

# **EXPLORING THE MYSTERIES OF TRENDS AND BUBBLES**

**By**

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## Exploring the mysteries of trends and bubbles

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It is a pleasure to visit the University of Adelaide and an honour to present the Joseph Fisher Lecture. This lecture series has a long list of eminent economists as past speakers. It is a particularly welcome opportunity therefore to present what appears to be the first lecture in this series on econometrics.

Econometrics is a statistical tool that forces economic ideas to face the reality of observations. As Milton Friedman once remarked about economics, simple theories are the most powerful, like the power of rational decision making that underlies most economic models. What makes the subject of econometrics difficult is that simple theories of human behaviour like rationality are never right. Econometrics must simultaneously confront the reality that economic theories are inevitably wrong yet in many cases contain a powerful kernel of truth. Measuring these kernels of truth in the presence of near universal model misspecification is one of the challenges that make econometrics an exciting and relevant subject.

### **Trends and bubbles in modern econometrics**

My subject in this lecture is trends and bubble phenomena. The primary focus is on economic activity. But as we all recognize, trends and bubbles occur in the natural and physical world. So their relevance extends well beyond economics and other matters of human affairs. To broaden its coverage this lecture draws upon examples of such phenomena in areas like climate change that are of pressing global concern in the modern world with their own concomitant economic

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<sup>1</sup> This paper is a revised version of the fifty-fourth Joseph Fisher Lecture presented at the University of Adelaide, 18 February 2010. The author thanks the School of Economics at the University of Adelaide for their hospitality and Jiti Gao for arranging this visit.

implications. Happily, one of the big export industries of econometrics is the novel and rapidly changing econometric technology of stochastic trends which has opened up many new areas of application in other disciplines over the last two decades

With the advent of the recent sub-prime financial crisis, we all know something about bubbles. The Asian financial crisis, the dot com bubble in the 1990s, and the latest global financial crisis have reawakened interest in this important and little explored field. It has alerted the new generation of economists as well as the public at large to the reality that bubbles intermittently occur in financial markets, that they have consequences on the real economy, and that we need methods to assist us in identifying them to avoid some of these consequences. Econometrics helps deliver such methods.

Trends are phenomena we like to think we know a great deal more about than bubbles, partly because they are omnipresent and have been studied so extensively. Macroeconomics, for instance, has had a long-time focus on modelling and explaining economic growth. Time series econometrics has produced a massive volume of research on nonstationarity and trends over the past three decades. And microeconometrics frequently focuses on changing behaviour over time. Yet in spite of the enormous attention, trends are phenomena about which we really know very little.

Trends and bubbles are mysteries. Trends are compelling mysteries to econometricians because they are a major characteristic of virtually all time series in economics and finance and they must be addressed in modelling. Bubbles are fascinating mysteries to economists because they are so difficult to anticipate, so difficult to model in terms of rational behaviour, and potentially tumultuous in their effects on human economic conditions and the course of human progress.

Trend is a simple five letter word whose modern dictionary meaning is ‘a general direction or tendency, particularly over time’. The definition has appealing econometric implications and gives an astonishingly simple way of thinking about data – trending data go up, down, or stay constant. Public discussion and media commentary repeatedly rely on these simple characterisations in describing the world around us. We talk of trends in education, in health, in sociological

characteristics such as crime, suicide and divorce, and in human characteristics such as body mass indices, obesity, senility, longevity, and sports performance. All these topics are discussed and analysed in terms of their trends. The discussion captivates interest because trends point to the future – where the data are going – and this inevitably rivets public attention.

Professional economic commentary has the same preoccupation. Prominent economists such as the Chairman of the Federal Reserve or Governors of Reserve Banks regularly pronounce on trends in economic phenomena. We hear comments like “if current trends continue then we will be out of recession by the end of the year”, or “a newly emerging trend is the recovery in house prices”, or “long term trends in performance show that stocks outmatch other financial assets”. These pronouncements give the impression of scientific authority, especially when they appear in scientific presentations or as congressional testimony by a respected central bank authority. After all, central banks collect and publish data, have teams of economists on hand to analyse it, have public mandates to ensure price stability and economic growth, provide regular forecasts of key economic indicators, and their spokespeople are highly qualified professional economists. So the authenticity of central bank commentary on economic affairs often goes unquestioned.

But commonly used phrases such as “if current trends continue” do not stand up to the simplest scrutiny. What is meant by the word “current” – the last five days, five months or five quarters of data? How is the concept “trend” formalized and measured – a straight line through the data, a curve or some random drift? How are we expected to interpret and use quantities that are not properly defined? Once these questions are raised, the apparent precision of the statement vaporizes. In place of a clear message, we see something impressionistic – a hazy signal whose interpretation relies on some implicit understanding of the concept of a trend. The concept is so loosely defined and elusive that trend takes on a mysterious character. Like the inscrutable Hamlet, the protagonist in Shakespeare’s most famous play, you never really know what it is going to do next. In short, no one really understands trends but everyone sees trends in data.<sup>2</sup>

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2 This ‘law’ of econometrics was suggested in Phillips (2003). The analogy with Hamlet was given in Phillips (2010), on which some of the discussion in this paper draws.

Yet there is a basic human instinct that drives us all to look for trends in data. This instinct is a desire to bring order to disorder. Learning to understand the world around us (the seasons, the environment, topography and climate) is a basic human survival instinct. Bringing order to disorder is like creating a map to describe aspects of the territory which holds our interest. Maps can be very useful. But the territory is always more complex, just as living organisms are always more complex than the stylized diagrams of their component parts that we see in medical texts.

The same is true with data. The human instinct is to bring order to the disorder of data. When we see a cloud of points on a chart, we have an irrepressible urge to put a line through it – to show where it has been and where it is going. This human urge turns the observer into an eyeball statistician – a fellow who draws a line through a set of point based on unwarranted assumptions with a foregone conclusion.

One important characteristic of this human statistical instinct is that drawing a line through a set of points produces a smooth curve which has direction. That is how we usually see things and how we draw them. We don't take the pencil off the page. We draw a smooth curve or one with a kink if we really need to turn a sharp corner. Smooth curves are differentiable and curves with kinks are (one-sided) differentiable. A curve that is differentiable tells you where it's going at every observation. It's predictable. That is the outcome of this instinctive thinking – it reveals a direction vector for the future from a cloud of points. It is this characteristic, this limiting characteristic of the human statistical instinct, that is implicit in media and public scientific commentary about trends. It explains why public pronouncements about trends are so frequently accepted – people are by nature sympathetic to this form of trend analysis and they like to think they know what these pronouncements mean.

Modern econometrics has challenged this simplistic view. The biggest change in econometrics over the last three decades is the recognition in empirical research that trends are stochastic. Trends involve inherently random elements – like Hamlet we never know what to expect next – and yet the trend process may explore the whole sample space in a recurrent non-differentiable manner like a Brownian motion. With non-differentiability we lose the direction vector and no

longer have the forecasting capability at any point in time that is delivered by a smooth curve. The modern dictionary definition of trend is no longer relevant. A more fitting characterisation is given by the middle English (circa 1590) verb “trenden”, from which the word trend is derived and whose meaning is “to turn or roll about” like the wandering course of a coastline or a river. The recent usage of trend as a general direction or tendency originates from 1884 and that usage soon became dominant and was popularized in reporting economic statistics. By the 1960s the usage in statistical time series analysis and econometrics had narrowed further and trend had come to mean a simple deterministic function like a time polynomial or sinusoidal time polynomial. It is this perspective on trend that is presented in classic time series treatments such as the texts of Grenander and Rosenblatt (1957) and Anderson (1971).

Analysing trends that are inherently stochastic is a far more challenging task for the econometrician than drawing a line through a set of points, which partly explains why so much has been written on this subject over the past 30 years. A Google search (October, 2012) on “unit roots”, which we often take as the simplest embodiment of a stochastic trend, produces 252,000 thousand hits, which exceeds “microeconometrics” (150,000 hits), “time series econometrics” (144,000 hits), and “ARCH models” (118,000 hits).<sup>3</sup> A vast amount of empirical evidence now supports the presence of unit autoregressive roots or near unit roots in economic and financial data. Theories of efficient markets and martingale-like phenomena in capitalist economies are consonant with this econometric notion of a unit root and the shock persistence that comes from temporal aggregation. The best predictor of tomorrow’s price is typically still today’s price.

Bubbles differ from trends because the general tendency during an upswing contrasts with the general tendency during collapse. During an upswing we have sub-martingale behaviour where the conditional expectation is a price rise tomorrow whereas, during a collapse, the conditional expectation is a price fall, giving super-martingale behaviour. The silent elephant in the room, of course, is that we don’t know when the behavioural mechanism will shift from martingale to sub-martingale or sub-martingale to super-martingale. With financial asset prices, the upswing uncertainty stems from doubts over the continuation of a

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<sup>3</sup> “Cointegration” – the sister subject of “unit roots” – records 901,000 hits.

rally and whether or when a correction or collapse will begin. During the 1990s Nasdaq bubble, the Federal Reserve Chairman Alan Greenspan articulated this type of uncertainty as a loaded question in his famous 1996 dinner speech with:

“How do we know when irrational exuberance has unduly escalated asset values?”

Greenspan’s remark underscores the fact that we usually don’t know when an asset price bubble begins and, even after a collapse, academic disputes arise over whether a bubble has actually occurred. Such disputes are often ridiculed in the press and popular writing.<sup>4</sup> These are some of the many issues that modern econometric methodology can address and clarify.

In view of the ubiquity of trends across the business, social and natural sciences, methodology for analysing and interpreting trend behaviour has wide applicability. In consequence, the rapidly developing technology of stochastic trend analysis in econometrics has been imported by other disciplines and many new applications have emerged. Two areas that bear particularly on the present discussion are planetary climate change and biodiversity (the number of different species or genera of life forms). Data sets for these phenomena are the longest to which econometric methods have ever been employed. The time frames involve hundreds of millions of years in the case of fossil records in counting genera and hundreds of thousands of years in the case of climate change based on ice core samples and sea sediment data. These long range data embody planet-wide trends that call out for analysis which can help us understand the course of Earth’s climate and life forms over time.

## Long term trends in climate

To illustrate, we look at climatological data based on ice core samples that extend over geologic time frames and are measured in thousand year (kyr) or million year (myr) units. Against this time frame economic time series are extremely

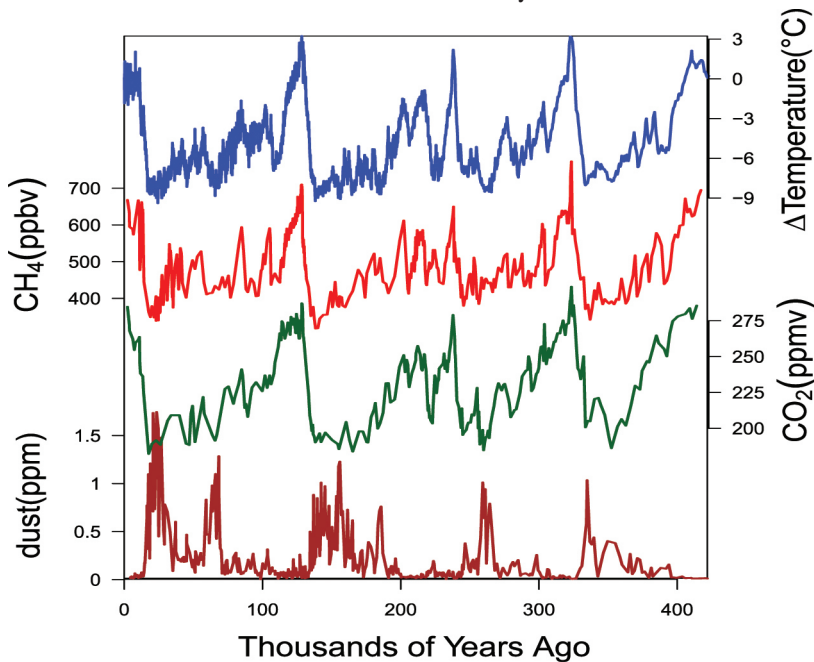
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<sup>4</sup> See the article by Pástor and Veronesi (2006) and the biting critique in Cooper (2008, p. 9): “People outside the world of economics may be amazed to know that a significant body of researchers are still engaged in the task of proving that the pricing of the Nasdaq stock market correctly reflected the market’s true value throughout the period commonly known as the Nasdaq bubble. ... The intellectual contortions required to rationalize all of these prices beggars belief.”

short, especially when it comes to studying trend behaviour. Yet many of the same problems (such as the inherent random elements in trend, shortfalls in theory guidance, and ambiguities between trend and cycle) continue to manifest themselves. Having more data, in effect, does not always lead to an improvement in analysis or understanding. Sometimes, especially with trending time series, the advent of more data simply means that the investigator has more to explain. In this event, trends appear endogenous to the sample. Then, as in economics, it is the synergy of good theory, data, and statistical methodological that is most likely to enhance understanding.

The graphs shown in Figure 54.1 are based on (linearly interpolated) data constructed from ice core samples at the Vostok station in Antarctica (Petit et al. 1999). These data cover the past 420kyrs with time measured from right (past) to left (present) on the horizontal axis. The figure contains four (slightly overlapping) panels that show the time paths of different variables over this historical period, each series having its own axis: (i) temperature measured in °C deviations from mid-twentieth century levels; (ii) methane gas (CH<sub>4</sub>) levels in parts per billion

**Figure 54.1: Vostok ice core data from Antarctica over 420kyr for temperature (deviations from mid twentieth century levels), CO<sub>2</sub>, CH<sub>4</sub> and dust**





volume (ppbv); (iii) CO<sub>2</sub> levels in parts per million volume (ppmv); and (iv) dust levels in ppm. The temperature graph reveals many well-known features: (i) the (relative) stability of temperatures over the holocene (the last 12kys), considered to be decisive in the neolithic revolution and the emergence of human civilization; (ii) the long but variable cycle (with periods between 80–120kys) between major glacial epochs; (iii) the relatively short inter-glacial periods; (iv) some less dominant subcycles, also of variable period; and (v) evidence of random wandering behavior between episodes of deglaciation.

Spectral analysis of these series reported in Petit et al. (1999) shows spectral peaks around 100kyr, 41kyr, and 19–23kyr periods. These peaks are thought to be partly associated with certain orbital forcing mechanisms (orbital eccentricities, obliquities and precession), although the links are by no means unequivocal and there is considerable variation in the empirical periods compared with the orbital mechanisms. An alternative astronomical theory involving three dimensional orbital inclination to the invariable plane (the plane of the solar system) leading to 100kyr cycles arising from dust accretion within that plane has been advanced by Muller and MacDonald (1997). Unit root tests that I have conducted confirm evidence of random wandering behaviour in the series between these various glacial epochs, so there is strong evidence of stochastic trends in the data.

No present climatological (or planetary) simulation models are capable of generating time paths of this type over long geologic periods. Frequency domain methods, while informative about dominant periodicities, struggle to deal with the many separate components in these trajectories, particularly the unit root nonstationarity, the irregularity in cyclical behaviour, the abrupt terminations, and the prolonged holocene period which is a singular event in the record. Causal analysis among the series is complicated by the intermittent, irregular and non-concurrent sampling of the different series. Co-movement analysis does not fit within the usual cointegrating model framework of econometrics, yet co-movement is clearly apparent and of great importance, not only in terms of ongoing discussions on anthropogenic driving forces of climate change<sup>5</sup> – measured by recent increases in greenhouse gas emissions (carbon dioxide, methane, and

5 The Intergovernmental Panel on Climate Change (IPCC) Fourth Report released in 2007 confirmed that atmospheric CO<sub>2</sub> concentrations rose from 280ppm in 1750 to 379 ppm in 2005 (see <http://www.ipcc.ch/>). As is apparent from Figure 54.1, the level 379 ppm exceeds by around 100 ppm all previously recorded levels of atmospheric CO<sub>2</sub> over the last 400,000 years.

nitrous oxide) – but also in terms of the possibly causative relationship between atmospheric dust particulates and temperature.<sup>6</sup>

Another option for modelling these series might be the use of breaking trend functions, such as those that have been popular in econometrics over the last two decades. Structural break models offer flexibility to capture differences as well as commonalities across epochs and could be used to fit trigger point thresholds for the initiation and termination of glacial periods. However, these models have typically been developed in a univariate context and would need to be extended to multiple, sequenced, alternating breaks with common thresholds and feedbacks among the series and to allow for random wandering behaviour and cyclical features associated with orbital forcing in order to achieve congruence with these data. All of these requirements, combined with break point and threshold determination and the singularity of the holocene era, push the envelope of present econometric capability and reveal the fragility and arbitrariness of structural break modelling when it is carried to excess.

Finally, direct nonparametric fitting and data smoothing offer alternate modelling methods. Neither approach deals well with abrupt terminations, threshold triggering or random wandering behaviour within epochs. Neither do these methods allow for the use of astronomical forcing variables or other causal effects known to be important from climate theory, such as greenhouse gas amplification or ocean current influences. Nor do they allow easily for multivariate treatment that permits interaction between the series.

In short, none of the models or econometric methods for studying trends seem to measure up to the task of modelling these series. To take the problem to the next level, these series can be viewed in the context of even longer climate trajectories. Paleoclimate records from various sources are now available over very long time frames extending to hundreds of millions of years. The data are partially based on deep sea sediment cores extracted at a large number of oceanic sites, as described in Muller and MacDonald (1997) and Lisiecki and Raymo (2005a, b).

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<sup>6</sup> Some alternate planetary evidence of climatic causative forces arising from dust storms is available from astronomical observation. Ten planetary dust storms have been observed on the planet Mars since 1877. Over the last decade two major planetary dust storms (2001 and 2007) have been closely monitored by the Hubble telescope and Mars rovers. It was observed that the 2001 dust storm led to a temperature rise of some 30°C, affirming a strong planetary link between dust and temperature.

These extremely long series raise the difficulties of trend modeling to an entirely different level. Sediment core data reveal a steady downward drift in temperature over the last 5myr period, leading to a growing incidence of glaciation accompanied by an increase in the amplitude of the glacial/deglacial fluctuations (appearing like nonstationary volatility on this time scale). The 41 kyr cycle is a dominant characteristic 3 to 1 million years ago, whereas the  $\sim 100$ kyr cycle appears dominant over the last million years.<sup>7</sup>

The picture is further complicated over the far longer 65myr period following the Cretaceous-Tertiary (or so-called KT) boundary event to the present. While the drift in temperature over this period has generally been in a downward direction, it is by no means linear or monotonic and there have been substantial periods of warming, associated with an Antarctic thawing 25myr ago, prior to reglaciation some 12myr ago. Finally, the estimated climate record over the last half billion years has a pronounced cyclical pattern embodying much of the variation that over shorter geologic periods is reasonably perceived as upward or downward trend.

These long span paleoclimate data highlight that trend is a complex phenomenon with features that are random and endogenous to the sample size. As we lengthen the time span of observation, what first appears as a pattern of drift later becomes absorbed into a cycle with a longer period or even manifests as volatility. The pattern continues to repeat itself over different time scales.

Is trend itself then a phenomenon that is relative to time scale? If so, when we model trend how do we take account of the wider picture presented by a longer time frame when that data is not available to us? And what form of asymptotic theory is appropriate in a finite sample where the trend form is random and endogenous to the sample size? These are hard questions that push the limits of present understanding and methodology. In the absence of data, the answers must lie in good theory, better econometric technique, and fast algorithms for adapting models that are inevitably misspecified.

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<sup>7</sup> The orbital inclination theory of Muller and MacDonald (1997) offers an explanation of this major change in climate trend. Changes in orbital inclination take the Earth periodically (around 100kyr) into a dust belt. Dust accretion is affected by random astronomical events such as asteroid collisions which periodically replenish dust in this belt around the sun, thereby disturbing the glacial cycle.

To capture the random forces of change that drive a trending process, we need sound theory, appropriate methods, and relevant data. In practice, we have to manage under shortcomings in all of them. It is at least some comfort for the econometrician to know that these manifold difficulties of modelling trend are not confined to economics.

## Detecting financial bubbles

In his book *The Adventure of English* the famous author and broadcaster Melvyn Bragg (2003) wrote that “hindsight is the easy way to mop up the mess we call history.” While directed towards the study of history, this profoundly perceptive remark exposes some of the limitations in ex post econometric research. It is always easy, and can be misleading, to characterize past data – mop up the sample variation – by adding lags, covariates or using structural breaks to dummy out individually awkward observations. Far more challenging is to develop a truly anticipative ex ante econometric methodology that might be used as a warning alert system of changes in behaviour or system responses.

Some economists believe that the creation of such methodology may be altogether too challenging, especially with regard to financial markets and asset price bubbles – witness the statement of this commonly held position in *The Economist* newspaper (15 June 2005) that “bubbles can be identified only in hindsight after a market correction”. Only when the full cycle of exuberance and collapse is complete, it is suggested, can a financial bubble be identified.<sup>8</sup>

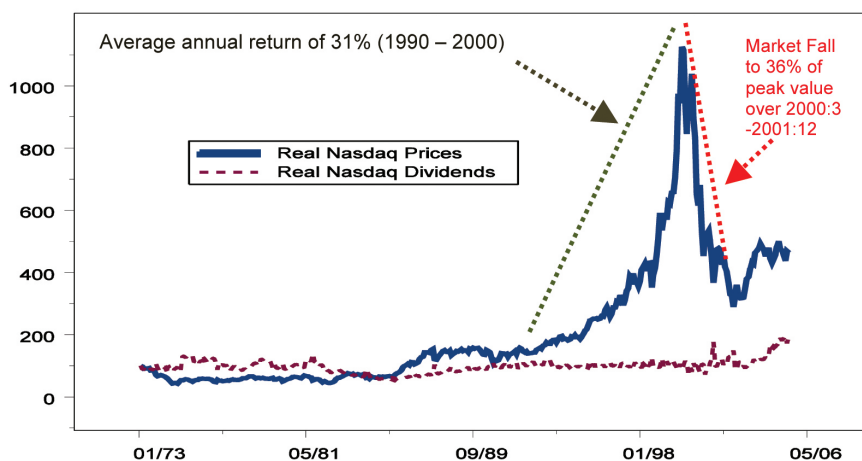
Displayed in Figure 54.2 is the dot com bubble in the 1990s which is said to have created and destroyed about 8 trillion dollars of shareholder wealth over a period of 6 or 7 years. The data are given in real terms, including fundamentals – dividends – which behave very differently from prices. From this descriptive characterisation, the market fell first to 36 percent of its peak value and then to 24 percent of its peak value.

The warning cited earlier that Alan Greenspan made in his dinner speech about financial markets in the 1990s was cast as a question – how do we know when

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8 Even then, as we have discussed in footnote 4, academic disputes continue over whether a bubble has actually occurred.

**Figure 54.2: Monthly real Nasdaq prices and dividends 1973:2 – 2005:6. Both series are normalized to 100 at the beginning of the sample. (Adapted from Phillips, Wu and Yu 2011).**



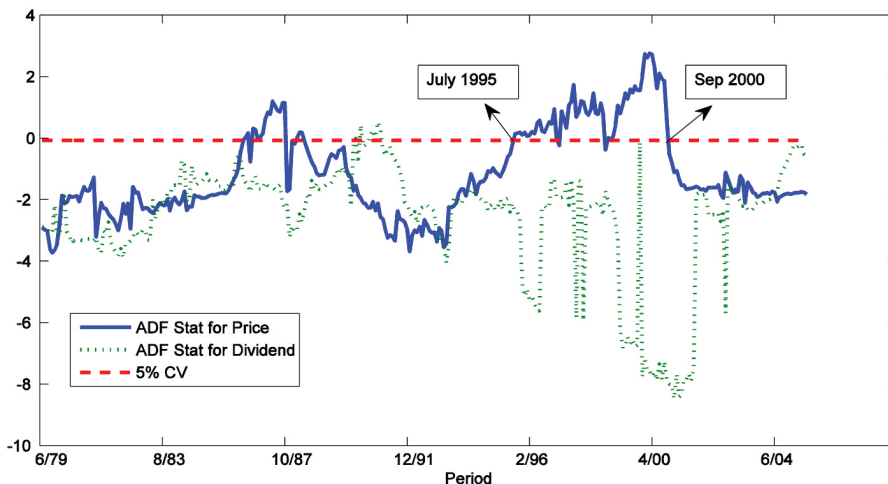
irrational exuberance is escalating asset values? How too might we distinguish between a long-term upward drift in stock prices and such exuberance? Such slow drifts are expected – they represent the long run return from investing in stocks as a risky asset – but they are usually imperceptible and undetectable over short periods of time because their magnitude is swamped by noisy volatility. Figure 54.2 shows that with the Nasdaq data something much more dramatic than a small drift was going on over a short time frame in the 1990s. Greenspan’s speech was given in December 1996, by which time the graphic shows that there had been some escalation in prices. The first econometric question is how to define irrational exuberance. The second is how to detect it when it is occurring and the third is whether it can be anticipated. In effect, in December 1996 was Greenspan speaking on the basis of empirical evidence? Did the data at that point in time support his concerns over market exuberance?

It is unclear from Greenspan’s speech whether the Fed had conducted any empirical research analysing the data and assessing evidence for exuberance. Given its substantial team of researchers, massive data archives, and expertise in empirics, it seems likely that some empirical analysis had been attempted. However, at that time (1996) there were no *ex ante* econometric tests for financial bubbles. In recent work Phillips, Wu and Yu (2011) show that by using recursive calculations of right sided unit root tests it is possible to distinguish submartingale

(exuberant or mildly explosive) behaviour from martingale behaviour soon after the change in behaviour occurs. These right sided unit root tests are econometric tests for the emergence of a bubble in the data. With this approach it is possible to date stamp the emergence of exuberance and the termination or collapse of the bubble. No methods are currently available to determine the peak of a bubble.

Figure 54.3 shows the results of one of these recursive tests applied to the Nasdaq asset prices and dividends graphed in Figure 54.2. The test used here is a simple ADF unit root test with a 5 percent size. The direction of the test is not against stationarity on the left tail, as the ADF test is commonly used, but on the right tail against explosive (submartingale) alternatives. The test is conducted recursively, so that the calculated statistic provides an observation by observation measure of exuberance in the financial market. When the trajectory of the statistic hits the critical level (obtained from the limit theory of the test statistic under the null hypothesis of unit root or martingale behaviour), the crossing time determines the origination of the financial bubble. As seen in Figure 54.3, empirical application of this test dates the emergence of financial exuberance or mildly explosive market behaviour in Nasdaq prices to June 1995, some 18 months prior to Greenspan's statement about irrational exuberance. Thus, empirical evidence supports the view that Greenspan's remark had evidential basis

**Figure 54.3: Time Series of the ADF t-statistic for the log real Nasdaq prices and log real Nasdaq dividends from April 1976 to June 2005. (Adapted from Phillips, Wu and Yu 2011)**



even though this type of anticipative test was unavailable at that time. Similarly, when the time series of recursive calculations falls below the critical value, the crossing time determines the termination of the bubble. Figure 54.3 shows the termination of the Nasdaq price bubble as September 2000, at which point there is a return to normal martingale-like behaviour. Throughout the period of the bubble in the 1990s there is, by contrast, no evidence of ballooning in dividend fundamentals, confirming that Nasdaq asset prices diverged from fundamentals over 1995–2000.

The econometric methodology in this empirical exercise involves the simple reduced form autoregressive model

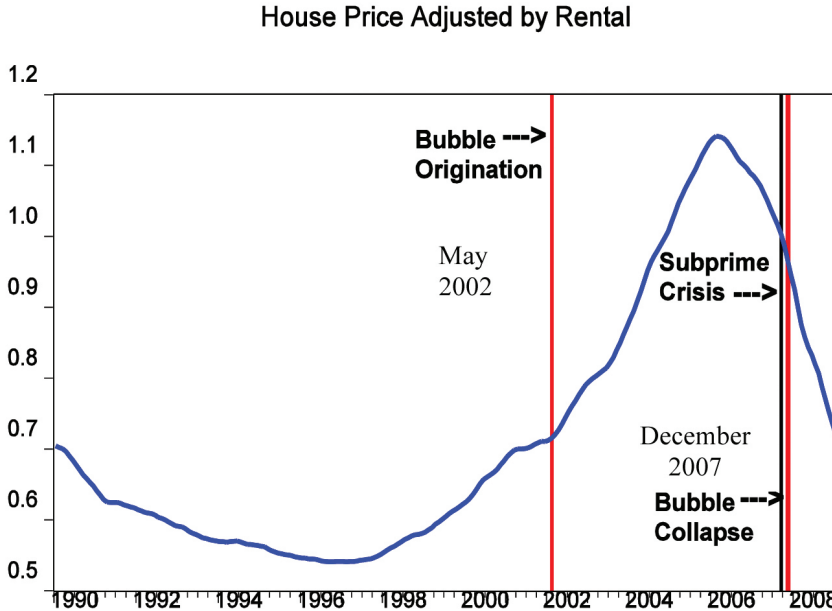
$$X_t = X_{t-1}1\{t < \tau_e\} + \delta_n X_{t-1}1\{\tau_e \leq t \leq \tau_f\} + \left(\sum_{k=1+\tau_f}^t \varepsilon_k + X_{\tau_f}^*\right)1\{t > \tau_f\} + \varepsilon_t 1\{t \leq \tau_f\}$$

where allowance is made for structural change in the autoregressive coefficient. The time series  $X_t$  follows a unit root autoregression with innovation  $\varepsilon_t$  over period  $t < \tau_e$ , which transforms into a mildly explosive<sup>9</sup> time series over the period  $\tau_e \leq t \leq \tau_f$  (with autoregressive coefficient  $\delta_n = 1 + c/k_n > 1$  where  $k_n$  tends to infinity slower than the sample size  $n$ ), and then reverts to a unit root autoregression for  $t > \tau_f$  from some re-initialization  $X^*$  that may be related to the level of  $X_t$  prior to the origination of the bubble. This simple model has two structural breaks that capture the transition to and from a mildly explosive process which characterise the emergence of a bubble and its subsequent collapse. This model is readily extended to accommodate further transitions that might occur during the sample period if multiple bubble episodes were present in the data. Methodology for detecting multiple bubbles is now available using a rolling window version of the recursive tests just described (see Phillips, Shi and Yu 2012).

A central advantage of the autoregressive structure in comparison with more complex time series models is that all of the energy in distinguishing the martingale and submartingale behaviour is concentrated in the autoregressive coefficient which produces a powerful statistical test. Unlike left sided unit root tests against stationary alternatives which are well known to lack power, right

9 The concept of a mildly explosive time series and the associated asymptotics for this type of process were developed in Phillips and Magdalinos (2007a, b).

**Figure 54.4: Time series plot of the US monthly real house price index over January 1990 to January 2009 adjusted by the rental price. The estimated bubble origination and collapse dates are shown, together with the August 2007 commencement date of the subprime crisis (Adapted from Phillips and Yu 2011)**



sided tests are very sensitive to explosive departures from the null and this remains so for models with weakly dependent innovations.

In order to ensure a consistent dating algorithm, we arrange for the size of the test to go to zero as the sample size tends to infinity. The critical value of the test then passes to infinity, ensuring that there are no false positives asymptotically and leading to consistent determination of the bubble origination and termination dates. Various modifications of this test procedure are possible to enhance its performance in detection and avoid unnecessary warning alerts when the statistic crosses the threshold for a very short period of time in relation to sample size.<sup>10</sup>

Figure 54.4 shows the results of a further application of this detection procedure by Phillips and Yu (2011) to US rental-adjusted real house prices

<sup>10</sup> Technically, this adjustment can be achieved by factoring into the critical value a slowly varying function of the sample size.



based on the Case – Shiller composite 10 index (sourced from Shiller’s website) standardized by the CPI. As shown in Figure 54.4, a significant bubble is found by the recursive test during the early part of the 2000s. The estimate of the bubble origination date is May 2002, which strongly supports the position taken by Baker (2002) who claimed that there was a housing bubble at that time, well before other commentators. The dating mechanism shows that the bubble collapsed in December 2007, soon after the subprime crisis erupted. The bubble is analysed by these methods in Phillips and Yu (2011) in the context of the broader timeline of the global financial crisis of 2007–2008 and its aftermath. This study also developed tests of the transmission of exuberance across markets that included housing, commodities (oil) and asset backed commercial paper, finding that there were contagion effects across these financial markets.

## Conclusion

One of the recent contributions of econometrics has been the development of tools for studying trends and bubbles. Both phenomena take us away from the regular world of stationary processes into the broad, complex universe of nonstationary time series. Important to the progress that has been made, this work acknowledges salient features of economic and financial reality – that trends have stochastic elements and that bubbles do occur. Accordingly research has fostered new techniques to evaluate trending mechanisms and distinguish among random wandering behaviour, trend stationarity, breaking trend behaviour, and the mildly explosive processes that underlie bubble phenomena. We now have the capability to evaluate nonstationarity in terms of the memory characteristics displayed by the time series and explore potential relationships between variables that embody long range dependence. Many of these elements are relevant in empirical work with trending data such as the climate data discussed in this lecture. In that context, it quickly becomes apparent that trends are poorly understood in relation to both underlying theory and econometric methodology. Without improvements in both theory and methodology, empirical work is simply little more than a glorified version of running a line through a set of points.

Complex models are sometimes needed to provide sufficient detail for empirical research to be useful. But simple econometric models, like simple

economic theories, have powerful advantages of focusing attention on key features of interest. In studying bubble phenomena, this principle is well illustrated by a mildly explosive autoregression which captures the key distinguishing characteristic of exuberance and thereby enables powerful new methods of bubble detection. That technology provides a date stamping methodology for use in empirical research and gives policy makers an early warning diagnostic to alert them to changes in financial markets. While further research on theory models and econometric methodology is needed, the methods we have developed are now being used by central bank surveillance teams in many countries. One positive externality of the global financial crisis is that there is now intensive professional interest in this area and much ongoing research that covers theory, econometrics, and empirics of financial bubbles.

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