises. Their evidence suggests that the market responds only gradually to new information. A recent study (Chan, 2003) finds very pronounced drifts after bad news, which is viewed as evidence that investors react quite slowly to this kind of information. The study also finds reversals after extreme price movements unaccompanied by public news.

Reactions to information could differ from period to period. For example, Veronesi (1999) reports that because of uncertainty about the level of future dividend flows, investors are inclined to ‘hedge’ against changes in the level of uncertainty, overreacting to bad news in good times and underreacting to good news in bad times. This makes the price of an asset more sensitive to news in good times than in bad times.

Concerning the different kinds of systems, there might be some difference in the incorporation of information into prices. Vives (1995) wrote an article concerning the incorporation of private information into prices (of course private information makes this a special case, while there is true informational advantage) and concluded that in systems where there are market makers present the incorporation is much faster. According to Vives, ‘in any case the asymptotic precision of prices is negatively related to the degree of risk aversion and the amount of noise in the system’.

Costs of acquiring information: In today’s world, although the flow of information available to investors is overwhelming, there could be some differences in costs of acquiring information (eg a news service), which may affect the speed at which different investor-groups learn of new information. Trading costs of course also affect the speed at which new information is incorporated into prices. As Fama (1991) puts it, ‘since there are surely positive information and trading costs, the extreme version of the market efficiency hypothesis is surely false’.

Excess volatility: The academic literature concerning excess volatility burgeoned in the 1980s. The main results of this work are that stock prices seem to be more volatile relative to what would be predicted by efficient market models[41] in which valuations are based on fundamentals. As Shiller (2000) writes, ‘Fluctuations in stock prices, if they are to be interpretable in terms of the efficient market’s theory, must instead be due to new information about the long run outlook for real dividends. Yet in the entire history of the US stock market we have never seen such fluctuations, since dividends have fairly closely followed a steady growth path.’ In fact, in (1988a), Campbell and Shiller estimated that 27% of the annual return volatility of the US stock market is explained by information about

[41] Shiller (1981) was later criticised for misspecified fundamental values. But it did not remain as the only study to generate similar results, as witnessed by Leroy and Porter (1981), Campbell and Shiller (1987, 1988b), and Campbell and Ammer (1993). Reviews of this literature are available, as eg Cochrane (1991).

future dividends.[42] Thus prices clearly seem to react not only to information concerning changes in fundamentals but also to other arriving information.[43]

II b) The EMH assumption that asset prices fully reflect all available information on fundamentals: What kinds of information are actually incorporated into market prices?

A pricing process is a martingale if the best guess for next period's price is today's price, when expectations are formed in the current period and are thus conditioned on currently available information. The efficient market hypothesis and martingale process are equivalent concepts.

Instead of reacting only to currently available information concerning fundamentals, stock prices seem to react to non-information: For example, there was no new astounding news concerning fundamentals just before the 1987 stock market crash, at least not of a magnitude that would justify the draconian correction in stock values of 19 October. Therefore it would seem that the correction was based on other factors (Beechey, Gruen and Vickery, 2000). In fact, Cutler et al (1991) studied the 50 largest one-day movements in stock prices in the United States since World War II and found that many of the movements occurred on days when there were no major announcements concerning fundamentals. Moreover, Roll (1988) found that news of fundamentals was not the only factor that impacted prices and price changes. Another interesting development is that of Daniel and Titman (2003), who separated information that moves stock prices into the categories tangible and

[42] In their latest study, Campbell and Shiller (2001) found that price-earnings ratios and dividend-price ratios are poor forecasters of dividend growth, earnings growth, and productivity growth. Contrary to the simple EMH, these ratios seem to be useful for forecasting movements in stock price changes.

[43] An interesting addition to this anomaly is that some researchers have suggested that the present value model's inability to account for price fluctuations could owe to the inadequacy of dividends as a proxy for total payoffs to shareholders. Teselle (1998) notes that tests using 'narrow dividends' suggest that stock prices fluctuate too much compared to what can be explained by a simple present value hypothesis, whereas some tests using 'broad dividends (narrow div + share liquidation proceeds) do not detect such excess volatility.

intangible[44] and found evidence that 'Intangible information reliably predicts future stock returns. However, in contrast to previous research, we find that tangible returns have no forecasting power.'

There is an interesting new genre in the literature that focuses on asset prices and the impact of non-information on them. This literature is concerned with the balance between market demand and supply. The earliest studies to document a demand impact on prices were Shleifer (1986) and Harris and Gurel (1986), which presented evidence that adding a stock to the S&P500 increased the demand for it and caused a permanent price change of about 2%.[45] Later Warther (1995) analysed US data on mutual fund flows and found that a 1% increase in mutual funds' stock holdings leads to a permanent increase of 5.7% in stock prices. Wermers (1999)[46] presented evidence of herding by equity mutual funds. A fresh contribution to this literature is Evans (2003), which finds that innovations in net issues, mutual fund flows, and foreign portfolio investment explain a significant proportion of variance in stock prices.

Some of the documented anomalies under this heading are the 'weekend', 'January' and 'holiday' effects, which reflect repeating patterns in the stock markets.[47] But some analysts have argued that these fairly small seasonal movements in returns may be explained in terms of market microstructure (see eg Fama 1991).

Informational cascades:[48] An informational cascade is said to occur when some investors' actions are viewed as an additional source

[44] Tangible information is performance information such as sales, earnings, and cash flow growth, which can be extracted from the firm's accounting statement and intangible information comprises the other determinants of a stock's past returns. Thus tangible returns are linked to accounting growth numbers and intangible returns to changes in expectations about future cash flows or discount rates.

[45] The reason for a demand increase is easily seen in portfolio managers' behaviour, especially if they closely track the components of benchmark indices. For example, Chan, Chen and Lakonishok (2002) show that mutual funds have their own investment styles in that they tend to cluster around certain broad indexes. This kind of behaviour will increase a fund's demand for a particular stock when that stock is added to the fund's favourite index.

[46] Wermer's study has been criticised for not sufficiently accounting for fundamentals. If this is true, there is a definite risk that one will conclude that mutual fund flows are driven by investor sentiment rather than fundamentals and hence that the price level is also driven by sentiment due to increased demand.

[47] Thaler (1987) reports that stock prices tend to rise in January, particularly prices of small firms and firms whose prices have declined in the past few years. Rogalski (1984), in contrast, found that prices rose on Mondays from open to close, which meant that the documented negative returns on weekends all occurred between the close on Friday and opening on Monday, a period that is hardly the busiest time for company announcements.

[48] There is much literature on informational cascades; see eg Banerjee (1992), Welch (1992) or Bikhchandani et al (1992).

of information to others. The latter investors may then decide to act on the information extracted from market behaviour, which is not necessarily related to news that would affect the fundamentals. As Hirshleifer and Teoh (2003) put it, 'Cascades tend to be associated with informational blockages. Such blockages are an aspect of an informational externality: An individual making a choice may do so for private purposes with little regards to the potential information benefit to others.' Therefore acting according to information attained from other market participants' trades (ie on times to buy, sell or hold) cannot be described as purely informed trading, which should be directly related to news on fundamentals.

Of course when an informational cascade develops, one must assume the presence of informational asymmetry in the market. In such case, it is presumed that there are some investors in the market who possess, or at least have access to, superior information. One would then assume that the trades in question reveal some of that superior information. An informational cascade can also be seen as an opportunity for investors to exploit others' information on market conditions. As Hirshleifer and Teoh (2003) write, informational cascades one can refer to 'observational learning in which the observation of others (their actions, payoffs, or even conversation) is so informative that an individual's action does not depend on his own private signal'.

When an investor is thought to possess some private or superior information, it might be wise for others to imitate that investor's actions.[49] But it should be noted that if people merely imitate each others' actions, actions of later imitators – possibly even from the first imitator onwards – will not necessarily reveal any new information, as

[49] The problem might arise in an asymmetric information situation if the actions of the masses would somehow hurt the investor possessing superior information. In this case, the better informed investor would not have an incentive to reveal his superior information eg by trading at a price more in line with fundamentals. An example of such a situation would be where the better informed investor knows that a stock is overvalued compared to fundamental value - normally a time to sell out. But if he were to sell a large number of shares, this might be a sign to other market participants that the stock is overvalued. Then the less-well informed investors would also be inclined to sell. This would put further downward pressure on the price of the stock and might prevent the better informed investor from liquidating his entire holding at the higher price. The better informed investor might do better by selling in small amounts and thus hiding his information in the hope that the period of overpricing will last long enough for him to be able to liquidate his entire holding. For more on this subject, see eg Spulber (1999) and Barclay and Warner (1993). Barclay and Warner suggest that informed investors engage in 'stealth-trading', ie medium-sized trades that enable them to hide within the uninformed flow.

the information content of trades and prices will diminish as more and more trades occur.

III. EMH assumption linked to trades being uncorrelated. Can trades of nonrational investors be considered random and uncorrelated and hence without price effects?

Investors who act irrationally, ie those whose demand for a risky asset is based of beliefs that are not justified by fundamentals, are often called 'noise traders'.[50] These are typically individuals and other less sophisticated investors.

Black (1986) wrote that noise traders base their investment decisions purely on past price movements and so become more aggressive as a speculative bubble increases and positive feedback from rising prices accumulates. With the price thus elevated, arbitrage may entail risk, which will dampen arbitrage activities in the market.[51] Shleifer and Summers (1990) divided investors into two groups: arbitrageurs, whose expectations of equity returns are rationally developed, and noise or liquidity traders, whose opinions and trading are systematically biased.

The problem concerning irrational traders seems to be that their trades tend to be correlated rather than uncorrelated. This is one reason for the abundance of literature on uninformed individual investor trading on the basis of sentiment, ie herding[52] (behaviour convergence), which may seem rational for the individual but produces inefficient outcomes at market level. A good source for the literature on individual investors' herding behaviour is Nosfinger and Sias (1999).

One of the reasons for herding behaviour among individual investors is related to the manner in which they make trading decisions. Both Shiller (1984) and De Long et al (1990) claim that influences of fashion and fad are likely to impact an individual investor's investment decisions. Shleifer and Summers (1990) suggest that individual investors may herd because they respond to the same

[50] A noise trader trades for noninformational reasons.

[51] Evans (2003) makes an important point concerning Black's (1986) concept of noise traders: 'By simply changing the wording in Black's noise trading model reveals a closer association to Shiller's fad model than the efficient markets model it attempts to reclaim'.

It is true that if every investor were rational and understood information perfectly, there would be very little trading, as informed traders are not inclined to trade with each other. Thus it is the noise traders who provide the market with the necessary liquidity.

[52] An excellent summary of herding can is found in Hirshleifer and Teoh (2003).

signals. Similarly, Hirshleifer and Teoh (2003) argue that the trades of individuals are irrationally correlated as ‘a result of herding (which involves interaction between the individuals), or merely a common irrational influence of some noisy variable on individuals´ trades’. On the other hand, Lakonishok, Shleifer and Vishny (1994) write that individuals may extrapolate past growth rates and therefore engage in irrational trading in an environment of rising prices. It also seems that individuals are easily influenced by decisions made by other individuals in their immediate surroundings. For example, Kelly and O’Grada (2000) and Hong et al (2001) provide evidence that social interactions between individuals affect their decisions concerning equity participation and other financial matters. DeLong, Shleifer, Summers and Waldmann (1990) state that ‘Individual investors typically fail to diversify, holding instead a single stock or a small number of stocks.[53] They often pick stocks through their own research or on the advice of the likes of Joe Granville or ‘Wall Street Week’.’

The above research results clearly show that the issues of correlation and randomness of individual trades is not at all clear-cut. This is the case particularly as regards individual investors’ herding behaviour. Concerning the validity of EMH, it is crucial to know whether individual herding is constantly or only now and then present in the market. Constant presence would seriously violate EMH. Another factor is of course is whether there are enough rational arbitrageurs in the market to eliminate irrational traders’ possible effects on prices.

IV. EMH assumption regarding rational arbitrageurs’ correctional influence on market prices. If there are irrational traders whose trades are correlated, are there enough rational arbitrageurs to eliminate price-effects of the irrational and correlated traders?

The basic question seems to be about exactly which investors can be deemed rational? A typical response is that they are the institutional investors, who are generally more sophisticated and have an information advantage. But unfortunately it has been shown that even this group is not completely rational. There is documented institutional herding behaviour based on irrational psychological factors etc.

[53] Lewellen, Schlarbaum and Lease (1974).

As Nofsinger ans Sias (1999) write, 'one popular view holds that institutional herding is primarily responsible for large price movements of individual stocks, and, moreover, it destabilizes stock prices'. The evidence that institutional herding moves prices is not necessarily a bad thing. If institutional investors are actually better informed and their herding behaviour is based on information, they may move prices closer to true fundamental values.[54] But when institutional herding is not based on information, institutional herding can certainly hamper the price-formation process. There are many possible reasons for uninformed institutional herding.[55] These include irrational psychological factors, agency problems, rewarding profiles, reputational incentives and stocks' desirable characteristics.[56]

Another problem is whether there will be an adequate amount of rational arbitrage.

The process of arbitrage in the markets might not be trouble-free. As Shleifer (2000) writes, 'With a finite risk-bearing capacity of arbitrageurs as a group, their aggregate ability to bring prices of a broad group of securities into line is limited as well'. Briefly stated, arbitrage cannot bring prices down to fundamentals if there is some risk inherent in arbitrage. Such risk may derive from a lack of perfect asset substitutes or – with perfect substitutes – from uncertainty about future price movements of mispriced securities. The latter risk is due to the possibility that mispricing will become more severe (eg due to noise traders' actions) before finally disappearing. An arbitrageur should be able to get through such a period of negative revenues. These sources of risk to arbitrageurs are discussed eg in Figlewski (1979), Shiller (1984), Campbell and Kyle (1987), Shleifer and Summers (1990), and De Long et al (1990).

Another problem regarding fully functioning arbitrage is the possible constraints on short selling. To short sell an asset one must first borrow the asset. Borrowing costs of stocks can be so high that it is not profitable to carry out such a strategy (see eg Cochrane, 2003). Lamont and Thaler (2003), show that short-sale constraints eliminate arbitrage opportunities.

Some of the strongest arguments questioning the validity of EMH can be found in the above-mentioned studies, which show that

[54] Eg Lakonishok, Shleifer and Vishny (1992).

[55] Interestingly, Chan, Chen and Khorana (2000) find cross-country differences in stock market herding. They say that herding seems to be more common in emerging markets, where it seems to be related to macroeconomic rather than firm-specific factors.

[56] Good overviews of the literature on these topics can be found eg in Hirshleifer and Teoh (2003) and Nofsinger and Siah (1999).

arbitrageurs might not act rationally all the time (due to uninformed herding, risks, or operational limitations on arbitrage). Once again the crucial question concerning the validity of EMH is whether arbitrageurs are able to act rationally. If not, EMH is clearly on a shaky foundation. As the previous examples show, the assumptions behind market efficiency are by no means unambiguous. Many of the results from studies conflict with the basic assumptions of market efficiency. The main question is whether the arguments against market efficiency are so strong that we should reject EMH at all times. To my mind, they are not. But I would certainly accept the hypothesis of occasional deviations from EMH.

Appendix 2

Summary or earlier bubble tests in the literature

Table A2.1 **Summary of bubble tests**

Author	Data	Method	Bubble?
Balke and Wohar (2001)	S&P500 data from 1881–1999	Determine whether market fundamentals can explain observed price peaks in stock markets.	**Not** necessarily: plau-sible changes in ex-pectations of real dividend growth and discount rate can explain stock prices in the late 1990s.
Diba and Grossman (1984, 1987, 1988)	S&P composite stock price index 1871–1986, annual, divided by wholesale price index for1988.	When nonstationarity of dividends accounts for nonstationarity of stock prices, the two series are cointegrated. Tests for cointegration of prices and dividends. 1988 version takes into account the ‘unobserved’ variable.	**No**: stock prices do not contain explosive rational bubbles.
Flood and Garber (1980)		Pioneering article on bubbles that focuses on deterministic component of hyperinflation model.	

Author	Data	Method	Bubble?
Flood, Hodrick and Kaplan (1987)	S&P data for 1871–1980 and modified Dow-Jones index for 1928–1978. Both datasets include annual real stock price indices and related dividend payments.	Extends and modifies West's work and testing procedure.	'Conditional on having the correct model and no process switching, the rejection has been taken to be evidence of bubbles. Since we find the model inade-quate, we conclude that the bubble tests do not give much information about bubbles.'
Hamilton and Whiteman (1985)	German hyperinflation and US stock market.	Two important points: interpretation of bubble tests → especially what does rejection mean. Also points out that all bubble tests are subject to concern that what appears to be a speculative bubble could 'instead have arisen from rational agents responding solely to economic fundamentals not observed by the econometrician'.	
Koustas and Serletis (2005)	S&P500 data incl. dividends data, annual, 1871–2000.	Examines the empirical validity of permanent deviations from present-value model of stock prices and focuses on possible nonlinearities in vari-ance of log dividend yield. Fractional inte-gration.	**Tests based on fractional integration: No bubble.** Evidence presented points to long memory in log dividend yield.

Author	**Data**	**Method**	**Bubble?**
Dezhbakhsh and Demirquc- Kunt (1990)	S&P500, annual and divided by PPI, dividend data corrected slightly eg from West's (1987), data, covers 1871–1981 and 1871–1988.	Builds on West's procedure with a modification concerning West's indirect test.	**No Bubble.** Contrary to West's (1987) result 'no-bubble' hypothesis is not rejected.
West (1987)	S&P500, annual data 1871–1980 divided by PPI and sum of yearly dividends deflated by average of year's PPI. Modified Dow Jones index 1928–1978.	The basic idea relates to Hausman's specifi-cation test. The test compares two sets of estimates of the parameters needed to calculate the expected present discount value. The sets will not be equal if the stock price comprises two components: efficient market model implied price + a speculative bubble. Speculative bubbles are tested by seeing whether the two sets of estimates are the same (apart from sampling error).	**Bubble.** The data reject null hypothesis of no bubble.
Evans (1991)		Points out that an important class of rational bubbles can not be detected by traditional tests.	
Flood and Hodrick (1990)		Survey of the testing literature and of observed shortages.	

Author	Data	Method	Bubble?
Froot and Obstfeld (1991)	Estimation is based on annual deflated S&P index data,1900–1988.	Intrinsic bubble	**Bubble.** Incorporating intrinsic bubble into simple present value model helps to account for long-run variability of US stock market data.
Craine (1993)	– Annual composite index data S&P, 1872–1988. – Value weighted New York stock market data, annual, 1927–1989. – Value weighted New York stock market data, quarterly, 1926(2)–1989(4).	Craine's model extends Campbell's & Shiller's (1987) cointegration restriction by allowing stochastic discount factors in expected present value model.	Bubble. 'Results of the paper indicate that either the price- dividend ratio contains a rational bubble, or the discount factor must be stochastic and contain a large predictable component'.
Campbell and Shiller (1987, 1988 a and b)	S&P composite stock price index, real annual prices and dividends, 1871–1986.	Validity of present value model, cointegration. 1988 papers make some modifications.	Spread between stock prices and dividends moves too much and deviations from present value model are quite persistent (re-sults sensitive to discount rate).
Pastor and Veronesi (2004)	Nasdaq, end of 1990s data. Purpose is to try to match prices observed on Nasdaq 10 Mar 2000 with prices given by Pastor's and Veronesi's valuation model.	Calibrate a stock valuation model that incorporates uncertainty about average future profitability in to the valuation model.	**Not** necessarily: The fundamental value of the firm increases with uncertainty. This could explain some of the valuations observed in the markets in the late 1990s.

Author	Data	Method	Bubble?
McGrattan and Prescott (2001)	US data Focuses first on 1929 and later on 2000.	Estimates fundamental value of corporate equity in 1929 using data on stock of productive capital and tax rates.	**No bubble**: Evidence strongly suggests that stocks were undervalued even at their 1929 peak. **No bubble** in 2000. In theory, market value of equity + debt liabilities should equal the value of productive assets + debt assets. In 2000 the net value of debt is low, so that market value of equity should approx. equal market value of a productive asset.
Siegel (2003)	Cowles Foundation data from 1871–1926 and the CRSP value-weighted data from 1926–2001.	Highlights the importance of long-term cash flow in determining the price of equity.	**No** bubble: in 1929 or 1987. Subsequent returns justified the price paid at market peak. After 1929 one had to wait for the cash flows of the 1940s.**Bubbles** in 2000 and 1932 (negative).
Adam and Szafarz (1992)		Focuses on difficulties in defining rational expectations bubble.	

Author	Data	Method	Bubble?
Van Norden and Schaller (1997) research (1993)	US stock market data for 3 subperiods: 1929–1945, 1946–1972, 1973–1989. (1993): From 1926–1989.	Testing for fads and bubbles using empirical strategy based on switching-regression econometrics.	**Mixed**: 'Our results suggest that there is more in the data than fads. The specific ways in which the data conflict with the fads model frequently is consistent with the bubbles model, but the evidence in favour of the bubbles is not decisive.' Research for 1994. Based on idea that overvaluation increases probability and expected size of stock market crash, evidence of speculative behaviour found in US market data. Evidence also found that prior to crashes of 1929 and 1987 the probability of collapse rose (not true for some other documented crashes).
Van Norden and Vigfusson (1996)		Examines the power properties of regime-switching bubble tests via Monte Carlo experiments using Evan's data generating process.	

Author	Data	Method	Bubble?
Funke, Hall and Sola (1994)		New test strategy for bubbles that allows for possibility of switching regimes in the data's time series properties. Funke & Hall & Sola tried this test on Poland's hyperinflation.	
Wu (1997)	Real S&P500 and real dividends (deflated by CPI), annual observations, 1871–1992.	Bubble treated as an unobservable state vector in state space model and is estimated with Kalman filter.	**Bubble.** Estimated bubble components account for substantial portion of US stock prices and fit the data well.
Bohl and Siklos (2002)	S&P stock price index data 1871:1–2001:9 (Shiller's web page http://aida.econ.yale.edu/~shiller).	Momentum threshold autoregressive technique to detect asymmetric short-run adjustments to long-run equilibrium.	For the **long run**, the present value model seems to work well, but for the **short run** US stock prices exhibit large and persistent bubble-like depar-tures from present value prices followed by a crash.
Wu and Xiao (2004)	S&P500 data, weekly, 1974:01–1998:09. Hang Seng index data, weekly, 1974:01–1998:09	New improved testing procedure is a modification of traditional unit root test.	**Not in USA**. Bubble evidence for US market is weak. **Bubble** in Hong Kong. Fairly strong evidence of a bubble in Hong Kong.

Author	Data	Method	Bubble?
Donaldson and Kamstra (1996)	S&P500 data, monthly, 1899:01–1934:12. Focuses on crash of 1929.	Introduces new procedure for estimating fundamental stock prices as present value of expected future cash flows. Future dividend paths (conditional on available info) are forecasted with Monte Carlo simulation.	**No bubble.** Finds fundamentals-related explanation. Without Donaldson's & Kamstra's simulation method, bubble cannot be rejected
Rappoport and White (1993)	US stock market data, 1929 boom.	Behaviour of interest rates on brokers' loans to investors for stock purchases. Dramatic rise in risk premia indicates that stock markets might collapse and value of collateral might be jeopardised.	**Bubble.** 'Traditional accounts of a bubble in the market cannot be so easily dismissed'.

Appendix 3

Monte Carlo simulations in the earlier research

Table A3.1 **Summary of the construction of Monte Carlo simulations**

	Schwert (1989)		**Cook and Manning (2002)**	**Cavaliere and Taylor (2008)**	**De Jong et al (1992)**		**Hassler and Wolters (1994)**
Unit root test analysed	Phillips Perron and Dickey Fuller		DF		100/250/500		100/200
Sample size (usually T = total sample)							
Error term			IID				
Trend or constant			DGP includes quadr. trend				
Control of initial effect (discard first x obs.)	yes		yes				yes
How many simulated breaks?	1		1	1	1		
Direction of the break?	From stationary process to unit root			Three different locations			
	Stationary	Unit root		for a shift:	Stationary	Unit root	
	0.8	1.0		beginning/middle/end	0.8	1.0	
	0.5	1.0		of data	until...		
					0.99	1.0	
AR-coefficient during stationary period	0.5 and 0.8		0.96 ... 0.99	0.5, 0.8, 0.95	0.8, 0.85, 0.9, 0.95, 0.99		
Total amount of MC replications	10 000		25 000	10 000	10 000		5 000

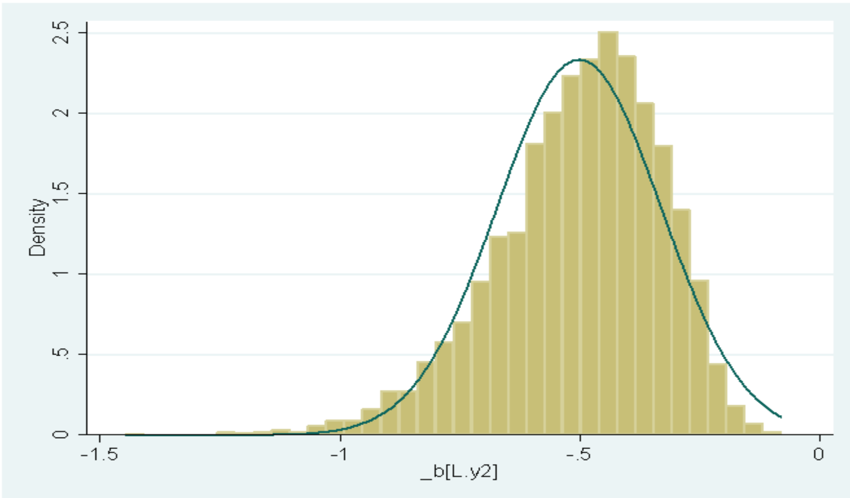
Table A3.1 **... continues**

	Leybourne et al (2002)	**Leybourne et al (2005)**	**Harvey et al (2006)**	**Leybourne et al (2006)**	**Taylor (2005)**
Unit root test analysed	Various	Various	Various	Various	Aug. Dickey-Fuller
	100/200	75/100	100/150/200/300/500	60/120/240/480	100/250/500 as well as
Sample size (usually T = total sample)					sub-samples 10, 20%, 30% ... etc. to 90%
Error term	IID	IID, also skewed	IID	IID	IID
Trend or constant					with and without linear trend
Control of initial effect (discard first x obs.)	yes			yes	
How many simulated breaks?	1		1	1	1 or 2
Direction of the break?	Location of the shift:		Location of the shift:	Location of the shift:	Location of the shift:
	First at 20%, then 80%		20% and 80% of the sample	30%/50% and 70%	1/2 or 1/4 of the sample
	of whole data			of the sample	
	Also 30%, 50%, 70%		Direction of change, both:	Direction of change, both:	Double change:
	tried later.		From I(0) to I(1) and from	From I(0) to I(1) and from	From I(0) to I(1) and back
			I(1) to I(0)	I(1) to I(0)	to (or vice versa)
AR-coefficient during stationary period	0.5, 0.8, 0.9		0.5, 0.7, 0.9	0.0, 0.5, 0.9	0.4, 0.6, 0.8
Total amount of MC replications	20 000	50 000	50 000	50 000	50 000

Appendix 4

Distributions of ADF and AR coefficients for normal and bubble perios[57]

Figure A4.1a **ADF**



[57] These coefficient value distributions are from ADF- and AR- regressions (lag AIC, without trend, including constant), which were run to data simulated by 0.6 (stationary period) including one 36 observations unit root period. Rolling sample size was 36. From figures A4.1a–A4.1e it is easy to see how the ADF-coefficient distributions shift to the right and become more leptokurtic as more unit root observations enter the sample. In figure A4.1a there are no unit root observations, in figure A4.1b there are 5, in figure A4.1c the sample includes 15 unit root observations and in figure A4.1d all 36 unit-root observations are included in the sample. Figure A4.1e shows how coefficient values have reverted and distribution shifted back as all 36 unit-root observations exit from the sample. Figures A4.1f–A4.1j show corresponding outcomes for AR coefficients.

Figure A4.1b **ADF**

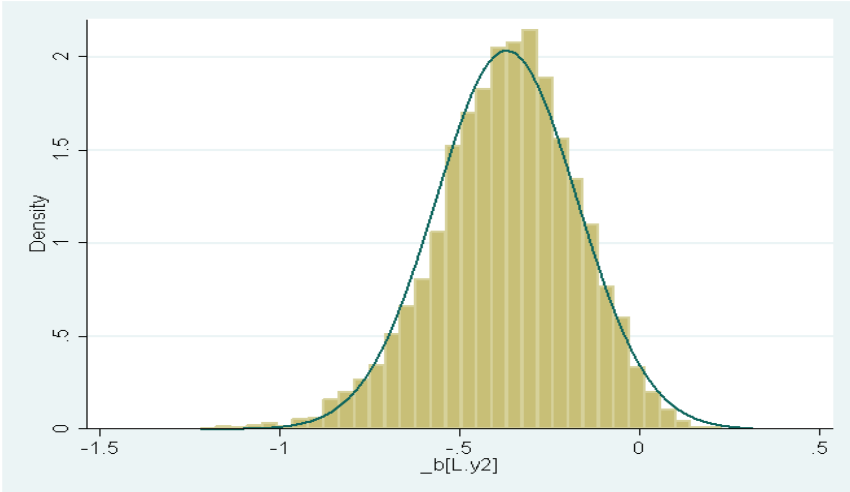


Figure A4.1c **ADF**

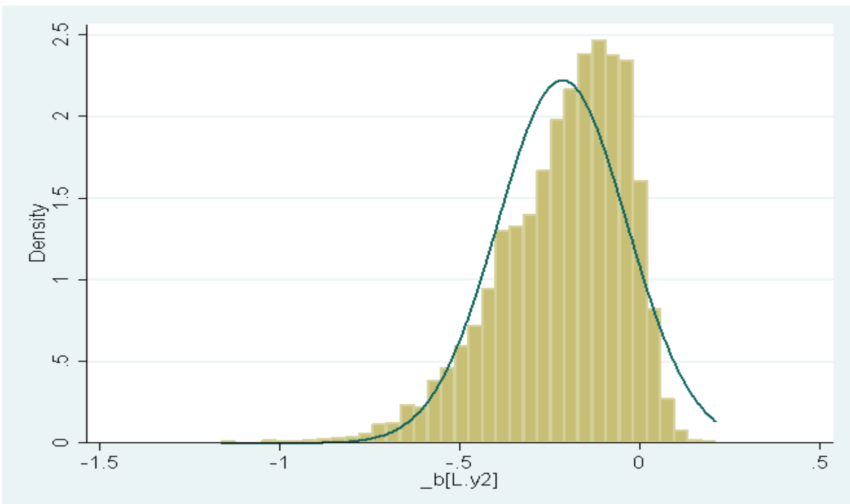


Figure A4.1d **ADF**

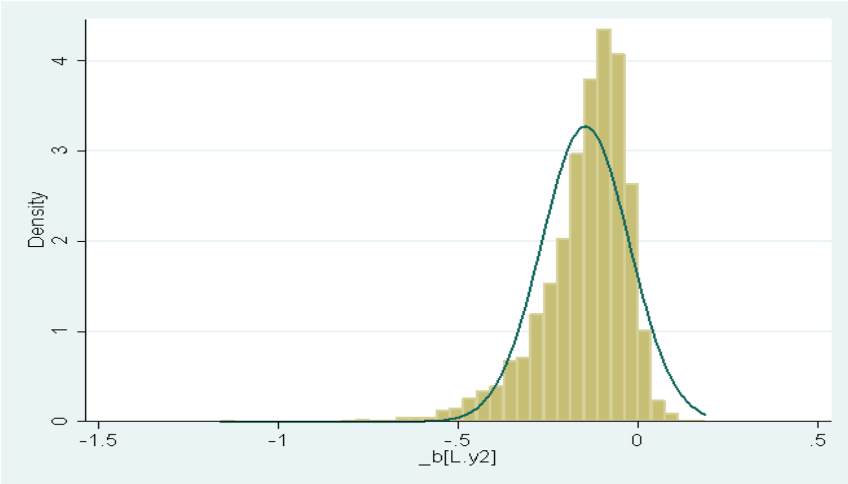


Figure A4.1e **ADF**

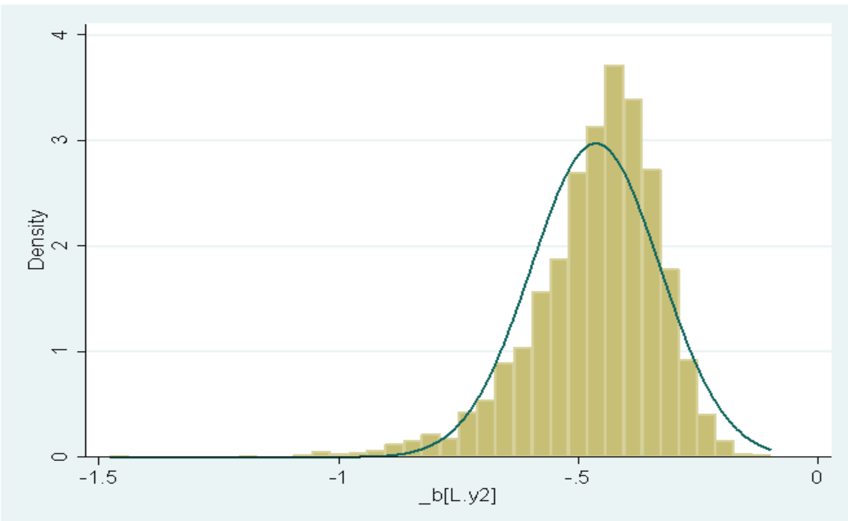


Figure A4.1f **AR**

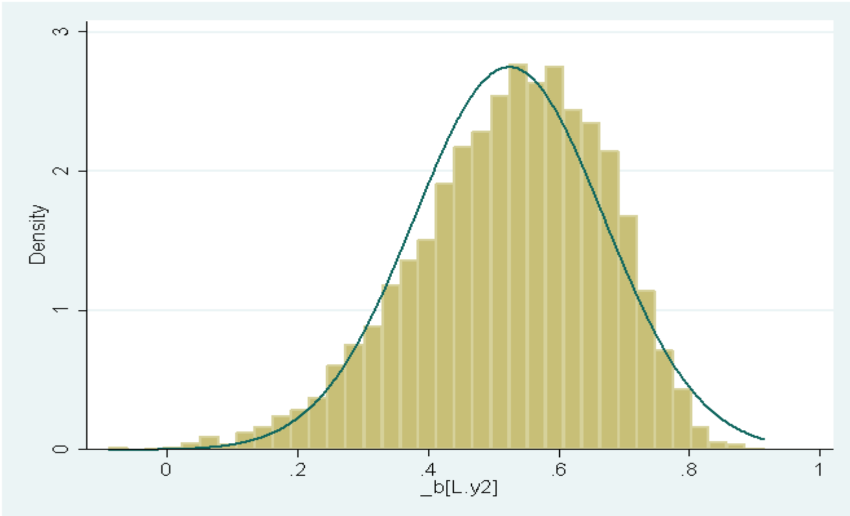


Figure A4.1g **AR**

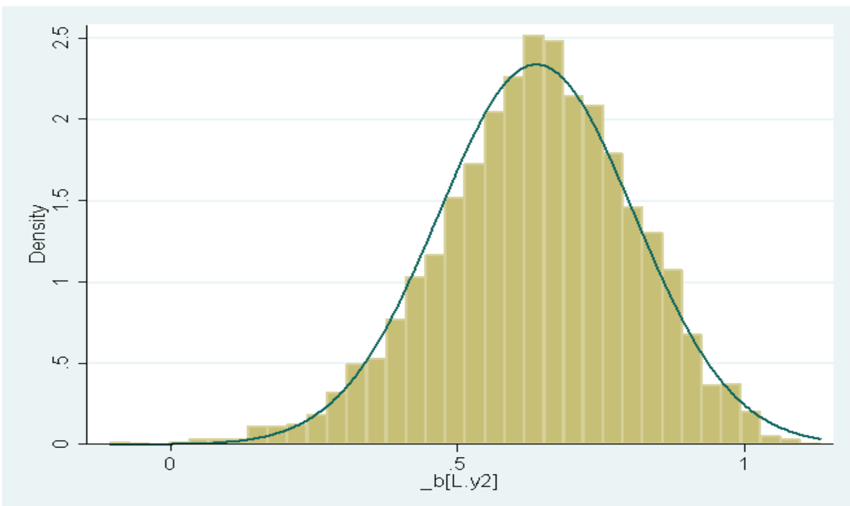


Figure A4.1h **AR**

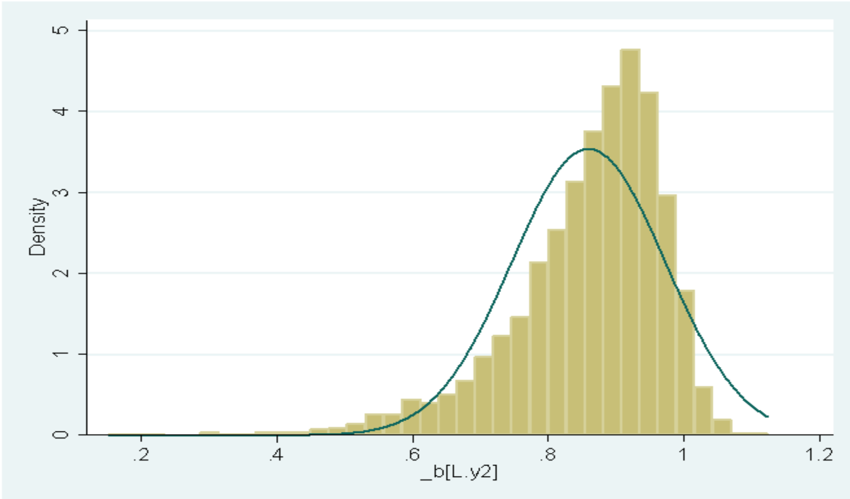


Figure A4.1i **AR**

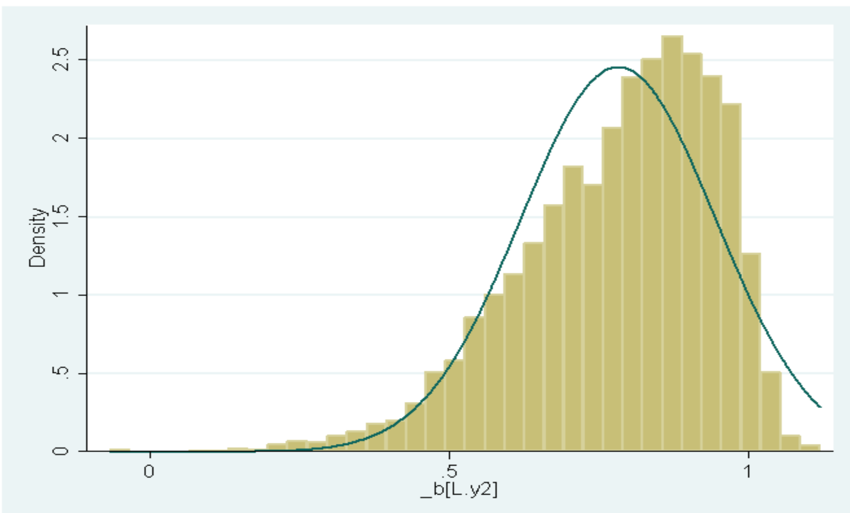


Figure A4.1j **AR**

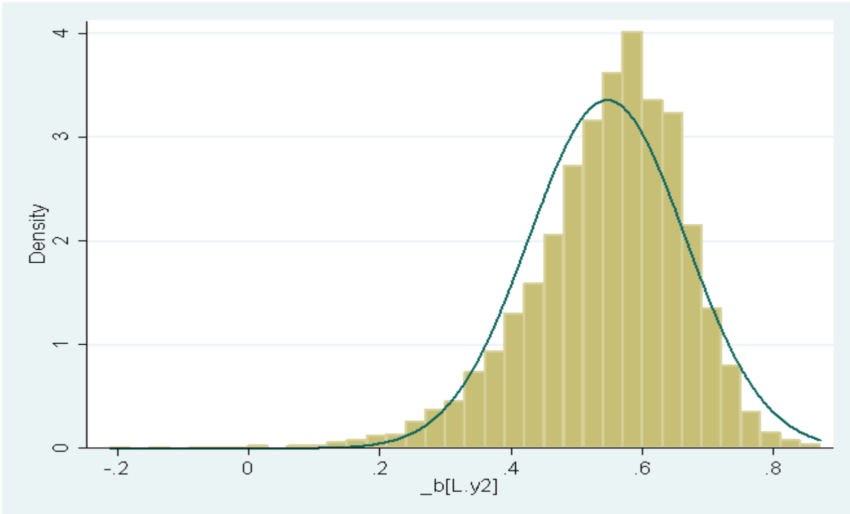


Figure A4.1k **Distribution of ADF coefficient values, convergence of average and precentiles. Simulated values are from stationary AR(1) process where the coefficient is 0.6**

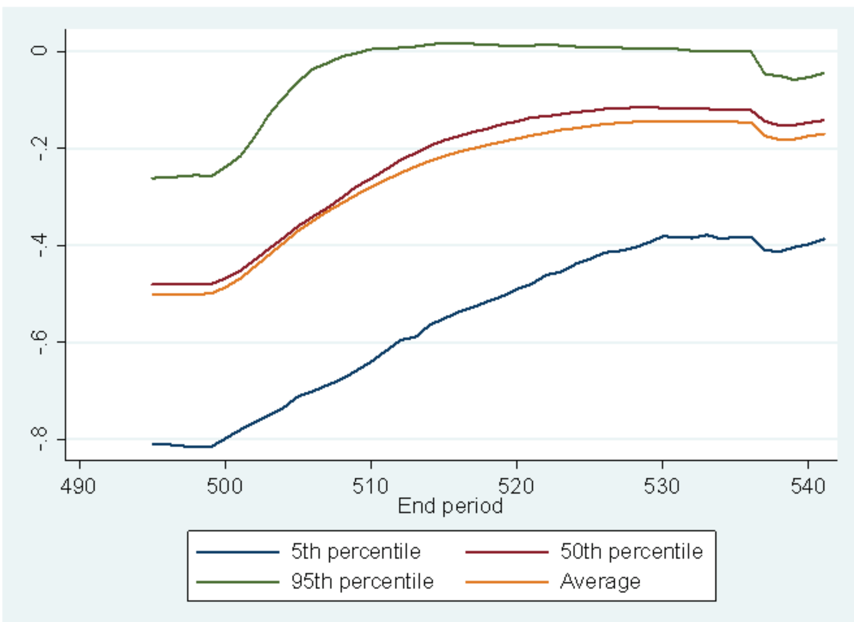


Figure A4.11 **Distribution of AR coefficient values, convergence of average and percentiles. Simulated values are from stationary AR(1) process, where the coefficient is 0.6**

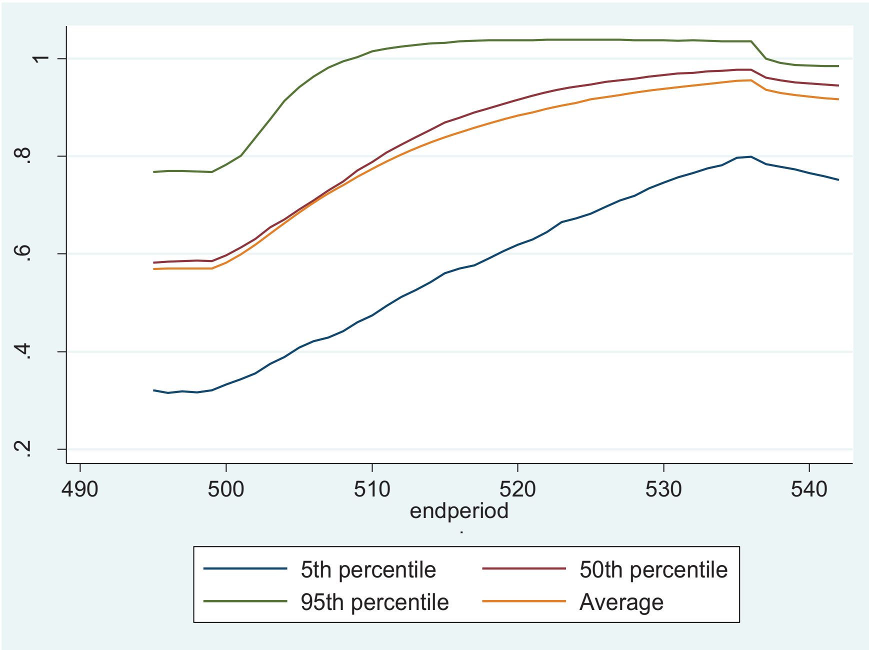


Figure A4.1m **Distribution of ADF coefficient values, convergence of average and percentiles. Simulated values are from stationary AR(1) process, where the coefficient is 0.8**

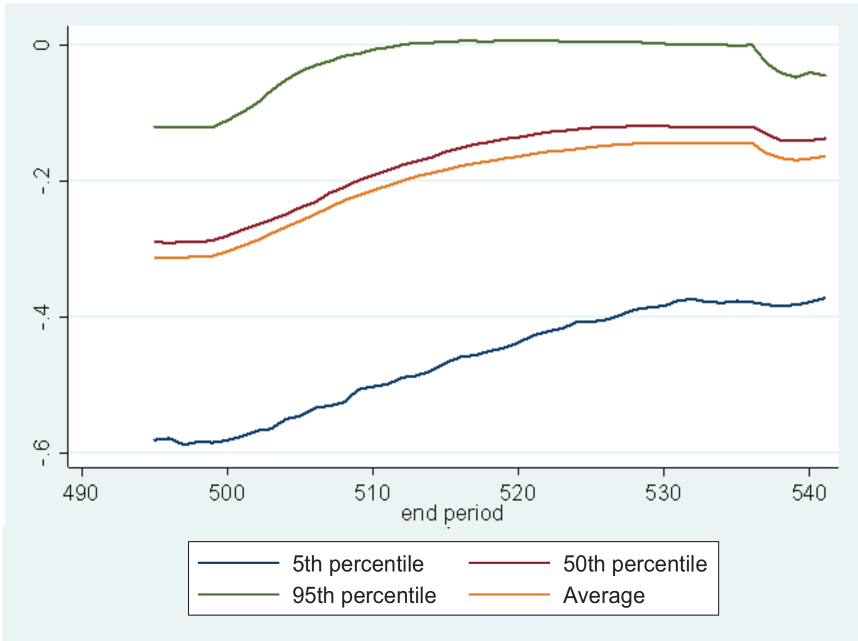
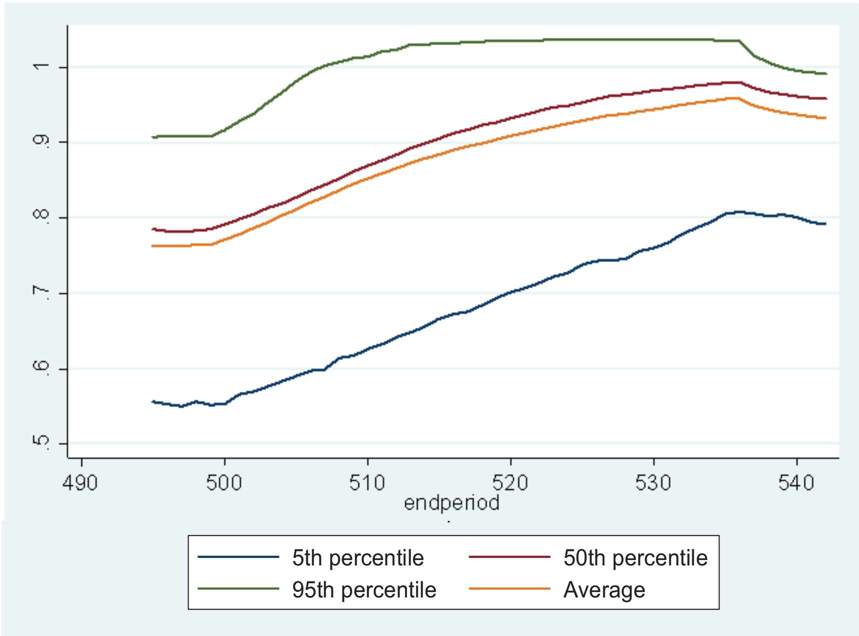


Figure A4.1n **Distribution of AR coefficient values, convergence of average and percentiles. Simulated values are from stationary AR(1) process, where the coefficient is 0.8**



Appendix 5

Critical values

ADF-regression (AIC lags = 1, no trend) coefficient values counted from simulated series (AR(1)), where the coefficient varies from 0.6 to 0.9, (left side column) and which includes one unit root period (with 36, 48 or 60 observations).

MC-Simulated critical values for the ADF-coefficient

AR-coefficient in stationary period	Length of simulated unit root	Length of the rolling window 36	48	60
0.6	36	–0,200	–0,189	–0,170
	48	–0,177	–0,150	–0,121
	60	–0,152	–0,117	–0,093
0.7	36	–0,153	–0,149	–0,142
	48	–0,140	–0,128	–0,111
	60	–0,127	–0,108	–0,888
0.8	36	–0,104	–0,102	–0,100
	48	–0,098	–0,094	–0,089
	60	–0,092	–0,086	–0,077
0.9	36	–0,051	–0,053	–0,053
	48	–0,053	–0,051	–0,051
	60	–0,048	–0,048	–0,047

5% upper tail limits for ADF regression coefficients, T = 5000

Appendix 6

Rejection frequencies

False alarms

%- of false alarms, where ADF coefficient 0 is used as a limit for the signal

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	0,02%	0,05%	0,07%
	48	0,00%	0,01%	0,04%
	60	0,00%	0,00%	0,01%
0.8	36	0,13%	0,17%	0,22%
	48	0,03%	0,07%	0,12%
	60	0,01%	0,02%	0,07%
0.9	36	0,82%	0,76%	0,80%
	48	0,30%	0,35%	0,41%
	60	0,12%	0,17%	0,22%

%- of false alarms, where ADF coefficient –0.05 is used as a limit for the signal

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	0,31%	0,49%	0,65%
	48	0,41%	0,72%	0,98%
	60	0,58%	0,99%	1,98%
0.8	36	0,93%	1,10%	1,28%
	48	0,87%	1,18%	1,45%
	60	1,04%	1,47%	1,86%
0.9	36	4,50%	4,29%	4,42%
	48	3,85%	4,10%	4,27%
	60	3,80%	4,16%	4,41%

%- of false alarms, where AR coefficient 1.0 is used as a limit for the signal

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	0,01%	0,01%	0,00%
	48	0,00%	0,01%	0,00%
	60	0,00%	0,00%	0,00%
0.8	36	0,07%	0,06%	0,06%
	48	0,02%	0,04%	0,04%
	60	0,01%	0,01%	0,04%
0.9	36	0,75%	0,76%	0,74%
	48	0,29%	0,30%	0,30%
	60	0,13%	0,16%	0,17%

T = 5000

Correct signals, unit root periods

%- of correctly signaled unit root periods, where ADF coefficient 0 is used as a limit for the signal

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	37,54%	45,30%	53,72%
	48	30,18%	36,74%	44,30%
	60	24,82%	31,10%	37,42%
0.8	36	35,00%	44,90%	22,86%
	48	27,54%	35,56%	29,92%
	60	22,44%	28,90%	36,20%
0.9	36	38,68%	45,96%	53,64%
	48	29,76%	35,86%	43,64%
	60	23,82%	29,72%	35,78%

%- of correctly signaled unit root periods, where ADF coefficient –0.05 is used as a limit for the signal

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	59,70%	71,36%	79,04%
	48	52,94%	65,90%	74,74%
	60	48,18%	61,02%	70,36%
0.8	36	60,48%	72,08%	53,04%
	48	53,64%	66,00%	63,76%
	60	49,38%	62,12%	72,02%
0.9	36	64,30%	74,86%	81,36%
	48	60,16%	71,46%	77,62%
	60	56,30%	67,34%	74,46%

%- of correctly signaled unit root periods, where AR coefficient 1.0 is used as a limit for the signal

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	55,00%	67,90%	74,42%
	48	41,88%	56,40%	63,22%
	60	30,18%	44,54%	54,20%
0.8	36	57,48%	68,34%	76,94%
	48	43,54%	57,46%	64,76%
	60	34,50%	47,62%	55,76%
0.9	36	58,22%	59,74%	76,88%
	48	46,26%	53,70%	66,20%
	60	37,22%	49,44%	57,06%

T = 5000

Correct signals

%- of correctly signaled single unit root observations, where ADF coefficient 0 is used as a limit for the signal

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	5,32%	5,15%	5,13%
	48	5,01%	4,89%	4,89%
	60	4,41%	4,71%	4,69%
0.8	36	4,71%	4,83%	2,26%
	48	4,24%	4,40%	3,35%
	60	3,70%	4,15%	4,42%
0.9	36	4,95%	5,06%	5,03%
	48	4,77%	4,60%	4,66%
	60	4,19%	4,28%	4,29%

%- of correctly signaled single unit root observations, where ADF coefficient –0.05 is used as a limit for the signal

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	15,74%	16,69%	17,50%
	48	16,77%	19,23%	20,98%
	60	15,91%	20,40%	23,39%
0.8	36	15,80%	16,95%	16,45%
	48	17,20%	19,86%	21,00%
	60	16,82%	21,31%	24,22%
0.9	36	17,28%	18,21%	18,59%
	48	20,63%	22,04%	22,92%
	60	21,64%	24,54%	26,46%

%- of correctly signaled single unit root observations, where ADF coefficient 1.0 is used as a limit for the signal

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	16,20%	20,41%	23,14%
	48	11,16%	15,47%	19,13%
	60	7,81%	11,40%	15,34%
0.8	36	17,36%	21,20%	23,75%
	48	12,27%	16,58%	19,77%
	60	8,89%	12,55%	16,12%
0.9	36	20,76%	22,80%	24,83%
	48	14,14%	18,08%	20,97%
	60	10,66%	14,08%	17,29%

T = 5000

Appendix 7

Power of multiple period test

MC-simulation: Normal process 0.6, bubble length 36 observations, rolling window 36 observations Bubble signal received after 5 continuous signals ADF-method	
How many false alarms before bubble?	0,0%
How many false alarms after bubble?	0,2%
How many single 5-obs. bubble sets are signalled correctly?	9,1%
Bubble period signalled; at least 1 (5-obs.) signal received during simulated bubble?	36,0%

MC-simulation: Normal process 0.6, bubble length 36 observations, rolling window 36 observations Bubble signal received after 5 continuous signals AR-method	
How many false alarms before bubble?	0,0%
How many false alarms after bubble?	0,0%
How many single 5-obs. bubble sets are signalled correctly?	10,1%
Bubble period signalled; at least 1 (5-obs.) signal received during simulated bubble?	34,2%

MC-simulation: Normal process 0.9, bubble length 36 observations, rolling window 36 observations Bubble signal received after 5 continuous signals ADF-method	
How many false alarms before bubble?	0,0%
How many false alarms after bubble?	1.9%
How many single 5-obs. bubble sets are signalled correctly?	9,7%
Bubble period signalled; at least 1 (5-obs.) signal received during simulated bubble?	37,6%

Appendix 8

Power of rolling R- and $DF^{f\,inf}$-tests

$DF^{f\,inf}$-results

%- of total correct rejections of H(0) = I(1) during stationary period

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	52,04%	52,15%	52,42%
	48	73,21%	72,84%	72,99%
	60	86,74%	87,45%	88,21%
0.8	36	21,83%	22,06%	22,19%
	48	29,79%	29,88%	30,12%
	60	39,25%	39,56%	39,33%

%- of correct rejections of H(0) = I(1) during stationary period, before and after simulated unit root

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
before				
0.6	36	55,80%	55,72%	55,85%
	48	81,07%	80,91%	81,04%
	60	97,33%	97,48%	97,61%
after				
0.6	36	49,60%	49,79%	50,10%
	48	68,28%	67,69%	67,73%
	60	80,33%	81,26%	82,28%

T = 5000

%- of false rejections of H(0) = I(1) during simulated unit root in case of single unit root observations

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	39,40%	33,35%	29,02%
	48	63,18%	57,14%	51,17%
	60	83,15%	79,82%	66,19%
0.8	36	16,83%	15,22%	13,83%
	48	24,83%	22,01%	20,68%
	60	33,87%	31,90%	30,16%

%- of false rejections of H(0) = I(1) during simulated unit root in case of unit root periods

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	29,90%	41,36%	38,02%
	48	25,12%	25,50%	23,20%
	60	11,42%	10,68%	10,08%
0.8	36	72,76%	70,18%	68,24%
	48	66,26%	65,68%	62,74%
	60	57,28%	56,30%	55,04%

T = 5000

R-results

%- of total false alarms during stationary period (ie erroneous signal of a break)

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	0,28%	0,57%	0,75%
	48	0,46%	0,64%	0,79%
	60	0,46%	0,70%	0,85%
0.8	36	0,56%	0,29%	0,37%
	48	0,28%	0,35%	0,42%
	60	0,29%	0,40%	0,50%

%- of total false alarms during stationary period (ie erroneous signal of a break), before and after the simulated unit root period

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
before				
0.6	36	0,00%	0,00%	0,00%
	48	0,00%	0,00%	0,00%
	60	0,00%	0,00%	0,00%
after				
0.6	36	0,46%	0,94%	1,26%
	48	0,75%	1,05%	1,31%
	60	0,75%	1,14%	1,39%

T = 5000

%- of correctly signaled single unit root observations

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	0,00%	0,00%	0,00%
	48	0,00%	0,00%	0,00%
	60	0,00%	0,00%	0,00%
0.8	36	0,00%	0,00%	0,00%
	48	0,00%	0,00%	0,00%
	60	0,00%	0,00%	0,00%

%- of correctly signaled unit root periods

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	0,00%	1,34%	1,82%
	48	0,00%	0,00%	0,20%
	60	0,00%	0,00%	0,00%
0.8	36	1,35%	2,94%	12,82%
	48	0,28%	0,60%	0,78%
	60	0,10%	0,14%	0,24%

T = 5000

Appendix 9

Power of rolling MAX-test

%- of total false alarms, where unit root signal was received during stationary period

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	34,68%	34,70%	34,72%
	48	16,77%	17,01%	17,21%
	60	8,64%	9,26%	9,88%
0.8	36	73,16%	73,12%	73,13%
	48	60,65%	60,58%	61,05%
	60	47,10%	47,12%	47,73%

%- of false alarms before and after simulated unit root

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
before				
0.6	36	34,30%	34,24%	34,16%
	48	14,15%	14,16%	14,20%
	60	4,29%	4,37%	4,43%
after				
0.6	36	34,93%	35,01%	35,10%
	48	18,40%	18,83%	19,18%
	60	11,26%	12,28%	13,31%

%- of correctly signaled single unit root observations

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	81,23%	84,40%	85,92%
	48	69,80%	75,66%	79,03%
	60	58,69%	66,31%	54,61%
0.8	36	89,94%	90,76%	87,72%
	48	83,21%	85,68%	87,42%
	60	75,38%	78,67%	82,00%

%- of correctly signaled unit root periods

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	99,63%	99,92%	99,98%
	48	98,10%	99,58%	99,90%
	60	93,98%	98,12%	99,80%
0.8	36	99,86%	99,96%	99,98%
	48	99,10%	99,82%	99,94%
	60	97,70%	99,18%	99,60%

T = 5000

Appendix 10

Power and accuracy of conventional ADF t-test in rolling samples

%- of total false alarms,(H(0) = I(1) is not rejected during stationary period)

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	65,89%	65,79%	65,72%
	48	45,97%	45,90%	45,88%
	60	28,11%	28,18%	28,15%

%- of false alarms before and after simulated unit root

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
before				
0.6	36	64,90%	64,84%	64,78%
	48	43,63%	43,61%	43,57%
	60	24,16%	24,14%	23,98%
after				
0.6	36	66,53%	66,42%	66,35%
	48	47,43%	47,35%	47,36%
	60	30,51%	30,67%	30,79%

%- of correctly signalled unit root observations, single observations or periods

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
single				
0.6	36	93,98%	94,73%	94,86%
	48	87,42%	89,97%	90,89%
	60	78,17%	83,02%	85,42%
periods				
0.6	36	99,90%	99,98%	99,98%
	48	99,62%	99,92%	99,96%
	60	98,84%	99,76%	99,94%

T = 5000

Appendix 11

Power of rolling CUSUM-test

Figures A11.1–A11.4 show how rolling CUSUM squareds change as more unit root observations enter the sample. In figure A11.1 there are no unit root observations in the sample, in figure A11.2 there are 5, in figure A11.3 the sample includes 25 unit root observations and signals of structural breaks are received as the lower bound is breached several times. In figure A11.4 all 36 unit-root observations are included in the sample. As all observations are unit roots, there are no signals of structural breaks.

Figure A11.1 **CUSUM squared**

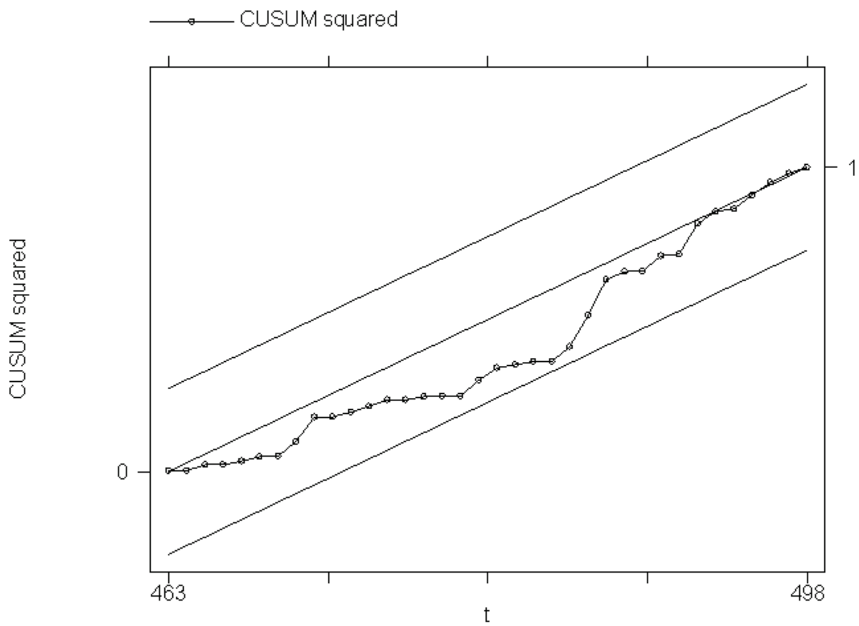


Figure A11.2 **CUSUM squared**

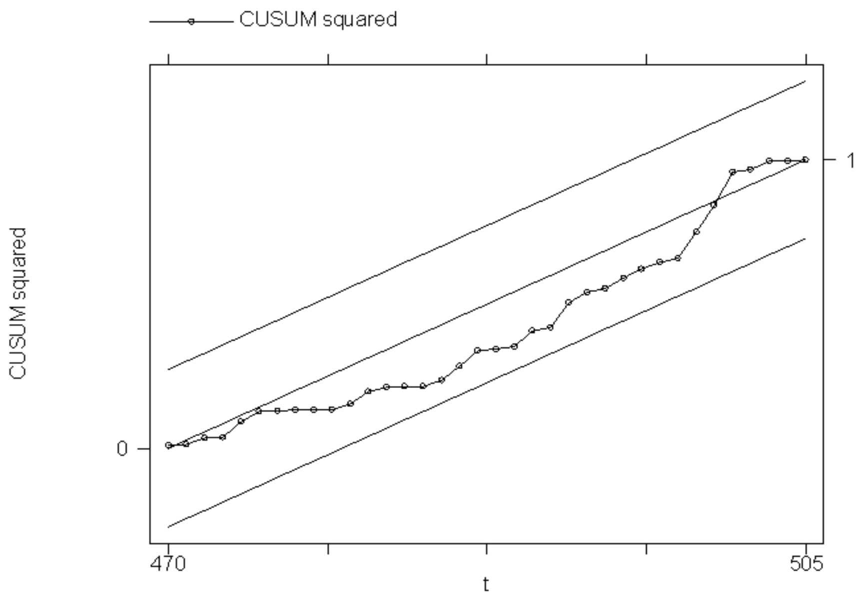


Figure A11.3 **CUSUM squared**

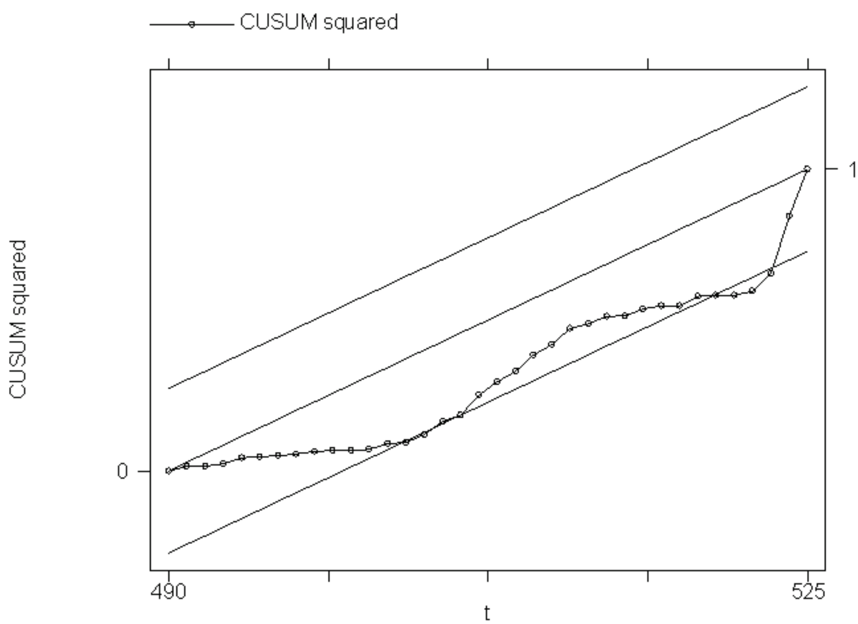
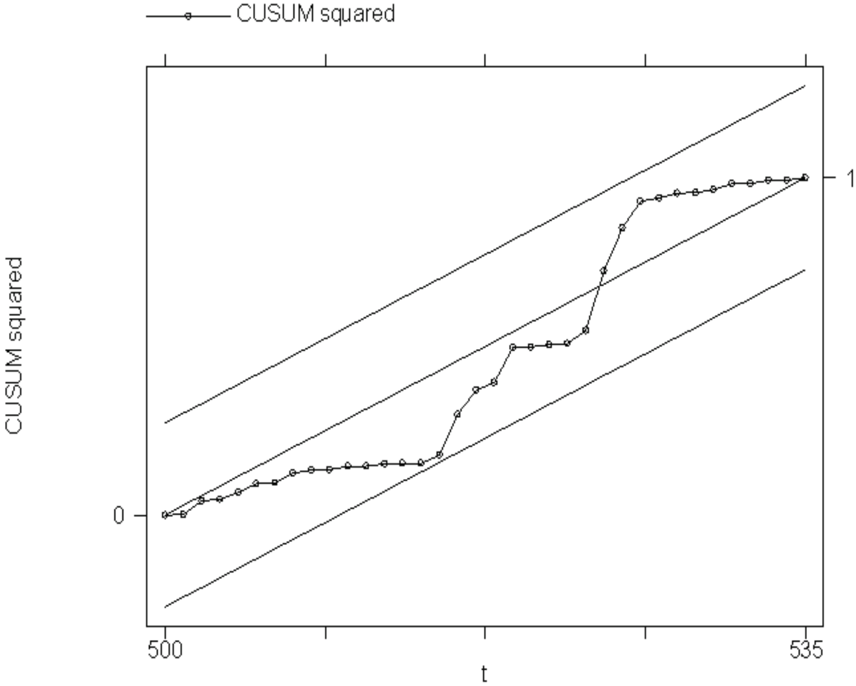


Figure A11.4 **CUSUM squared**



Power of rolling CUSUM-test

%- of total false alarms for CUSUM-test

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	1,06%	1,03%	1,06%
	48	1,58%	1,65%	1,72%
	60	2,28%	2,37%	2,47%
0.8	36	1,75%	1,72%	1,05%
	48	2,81%	1,57%	1,54%
	60	4,14%	2,40%	2,32%

%- of false alarms before and after simulated unit root

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
before				
0.6	36	1,00%	0,90%	0,92%
	48	1,29%	1,36%	1,37%
	60	1,71%	1,88%	1,87%
after				
0.6	36	1,10%	1,11%	1,15%
	48	1,27%	1,32%	1,40%
	60	1,81%	1,92%	2,05%

%- of correctly signaled unit root observations

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	48	60
0.6	36	1,33%	1,93%	2,19%
	48	1,77%	1,66%	2,30%
	60	2,50%	1,77%	2,37%
0.8	36	3,97%	3,50%	1,94%
	48	3,79%	2,97%	1,95%
	60	4,42%	2,50%	1,81%

T = 5000

Appendix 12

Power of rolling Variance Ratio test

%- of total false alarms for Variance Ratio -test

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	60
0.6	36	0,74%	1,01%
	48	0,47%	0,65%
	60	0,33%	0,57%
0.8	36	3,68%	--%
	48	2,65%	--%
	60	2,02%	--%
0.9	36	6,10%	--%
	48	4,93%	--%
	60	4,44%	--%

%- of total false alarms for Variance Ratio -test, before and after simulated bubble

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	60
before			
0.6	36	0,68%	0,60%
	48	0,32%	0,24%
	60	0,34%	0,15%
after			
0.6	36	0,78%	1,31%
	48	0,57%	0,96%
	60	0,40%	0,89%

%- of correctly signalled single unit root observations

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	60
0.6	36	2,97%	5,07%
	48	0,78%	2,80%
	60	0,17%	1,85%
0.8	36	5,83%	--%
	48	3,75%	--%
	60	3,36%	--%
0.9	36	6,44%	--%
	48	4,86%	--%
	60	4,56%	--%

%- of correctly signalled unit root periods

AR-coefficient in stationary period	Length of the rolling window	Length of simulated unit root 36	60
0.6	36	23,00%	42,00%
	48	9,00%	23,00%
	60	3,00%	19,00%
0.8	36	31,00%	--%
	48	19,00%	--%
	60	14,00%	--%
0.9	36	30,00%	--%
	48	23,00%	--%

Appendix 13

Bubble signals given by AR36 and ADF36 indicators in UK equity markets, 1965–2011

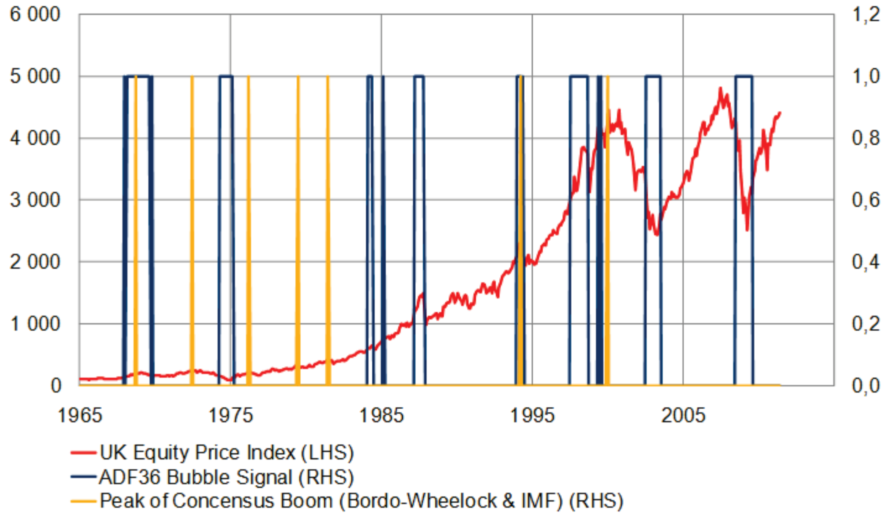
Table A13.1 **Precise bubble warnings by 3-year ADF and AR indicators**

UK Stock Market data 1965–05.2011
Sub-sample length 36

AR-signals bubble	**ADF-signals bubble**	**Major cause of boom and bust***	**Identifies boom or bust**
1.12.1967–1.3.1969	1.12.1967–1.10.1969	Sharp rise in UK stocks	boom
1.4.1974–1.1.1975	1.4.1974–1.2.1975	Oil shock, IMF help to UK	bust
	1.2.1984–1.5.1984, 1.2.1985	UK stock start to boom, followed by global boom	boom
1.6.1987–1.7.1987	1.3.1987–1.10.1987	Boom continues, Black Monday	boom
	1.12.1993–1.5.1994	UK specific short bust followed by global	bust
1.10.1997–1.7.1998	1.7.1997–1.8.1998	technology related boom	boom
	1.5.1999–1.7.1999	TMT-stocks peak	boom
1.8.2002–1.3.2003	1.7.2002–1.6.2003	Through of the TMT-related bust, WorldCom bankruptcy	bust
1.6.2008–1.3.2009	1.6.2008–1.7.2009	Burst of debt-bubble and bust related to global financial crises	bust

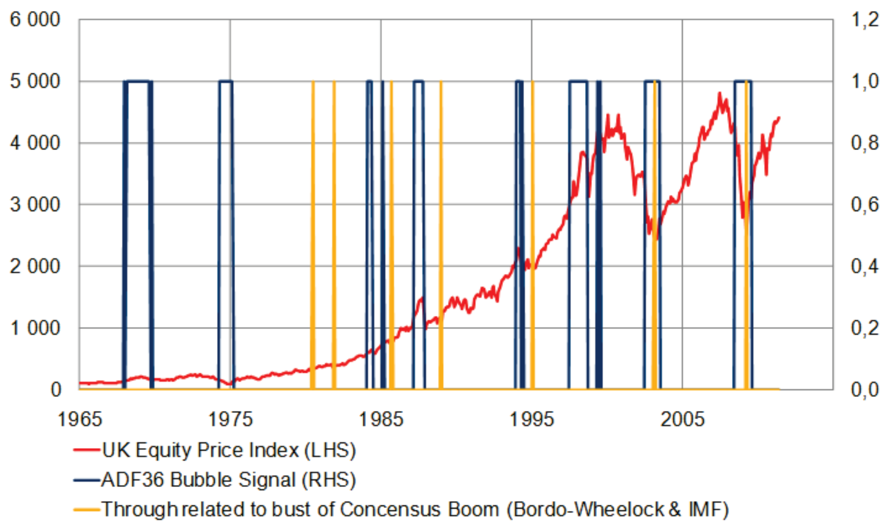
* For reference: IMF (2003), Bordo-Wheelock (2007).

Figure A13.1 **Bubble signals given by ADF36 for UK equity markets, 1965–2011 compared to consensus booms**



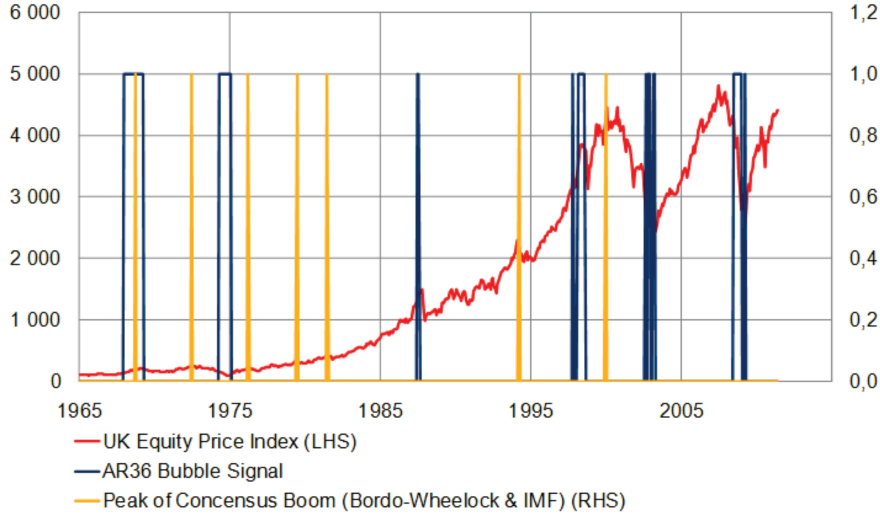
Source: Barclays Capital, Bank of Finland calculations and Datastream.

Figure A13.2 **Bubble signals given by ADF36 in UK equity markets, 1965–2011 comared to consensus troughs**



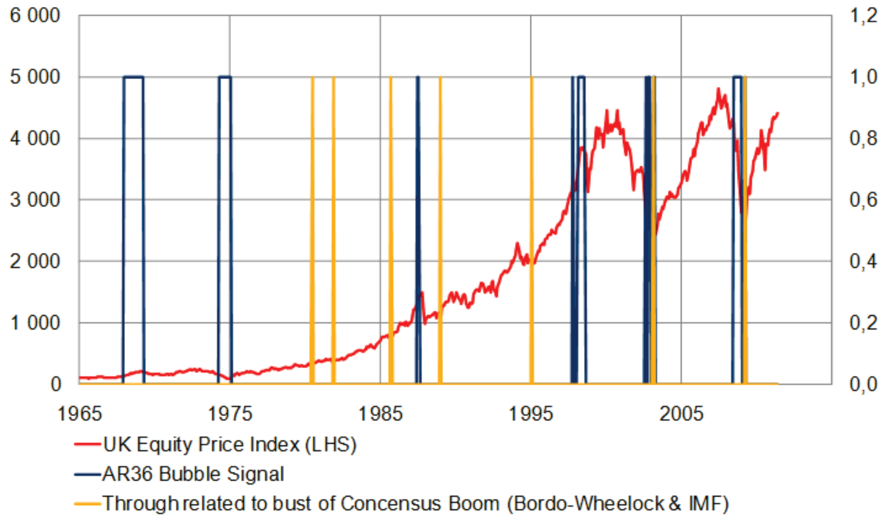
Source: Barclays Capital, Bank of Finland calculations and Datastream.

Figure A13.3 **Bubble signals given by AR36 for UK equity markets, 1965–2011 compared to consensus booms**



Source: Barclays Capital, Bank of Finland calculations and Datastream.

Figure A13.4 **Bubble signals given by AR36 for UK equity markets, 1965–2011 compared to consensus troughs**



Source: Barclays Capital, Bank of Finland calculations and Datastream.

Appendix 14

Bubble signals given by AR36 and ADF36 for Finnish equity markets, 1971–2010

Table A14.1 **Precise bubble-warnings given by 3-year ADF and AR indicators**

FIN Stock Market data
Sub-sample length 36

AR-signals bubble	ADF-signals bubble	Identifies boom or bust
05.1976–06.1976	--	boom
08.1979	--	boom
03.1983–04.1984	03.1983–03.1984	boom
01.1987–11.1987	04.1987–10.1987	boom
07.1990–01.1991	07.1990–01.1991	bust
01.2000	01.2000–02.2000	boom

* For reference: IMF (2003)

Figure A14.1 **Bubble signals given by ADF36 for Finnish equity markets, 1983–2010 compared to consensus booms**

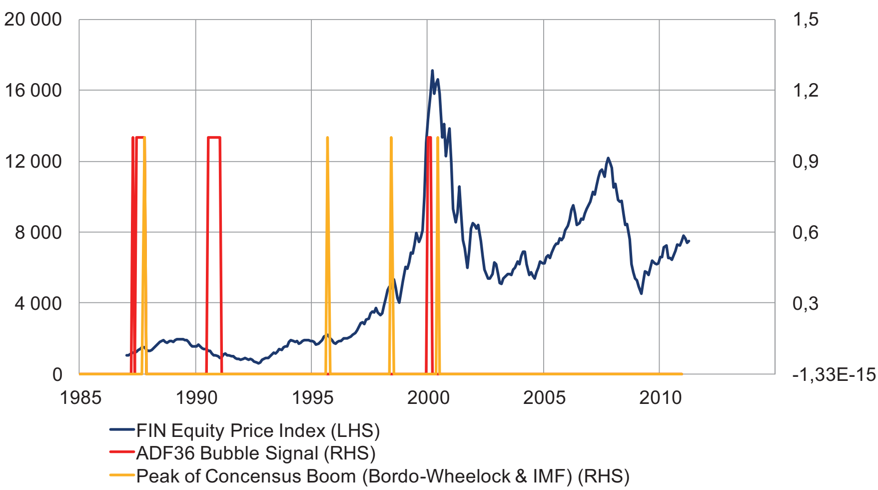


Figure A14.2 **Bubble signals given by ADF36 in Finnish equity markets, 1983–2010 compared to consensus booms**

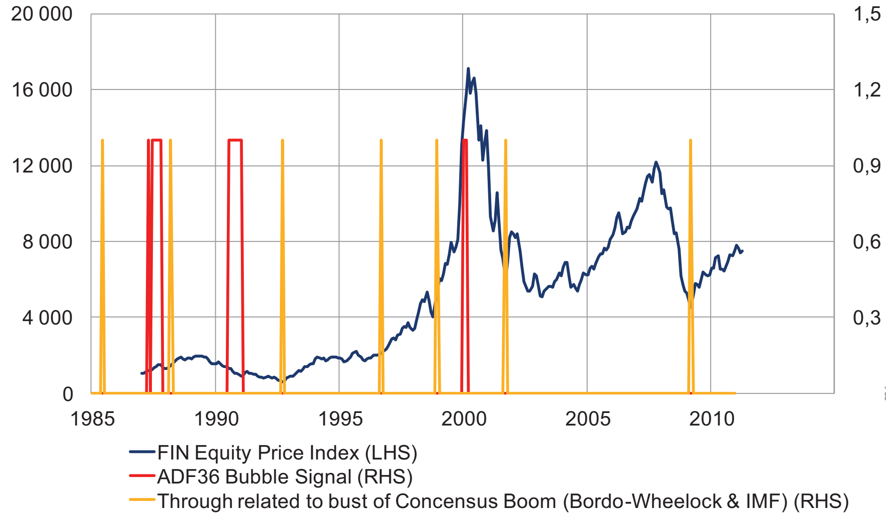


Figure A14.3 **Bubble signals given by AR36 in the Finnish equity markets 1983–2010 compared to consensus booms**

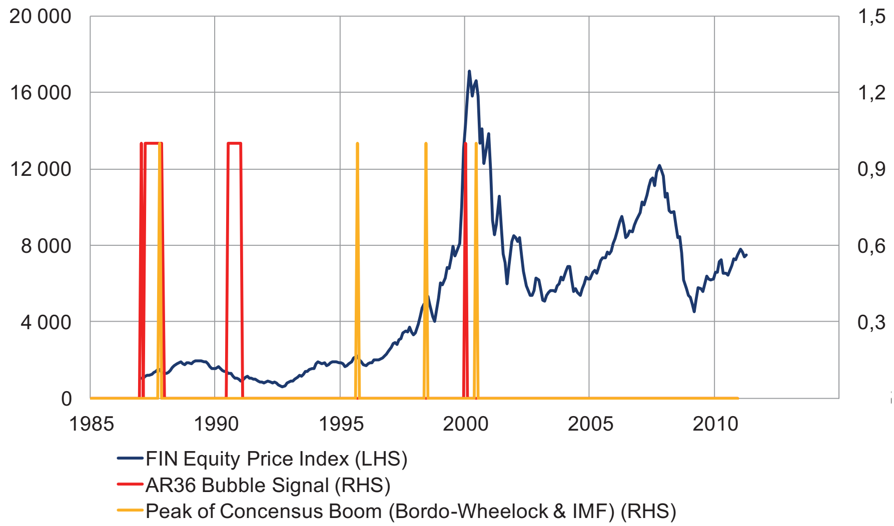
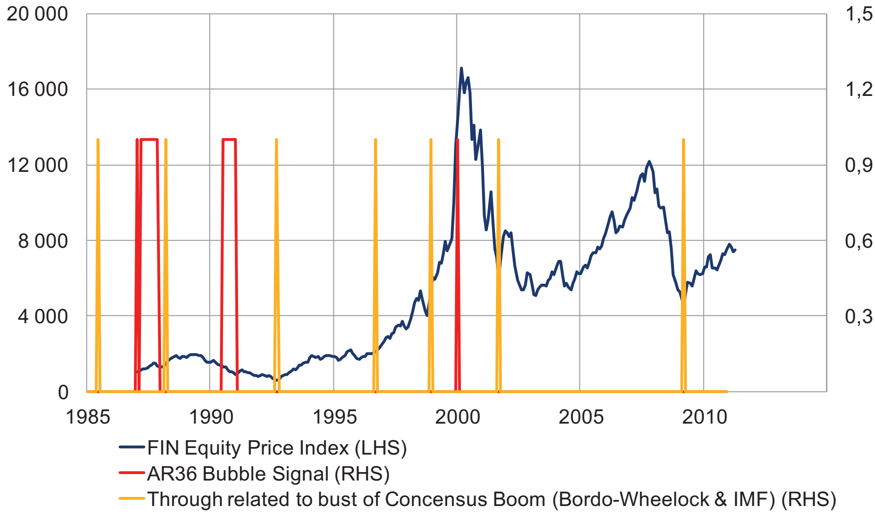


Figure A14.4 **Bubble signals given by AR36 for Finnish equity markets, 1983–2010 compared to consensus booms**



Appendix 15

Bubble signals given by AR36 and ADF36 for Chinese equity markets, 1997–2011

Figure A15.1 **Bubble signals given by ADF36 for Chinese equity markets (Shanghai se composite), 2000–2011**

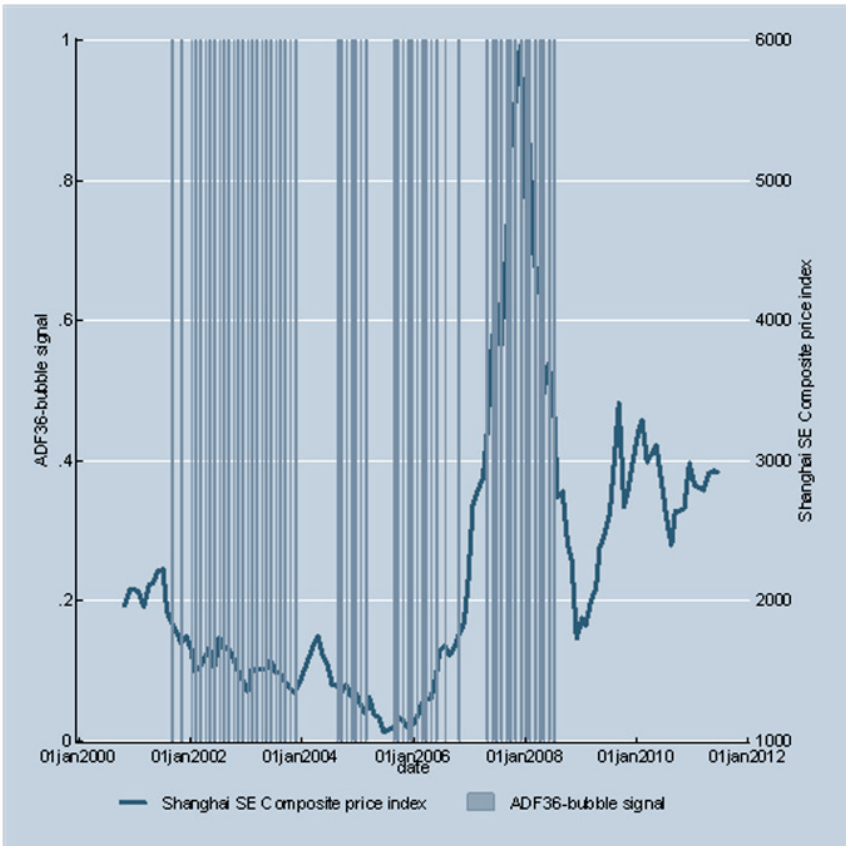
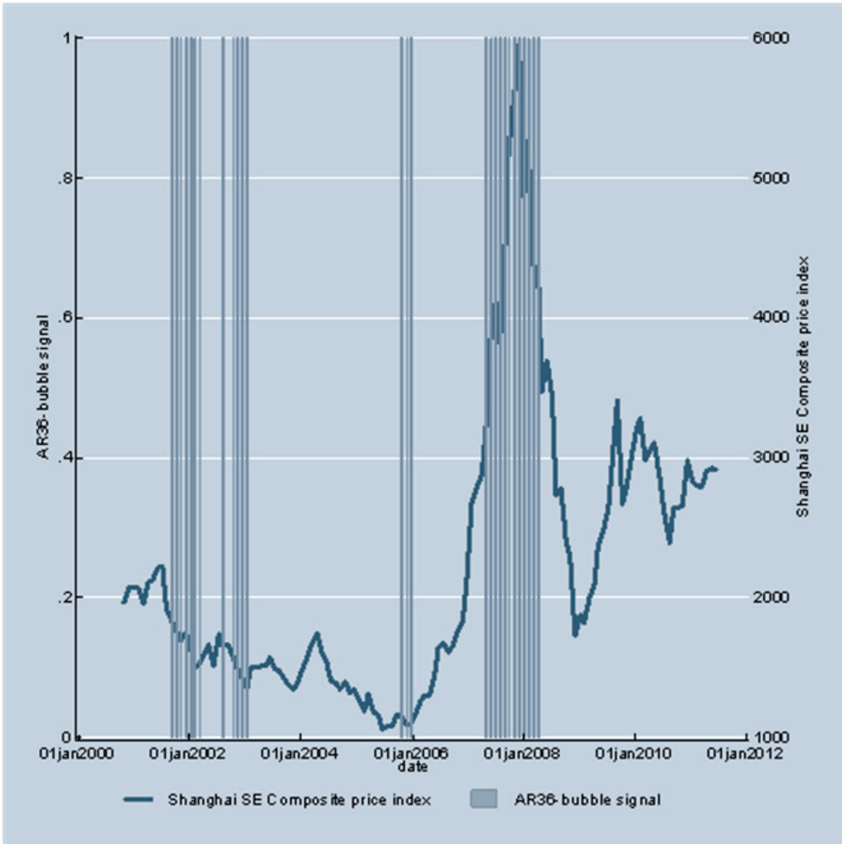


Figure A15.2 **Bubble signals given by AR36 for Chinese equity markets (Shanghai se composite), 2000–2011**



Appendix 16

Housing markets in Spain, monthly data

Figure A16.1 **Spanish housing price index and AR36 bubble signals, 2004–2011**

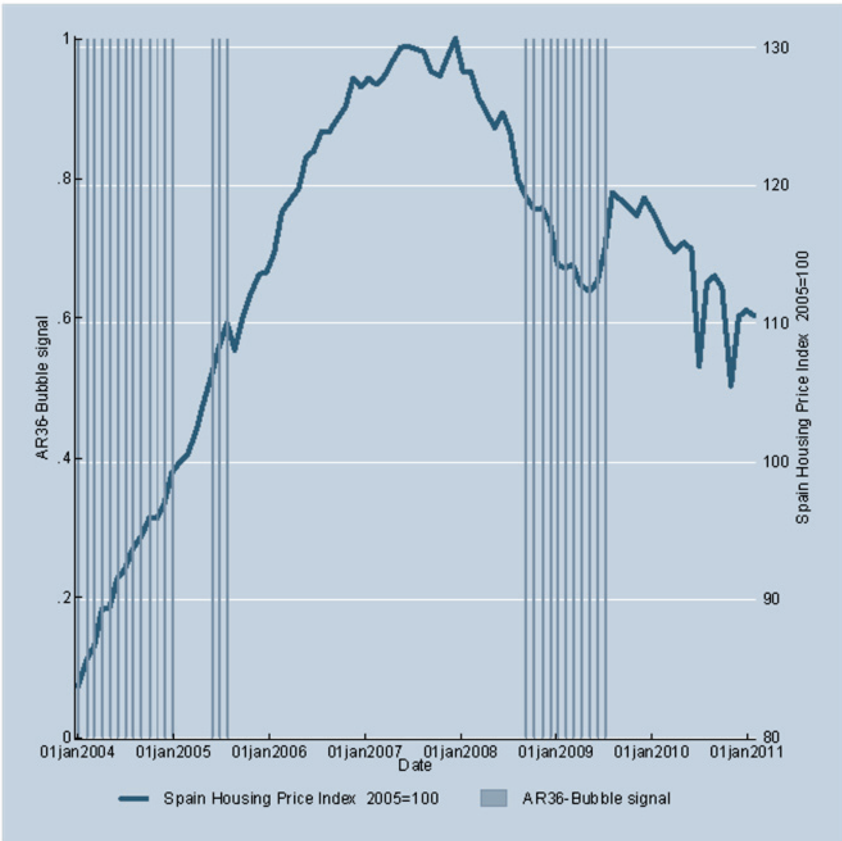
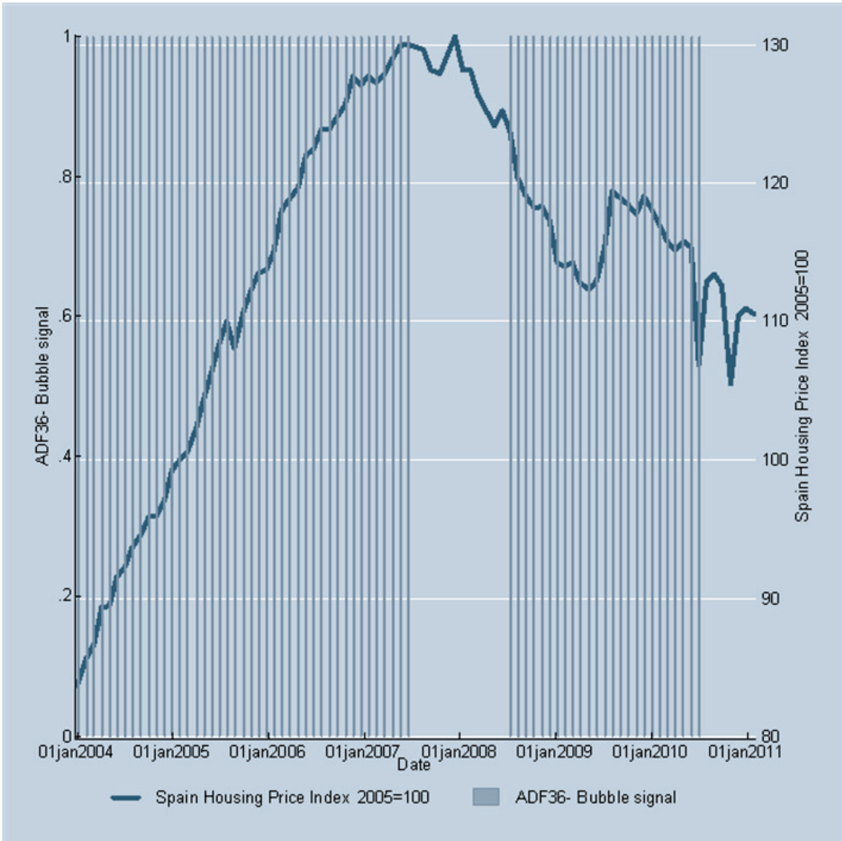


Figure A16.2 **Spanish housing price index and ADF36 bubble signals, 2004–2011**



Appendix 17

Real estate bubbles

Sub-sample length 36

AR-signals bubble	ADF-signals bubble (limit 0.0)	ADF-signals bubble (limit –0.05)	Timing of consensus boom or bust
Spain			
no data	no data	no data	Boom; 1987–1991, peak Q41991
05.–06.200		05.2000	Long boom: 1997–2007
04.–08.2001		02.–09.2001	
02.2002–07.2004		11.2001–06.2007	
03.–04.2005			Bust; prices started to plunge
10.2008–05.2010		10.2008–08.2010	sharply in summer 2007(*)
Ireland			
11.1992–01.1993		06.1985–07.1985, 09.1985, 04.1986	Boom: 1980–1987
06.1996–01.2000		11.1992–02.1993	Boom: 1996–2006
02.2003–01.2004		05.1996–06.2001	Peak in 2006, strong fall started Q2 2007
04.2004–06.2004		01.2003–06.2005	
11.2006–09.2008			
03.1987		02.1987–04.1987	Bust; 1987
		03.2007–10.2009	Bust; 2007 →

AR-signals bubble	ADF-signals bubble (limit 0.0)	ADF-signals bubble (limit –0.05)	Timing of consensus boom or bust
UK			
			Boom, peak in 1970Q3
			Boom, peak in 1973Q3
			Boom, 1977 →, peak in 1980Q3
			Boom in early 1980's, peak in 1983Q3
05.1987–08.1989	02.1988–05.1989	06.1987–12.1990	Boom 1987–1989, peak 1989Q3
07.1999, 10.1999	03.2000–05.2000	10.1999	Long boom: 1998–2007
03.2000–07.2000	05.2002–11.2003	12.1999–11.2000	
06.2001	04.–07.2005	03.2001–12.2006	
05.2002–11.2003		02.2002–07.2005	
04.–07.2004		09.2005–05.2005	
04.–07.2007		04.–10.2007	
			Bust: 1974–1977
04.1991–05.1992	07.1991–04.1992	02.1991–09.1994	Bust; 1990–1994
09.1992–02.1993	09.1992–02.1993	12.1994–02.1995	
10.1995, 12.1995–02.1996	10.1995	09.1995–03.1996	Bust; 1995–1996
	12.1995–01.1996		
09.2008–09.2009	10.2008–07.2009	08.2008–07.2010	Bust; 2008→

AR-signals bubble	ADF-signals bubble (limit 0.0)	ADF-signals bubble (limit –0.05)	Timing of consensus boom or bust
USA			
			Boom; 1973, peak in 1973Q3
12.1977–07.1978		12.1977–11.1979	Boom; 1979, peak in 1979Q2
		10.–11.1985	Boom; 1985–1989, peak in 1989Q4
11.1985		11.1986–03.1989, 06.–07.1989	
09.1986–10.1987		12.1994	
06.–07.1988	01.1999–08.2001	05.1998–03.2011	Boom; Long boom 1999–2007
10.1994–03.1995	07.2002	(do not clearly separate positive or negative bubble in the prev. period)	
05.1998–11.2001	09.2003–11.2005		
07.–09.2002			
09.2003–03.2006			
03.1980–10.1981	04.1980	02.1980–05.1980	Bust; 1980–1981
		08.1980–05.1983, 10.1983	
07.1990–12.1991	07.1991	11.1990–02.1993	1990–1992
04.1992			
			Prices peaked 2006, decline started 2007
04.2008–11.2009	04.2008–08.2008		2008→
	04.2009–06.2009		

Source for data: Author's calculation, IMF (2003), ECB (2003), McCarthy and Peach (2004), RICS European Housing Reviews, ESRI (2006), Chamberlin (2009), Shiller (1993), Case (2004), Shiller (2006), Shiller (2009), Agnello et al (2009).

* In many countries, prices were still falling at the cut-off date of the data used in this study.

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