EMPIRICAL ESSAYS ON STOCK MARKET BUBBLES

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Declaration

I confirm that the contents of this thesis are my original research work and have not been presented or accepted in any previous application for a degree. The overall word length is within the prescribed limit as advised by my school and all sources are fully referenced and acknowledged.

Ge Yu

Abstract

This thesis carries out a series of empirical investigations into the nature and evolutionary process of asset bubbles in global stock markets. It also provides insight into the issue of market predictability with the consideration of price bubbles in the US, and how those results might inspire policymakers to prevent future bubbles.

We start by reviewing the rational bubble theories which are used for modelling bubble process and discuss the rationale of the relevant testing methods for discovering bubbles. Overall, three main testing procedures are selected in Chapter 3 with the purpose of concluding whether bubbles exist in the global stock markets. Eventually, we confirm the presence of bubbles globally, and provide clear dates for each bubble's origination and collapse.

The bubble dates obtained provide a timeline for stock market exuberance, and their overlapping periods suggest that bubbles can migrate between countries. However, there has been very little research on this latter issue. Therefore, in Chapter 4 we undertake a large-scale empirical analysis to investigate the bubble transmission mechanism. Our vector autoregressive (VAR) and volatility results confirm that for some countries a contagion–effect exists, leading to bubble migration between countries.

Finally, in Chapter 5, we are particularly interested in whether empirical results on the predictability of stock market data by the dividend-price ratio is affected by the presence of a bubble, and by borrowing Campbell-Shiller's model but adding selected monetary variables, we further assess the forecasting performance of common monetary policy indictors in predicting the movement of price-dividend ratios in both bubble and non-bubble periods.

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Chapter 1 Introduction

The phenomenon of the stock market bubble has long been present in economic history. In the 1720s, the South Sea Bubble occurred: the price of the British South Sea Company increased to its highest value of £1000 from £130 within six months, followed by an extraordinary collapse to its original level in only another half a year. The DotCom Bubble, which happened more recently in the 1990s, led to an amazing surge in all major equity indices; however, its subsequent collapse destroyed the public's belief of a 'new economy'. The remark quoted by Greenspan (December 5, 1996) offered a phrase 'irrational exuberance' to describe this irregular expansion in the stock market. However, it seems that history has not been learned. In recent years, the 2008 global financial crisis occurred, originally triggered by the real estate bubble in the US. It is considered to be the worst financial crisis since the Great Depression in the 1930s. The Dow Jones Industrial Average (DJIA) stock market index dropped by more than 50% over a period of 17 months, which is similar to a 54.7% fall in the Great Depression, but then a total drop of 89% over the following 16 months.[1] The crisis rapidly spread into the UK, Euro Zone and a few developing countries, resulting in declines in the majority of stock indices. 'Between 40 and 45 percent of the world's wealth has been destroyed in little less than a year and a half', said by Stephen Schwarzman (March 11, 2009) which provides a vivid image for that disaster stamped deeply in the financial history.[2] The speed of destroying wealth within such a short period of time severely influences the stability of national financial system, and it is highly possible that bubbles contagiously move between markets to magnify their impact on global markets. Donald Kohn, the Federal Reserve Board Vice Chairman, has warned the policymakers that 'they should deepen their understanding about how to combat speculative bubbles to reduce the chances of another financial crisis'. Such alert calls for the research on financial turbulence.

The recent episodes of bubble provide new context for empirical research, and policymakers urgently require studies focused on fiscal, monetary, and regulatory policies in order to maintain financial stability within both booming and crisis periods. Potential questions

[1] Kawamoto, Dawn (March 2, 2009). 'Dow Jones decline rate mimics Great Depression, Business Tech-CNET News'. Available at: http://www.cnet.com/news/dow-jones-decline-rate-mimics-great-depression/.

[2] Schwarzman, S. (2009). Available at: http://www.reuters.com/article/us-blackstone-idUSTRE52966Z20090311.

beyond these immediate policy issues are closely related to both discovery and analysis into bubbles. Therefore, understanding their nature is of fundamental importance in order to assist practitioners to gain deeper insight about bubbles' origin and its evolutionary process. It is these issues that shape the objective of present thesis.

1.1 Motivations and Objectives of the Thesis

In this thesis, we address several problems in relation to stock market exuberance, particularly its nature and the evolutionary process of bubbles.

We begin with the discovery of stock price bubbles in the global stock markets. Historical evidence shows that asset prices can exceed their fundamental values. Great examples include the earliest South Sea boom (known as the very first exuberance), the Japanese real estate market boom (in the 1980s), and the well-known Dotcom market boom (starts from 1990 to the early of 2000). Economic professions attribute those episodes to asset bubbles, and many of them believe that bubbles would have a significant impact on market performance. For example, Shiller (2000) seeks to discover the attitude changes in bubble expectations and investor confidence, and how these changes bring potential impact on the behaviour of markets. Furthermore, Cooper, Dimitrov, and Rau (2001) study the reaction of market participants in relation to any new information announced during the exuberance period, especially for the announcement of corporate name changes to Internet-related Dotcom names. Other works such as Ritter and Welch (2002), Ofek and Richardson (2002), Lamont and Thaler (2003), and Cunado, GilAlana, and Gracia (2005) also investigate issues about how bubbles affect the performance of different markets, and finally, they claim that asset prices will be crucially affected through different channels within the turmoil periods. Since that massive upward and downward price movement critically influence the market stability, detecting explosive behaviour becomes one of the major concerns for market surveillance. However, a practical issue involves the assessment of what is 'excessive'. Many economists believe that task to be impossible, and it is imprudent to seek to prevent asset price bubbles. Then how can policymakers implement policies to offset a bubble when they are unable to define whether one exists in market?

One contribution that econometric techniques can offer is to define the entire bubble evolutionary process by using explicit quantitative measures. In chapters 2 and 3, we introduce and apply a series of econometric techniques on our unique global data to prove our hypothesis, that financial bubble is a general phenomenon across international markets. By implementing recursive testing procedures, we clearly reject conclusions reached by Diba and Grossman (1988) and Evans (1991), who argue that there is no bubble in the market; alternatively, we provide significant evidence that indeed, bubbles are widely existed. In fact, we confirm not only massive market bubbles in the US, but also extending findings to other regions such as the Europe and Asia, showing that bubbles are present in those areas, particularly for those periods when publics failed to recognize asset price bubbles. It is worth to note that Phillips, Shi and Yu (2015a, b; PSY hereafter) mechanisms have superior testing power as a real-time detection algorithm considering its better performance when our data are filled in.

The discussion in chapter 3 is the initial step of understanding stock price bubbles. To gain a deeper insight, we take one step further in chapter 4, where we extensively discuss the linkage between bubbles and financial contagion with the purpose of analyzing the bubble transmission mechanism. We initially propose a series of hypotheses to answer the question of how bubble moves between markets; to prove them, we use the data and testing results obtained in chapter 3, and utilize a unique testing framework including both vector autoregressive (VAR) and multivariate GARCH models. On one hand, VAR models with bubble indicators (dummies) are estimated to see how conditional-mean linkages between different stock markets differ over the bubble and non-bubble periods. One important feature is that we employ the data on the first difference of price-dividend ratio (i.e., the price-dividend ratio returns) rather than using the conventional price return with the consideration of linking the concept of bubble with contagion–effect. On the other hand, using the price-dividend ratio returns, we also investigate the volatility spillovers across the bubble and non-bubble periods by employing multivariate GARCH models.

The results from our analysis are interesting and potentially important. Firstly, for those indices which periods of explosive behavior are identified, their starting and ending dates strongly suggest that bubbles do move from one to another. Secondly, our VAR results provide convincing evidence for bubble transmission process: the impact of bubbles on financial contagion contains a characteristic of selection bias, that the bubble originated in some of the equity markets are more likely to have significant impact on correlations than the others. Finally, both of VAR and AG–DCC results show the evidence to support our hypothesis of contagion–effect, which helps to interpret the bubble movement. In contrast to Longstaff (2010) and many others, our results suggest that bubble transmission can occur when the bubbles are at an early stage, rather than at a later stage after the bubbles have burst. We envisage that our findings will be of interest to investors operating globally with investment horizons that span periods over which stock market bubbles might exist, and to central banks and financial regulators to help them identify priority countries as they attempt to combat the potential risk raised by exuberance.

Chapter 4 generally analyzes the bubble based on the global perspective and addresses the issue of bubble transmission. Then in Chapter 5, by adopting both monthly and weekly data, we attempt to reach a variety of research objectives. The whole chapter has been divided into two parts. In the first part, we are particularly interested in whether empirical results on the predictability of stock market data by the dividend-price ratio is affected by the presence of a bubble, whilst in the second part, by borrowing Campbell-Shiller's model but adding selected monetary variables, we aim to provide answers to the questions of whether monetary variables have the predictability to price-dividend ratio in both bubble and non-bubble periods.

Our results are intriguing. The results of monthly data without considering bubbles show that the 'stylized fact' commonly accepted in the literature only works during the period starting from 1950 to now, while to the period up to the end of Second World War, the opposite predictability pattern characterizes the US stock market: returns are unpredictable but dividend growth is predictable by the dividend-price ratio. Furthermore, by adding bubble indicator in the testing regression, we provide several important remarks: (1) for the period from 1871 to 1949, bubbles may have a negative impact on the predictability of dividend yield to dividend growth, (2) for the post Second World War period, it seems that bubbles do have a positive impact on the predictive power of dividend-price ratio to both return and dividend growth. In particular, for dividend growth, the dividend-price ratio now has predictive power with a 'wrong' (positive) slope parameter in the bubble period while according to the theory, the slope parameter for dividend growth should always be negative, not positive, and (3) government bond spread has a better performance in predicting returns than Baa-Aaa spread either in bubble or non-bubble periods; however, situation has reversed for dividend growth: corporate spread has taken over the position and now gains better predictability in both periods.

In the second part of Chapter 5, we fill the gap by studying the forecasting performance of several financial and monetary variables. Differing from previous works, the application of weekly data rather than monthly, provides better understanding for causality dynamics in both non-bubble and bubble periods. Overall, in the non-bubble periods, we reject the Campbell-Shiller's model under any assumptions regarding determinants of equilibrium expected returns, and we find significant differences in predictive power of monetary variables to price-dividend ratio when we split our sample into sub-samples. In the bubble period, rolling regressions are adopted, seeking to observe the performance of monetary policy in terms of dis-inflating the bubble. Our evidence empirically suggests that the higher growth rate in effective federal funds rate does not follow the expectation of policymakers to reduce the size of a bubble; alternatively, result of government bond spread, that the higher growth rate in spread leads to the lower growth rate in price-dividend ratio, implies that it can be adopted as a better target monitored by policymakers when working against bubble growth.

Taken all together, the present thesis contributes to the literature in the following aspects. First, our work adds to the growing literature which are focused on detection and studying bubble's nature. Previous works typically focus on just a small number of stock markets (very often, just the US stock market). Our analysis of bubbles is much broader, using data for 47 stock markets. Specifically, by comparing the testing power between PWY and PSY strategies, we provide empirical conclusion for the selection of testing and date-stamping mechanisms in real-time cases. Second, by adopting a unique testing framework that consists of both return and volatility analyses, we find that bubbles move among global stock markets may due to increased linkages after the bubble emerges, which directly corresponds to the concept of contagion–effect. In particular, results obtained from multivariate GARCH models provide an opportunity of having a deeper knowledge for correlation dynamics inside the bubble periods; by using this information, market participants are able to react quicker (maximize their portfolio return whilst reducing the relevant risk) in response to the global shocks. Finally, in chapter 5, we relax the condition which has been largely adopted in the literature when estimating the predictability of dividend yield to stock market data and provide convincing evidence that a price bubble *does* have a critical impact on forecasting ability of dividend yield. Moreover, by using our unique weekly monetary datasets, we further assess the performance of monetary policy over the past three decades but particularly within the period of exuberance.

1.2 Thesis Layout

The rest of the thesis is organized as follows. In chapters 2 and 3, we introduce the testing and date-stamping strategies that are applied throughout the entire work, and exhibit their respective results. Chapter 4 discusses the potential linkage between different equity markets conditional on the presence of bubbles, whilst in Chapter 5, we critically discuss the stock market predictability and performance of monetary policy against bubbles, and Chapter 6 concludes.

Chapter 2 Literature Reviews on Bubble Testing

2.1 Introduction

The asset bubble is an important puzzle in financial history – important because its extraordinary potentials for disruption; puzzle because it rejects conventional notion of efficiency. The term 'bubble' firstly becomes popular at the time of Mississippi Bubble in European stock markets that came to an end in 1720, a time is often mentioned as one of craziness, and since the bubble has characterized many crashes, they have received substantial attention by academics. Theoretical studies on bubbles in the stock market include Blanchard and Watson (1982), Evans (1989), and Olivier (2000), among many others; and empirical studies include Shiller (1981), Diba and Grossman (1988), and Evans (1991), Phillips, et al (2011) and Phillips, et al (2015). Most of them support the view that bubble is a common phenomenon not only in stock market, but also in other markets such as the real-estate market (see West, 1987; Phillips, et al, 2011; and Engsted, Hviid and Pedersen, 2015). However, fewer of works believe there is no bubble in markets but only short blips. For example, Diba and Grossman (1988) and Dezhbakhsh and Demirgukunt (1990) obtained results supporting the point that stock prices do not contain bubbles. Furthermore, rather than attributing the deviation between stock price and fundamental to bubbles, a number of theoretical studies reckon that such mismatch is due to the inappropriate measurement of market fundamental so that they are not reflect observed asset prices. For example, Santoni (1987) has discussed the reason behind the appearance of bull market in 1924 and 1982, that whether it is attribute to speculative bubbles or economic fundamentals. He found no evidence that changes in stock prices are attributed to speculative bubbles; rather, the data suggests that stock prices follow a random walk which is consistent with efficient market hypothesis. There are other theoretical studies focused on the real impact of speculative bubbles on the economy. The conventional view is that speculation in the market reduces long-run growth and welfare. For instance, Grossman and Yanagawa (1993) point out that bubbles, when they exist, will lower the growth of the economy and reduce the welfare of all generations born after the bubble appears. However, more recent study by Olivier (2000) challenges this point of view while he shows that the real impact of bubbles crucially depends on the type of asset that is being speculated on and speculative bubbles in equity markets can be growth-enhancing. Although bubbles have been critically discussed, the majority of works define the crisis and non-crisis periods mainly based on subjective judgement, while the type of mechanism, which can explicitly record the bubbles' origination and collapse dates, has been lacking.

To avoid this issue, economic professions have endeavored to develop methods that can reliably stamp bubble dates by adopting explicit quantitative measures. Several attempts have been made in the literature. Those empirical testing mechanisms are based on a common definition of bubbles, that bubble condition arises when asset prices significantly exceed their fundamental values. One important characteristic of such phenomenon is that during both run-up and run-down periods, assets encounter high volume trading in which the direction of change is broadly anticipated, and it is distinct from normal market conditions where asset price follows a near martingale. This distinction is recognized and discussed by Blanchard and Watson (1982) and Diba and Grossman (1988), and it is this deviation that provides an econometric mechanism to recognize the bubble. Importantly, above studies mainly represent one type of bubble named as rational bubble, whilst there are still other strands of bubble that have been critically discussed in the literature, such as the irrational bubble. The rational bubble model is fully consistent with rational expectations and constant expected returns. Blanchard and Watson (1982) use a discrete-time setting with homogenous rational investors and infinite periods, and specify the price of an asset with two components: a fundamental value and a rational bubble term. The fundamental value is determined by the asset's discounted cash flow and the rational bubble term is independent of the asset's fundamental and fluctuates over time on its own. As long as it grows on average at the same rate as the discount rate, it is consistent with the rational expectation. They also allow the bubble term to burst with a constant probability in a period. If it does not burst, it grows at a rate higher than the discount rate.

Alternatively, the irrational bubble generally stands for another type of bubble: a mean-reverting deviation from the fundamentals of assets caused by irrational behavior of agents in the form of a feedback trading strategy that agents buy when the stock prices have already risen with a hope of further rises, and sell when the prices have started to fall for a fear that they will drop more. Statman (1988) identifies irrational behavior of investors as: (i) trading for both cognitive and emotional reasons; (ii) trading because they reckon that they have information when they have nothing but noise; and (iii) trading because it brings personal satisfaction. Over the years, economists have developed different theories to explain how investor behavior will drive the asset price bubbles, the major ones consist of the behavior-based feedback loop theory, the agency-based bubble theory, and the heterogeneous beliefs theory.

The behavioral finance literature suggests that various behavioral biases, such as representativeness bias and self-attribution bias, can lead individual investors to positively feedback to past returns. For example, Barberis, Shleifer, and Vishny (1998) review the previous two families of pervasive regularities: (i) under-reaction of stock prices to news, such as earnings announcements; (ii) over-reaction of stock prices to a series of good or bad news. They further propose a parsimonious model of investor sentiment about how investors form beliefs. The model is supported by experimental evidence on both failures of individual judgement under uncertainty and trading patterns of investors in experimental situations. Particularly, their specification is also consistent with the important behavioral heuristic known as representativeness, which shows a tendency of experimental subjects to view events on a typical or representative of some specific classes and ignore the laws of probability in the process. Taking the stock market for instance, investors might classify some stocks as growth stocks based on the recent historical statistics, ignoring the likelihood that there are very few companies that just keep growing. Similarly, Daniel, Hirshleifer, and Subrahmanyam (1998) propose a theory of securities market under- and over-reactions based on two well-known psychological biases: investor overconfidence for the precision of private information; and self-attribution bias, which causes asymmetric shifts in investors' confidence as a function of their investment outcomes. They show that the overconfidence implies negative long-lag autocorrelations, excess volatility, and when managerial actions are correlated with stock mis-pricing, public-event-based return predictability. Biased self-attribution adds positive short-lag autocorrelations "momentum", short-run earning "drift", but negative correlations between future returns and long-term past stock market and accounting performance. Shiller (2015) advocates a feedback loop theory: the initial price increases caused by certain precipitating factors lead to more price increases as the effects of the initial price increases feedback into yet higher prices through increased investor demand. This second round of price increase feeds back again into a third round, and then into a fourth round, and so on. Therefore, the initial impact of the precipitating factors is amplified into much larger price increases than the factors they would have suggested. When the bubble bursts, the feedback loop goes into reverse, which leads to the dramatic drop in asset price.

Furthermore, Allen and Gorton (1993) and Allen and Gale (2000) develop models to show that bubbles can arise from agency problems of institutions. Allen and Gorton (1993) demonstrate that in the presence of asymmetric information and contract frictions between portfolio managers and investors who hire them, managers bear limited downside risk because the worst that can happen to them is that they get fired. As a result, they have incentives to seek risk at the expense of their investors. Allen and Gale (2000) analyze the risk-shifting incentive of investors who use borrowed money from banks to invest in relative risky assets and who can avoid losses in low payoff states by defaulting on the loan. In both models, assets can be traded at prices that do not reflect their fundamentals and those incentive issues are highly relevant in understanding the recent financial crisis in 2008.

Another theory, developed by Harrison and Kreps (1978), studies bubbles based on the heterogeneous beliefs. Generally, in a market where agents disagree about an asset's fundamental and short sales are constrained, an asset owner is willing to pay a price higher than his own expectation of the asset's fundamental since the owner expects to resell the asset to a future optimist at an even higher price. Such speculative behavior leads to a bubble component in asset prices. This approach does not require a substantial amount of aggregate belief distortions to generate a significant price bubble. Alternatively, the bubble term establishes on the fluctuations of investors' heterogeneous beliefs. Even when investors' aggregate beliefs are unbiased, intensive fluctuations of their heterogeneous beliefs can lead to a significant price bubble through frenzied trading. A more recent study by Scheinkman and Xiong (2003) proposes a model of asset trading based on the perspective of heterogeneous beliefs generated by agents' overconfidence, providing explicit links between the trading cost, information, behavior of equilibrium prices, and trading volume. They show that, although Tobin's tax can substantially reduce speculative trading when transaction costs are small, it has a limited impact on the size of the bubble or on price volatility.

Both rational and irrational bubbles would lead to asset price fluctuations, which bring the market with the instability and inefficiency. In general, when the asset prices diverge from economic fundamentals, bubbles will emerge because of the excessive optimism with the respect to fundamentals. In some cases, market participants may recognize an excess in asset prices compared with economic fundamentals, and they might find an arbitrage opportunity and believe that the excess will continue. However, in the long-run, it is relatively impossible that such rise in asset price is sustainable beyond the scale of economic fundamentals and thus, when asset price is inflated by a bubble, there will be an inevitable collapse.

In this thesis, our research objective does not focus on arguments between different bubble types; instead, we stick to the theoretical framework of rational bubble and implements a series of econometric methods to confirm explosive behaviors in the global markets. In the following sections, we will review several theoretical and empirical studies to obtain a deeper understanding in our research background.

2.2 Literature on Main Methods

2.2.1 Theoretical Background

A simple model normally applied to interpret movements in corporate common stock price indices asserts that real stock prices equal to the present value of rationally expected forecasted future real dividends discounted by a constant real required discount rate. This valuation model is often employed by economists and market analysts as a plausible model to evaluate the movement of aggregate market indices and is treated as providing a reasonable explanation to tell public what accounts for an unexpected surge in stock price indices. Shiller (1981) refers to this model as the 'efficient market model', although it should be recognized that this title has also been given to other models. However, it has often been claimed that stock price indices appear to be too 'volatile', that is, they could not truly be attributed to the release of new information since some invisible factors magnify the impact of subsequent events. The failure of applying the model in real case raises the question of why the movement of dividends is not 'volatile' enough to cause major change in asset prices. Shiller attempts to answer this question by exploring the volatility difference between real asset prices (market price but taking away the time effect) and rational prices (obtained through dividends by applying the efficient market model).

According to the simple efficient market model, the real price $p_t = E_t(p_t^*)$, where p_t is the real market price and p_t^* represents the present value of actual subsequent real detrended dividends, expresses that p_t is the optimal forecast of p_t^*. One can define the forecast error as $\mu_t = p_t - p_t^*$, where p_t is the mathematical expectation conditional on all information available at time t of p_t^*.A fundamental principal is that the forecast error μ_t should be uncorrelated with the forecast, which means that the covariance between μ_t and p_t must be zero. If the principle from elementary statistics is used, then an easy version of inequality will be obtained,

$$\sigma(p) \leq \sigma(p^*) \tag{2.1}$$

This inequity is violated dramatically by the data collected by Shiller (1981) through Standard and Poor's (S&P) Composite Stock Price Index and modified Dow Jones Industrial Average (DJIA), as the standard deviation of real price is much bigger than the standard deviation of rational prices p^* from the data. To clarify some theoretical questions that arise in relation to inequality (2.1), the efficient market model has been developed and then, some similar inequalities are derived by putting limits on standard deviation of the innovation in price and standard deviation of the change in price.

$$(\Delta p + d_{-1} - \bar{r}p_{-1}) \leq \frac{\sigma(d)}{\sqrt{\overline{r_2}}}, \tag{2.2}$$

$$\sigma(\Delta p) \leq \sigma(d)/\sqrt{\overline{r_2}}\,. \tag{2.3}$$

where p is the real detrended stock price index, d is the real detrended dividend, $\overline{r_2}$ is the two-period real discount rate for detrend series; $\overline{r_2} = (1+\bar{r})^2 - 1$, $\bar{r}$ is the real discount rate for detrended series. After applying S&P and DJIA datasets on inequalities (2.1), (2.2) and (2.3), it shows that none of the inequalities are satisfied. Therefore, final empirical findings conclude that over the past century, volatility appears to be far too high to be attributed to new information about future real dividends if uncertainty about future dividends is defined by the sample variance of real dividends around their long-term exponential growth path.

The initial debate for bubble phenomenon concentrates on discovering empirical evidence;

however, without establishing a theoretical model, it is insufficient to explain those anomalies. Blanchard and Watson (1982) therefore study on bubble's nature by discussing its rationality and further with the application of two tests (runs and tail tests) to statistically discover bubbles in the market. They begin with Shiller's model: the standard 'Efficient Market Model' with no arbitrage condition,

$$R_t = \frac{P_{t+1} - P_t + X_t}{P_t},$$

with $E(P_{t+1}|\Omega_t) = r$, or equivalently,

$$E(P_{t+1}|\Omega_t) - P_t + X_t = rP_t, \tag{2.4}$$

where P_t is the price of the asset; X_t is the direct return and the paper referred to X_t as the 'dividend'. R_t is therefore the rate of return on holding the assets, which consists of the capital gain and dividend return. Ω_t is the information set at time *t*, assumed common to all agents and therefore this condition states that the expected rate of return on the asset is equal to the interest rate *r*, which is assumed to be a constant. Given the assumption of rational expectations and that agents do not forget, equation (2.4) can be solved recursively forward. Thus, the following P_t^* is a solution to equation (2.4),

$$P_t^* = \sum_{i=0}^{\infty} \theta^{i+1} E(X_{t+i}|\Omega_t) \qquad \theta \equiv (1+r)^{-1} < 1, \tag{2.5}$$

where P_t^* is the present value of expected dividends and hence can be called as market fundamental value for corresponding asset. However, P_t^* is not the only solution to (2.4), any P_t of the following form is a solution as well,

$$P_t = \sum_{i=0}^{\infty} \theta^{i+1} E(X_{t+i}|\Omega_t) + C_t = P_t^* + C_t \text{ ,} with \tag{2.6}$$

$$E(C_{t+1}|\Omega_t) = \theta^{-1} C_t.$$

where C_t represents the deviation that the difference between market price and market fundamental value, namely the 'bubble' term. Notice that such deviation appears without breaking the arbitrage condition. Since $\theta^{-1} > 1$, the deviation C_t must be expected to grow over time.

Blanchard and Watson (1982) is the first to provide a precise definition of 'bubble' through the traditional 'Efficient Market Model' without violating assumption of being rational. They then define the notion of ‘bubble’ by giving several examples, which satisfy the equation (2.6). The simplest is that of a deterministic ‘bubble’, which follows the form of $C_t = C_0\theta^{-t}$. In this case, the higher capital gain leads to the higher price and the deviations grow exponentially. To be rational, such an increase in the price must continue forever, making such a deterministic bubble implausible. Another example absorbs the notion that bubble has a certain probability to burst,

$$C_t = (\pi\theta)^{-1}C_{t-1} + \mu_t, with\ probability\ \pi;$$

$$C_t = \mu_t, with\ probability\ 1 - \pi. \tag{2.7}$$

where $E(\mu_t\ |\Omega_{t-1}) = 0$.

This type of bubble will remain with probability π, or collapse, with probability $1 - \pi$. While the bubble exists, the actual average is higher than *r* to compensate for the risk of a burst. The probability that the bubble collapse may well be a function of the duration of the bubble, or a function of the variation between price and market fundamentals.

The second part of their study empirically investigates the possibility of discovering bubbles without using subjective method but econometric approach. They suggest that applying runs and tail tests is based on the idea that the bubble component of the price innovation appears likely to have both runs and fat tail distributions. To clarify, a run refers to a sequence of realisations of a random variable with the same sign. If bubbles grow for a period and then collapse, the innovation in the bubble will likely to be of the same sign when the bubble continues, then reverse sign when a collapse occurs. The runs for the bubble innovation seem to be longer than a purely random sequence, making the total number of runs over the sample smaller. Collapse will generate large outliers; hence the distribution of innovations will have fat tails. The study of Blanchard and Watson (1982) greatly contributes to the literature by exploring the theoretical background; however, the limits of their two empirical tests have also been emphasized. Testing results could not be used to interpret whether bubbles exist in markets since the very high coefficient of kurtosis may suggest either very leptokurtic market fundamentals or the existence of bubbles.

Several studies follow the step of Blanchard and Watson (1982). Many real-world examples have been given to prove that their promoted process is realistic, but the lack of empirical testing mechanism forces the research into a dilemma, since academics cannot precisely justify whether bubbles exist in the market. With such motivation, Diba and Grossman (1988) follow the idea of rational bubble and suggest to apply stationary and cointegration tests. They propose these tests initially on equity price with a model which assumes a constant discount rate, but allows unobservable variables to have an impact on market fundamentals and permits different valuations of expected capital gains and expected dividends. Their theoretical model is similar to the one described by Blanchard and Watson (1982), which consists a single equation that relates the current stock price to the present value of future expected stock price and dividend payments and to an unobservable variable,

$$P_t = (1 + r)^{-1} E_t(P_{t+1} + \alpha d_{t+1} + \mu_{t+1}); \tag{2.8}$$

Equation 2.8 is a first-order expectational difference equation. Since the eigenvalue, $1 + r$, is greater than 1, the forward-looking solution for the stock price involves a convergent sum, as long as $E_t(\alpha d_{t+j} + \mu_{t+j})$ does not grow with j at a geometric rate equal to or greater than $1 + r$. This forward-looking solution, denoted by F_t and referred to as the market-fundamentals component of the stock price, is

$$F_t = \sum_{j=1}^{\infty} (1 + r)^{-j} E_t(\alpha d_{t+j} + \mu_{t+j}), \tag{2.9}$$

where P_t represents the stock price at date *t*. *r* is a constant real interest rate that is appropriate for discounting rate. d_{t+1} is the real before-tax dividend paid to the owner of the stock between dates t and $t + 1$. μ_{t+1} is a variable that market participants either observe or construct whereas the research does not observe. The general solution to equation (2.8) is,

$$P_t = B_t + F_t \; where \; E_t B_{t+1} = (1 + r) B_t, \tag{2.10}$$

where B_t is defined as the bubble term and F_t is the market fundamental component. They also review and extend theoretical arguments for ruling out rational stock-price bubbles on the basis of the non-negativity of stock prices and optimizing decisions of asset holders. All these theoretical analyses are complemented in the empirical analysis employed in this thesis.

Their empirical framework considers the market fundamental component given by equation (2.9), and assumes that the process of generating d_t is nonstationary in levels, but the first difference of d_t and μ_t are stationary. Then theoretically, if bubble does not exist, stock prices would be non-stationary in levels whilst stationary in first difference. However, if stock prices contain a bubble part, then differencing stock prices a finite number of times would not produce a stationary process. They apply the right-tailed Dickey-Fuller tests for unit roots in the autoregressive representations of real stock prices, dividends, and their first difference. The estimated OLS regression for each time-series x_t is,

$$x_t = \mu + \gamma t + \rho x_{t-1} + \sum_{i=1}^{k} \beta_i \Delta x_{t-i} + residual, \tag{2.11}$$

The regression sets k equal to four and, thereby, allows Δx to follow an AR (4) process. The application of cointegration test employs the similar idea of stationary test. Rearranging terms in equation (2.9) and substituting the resulting expression for F_t into equation (2.10),

$$P_t - \alpha r^{-1} d_t = B_t + \alpha r^{-1}\left[\sum_{j=1}^{\infty}(1+r)^{1-j} E_t \Delta d_{t+j}\right] + \sum_{j=1}^{\infty}(1+r)^{-j} E_t \mu_{t+j}. \tag{2.12}$$

If the unobservable variable in market fundamentals is stationary in levels and if dividends are first-difference stationary, with assumption that bubble does not exist, then the sum given by equation (2.12) should be stationary. Thus, although P_t and d_t are nonstationary, their linear combination $P_t - \alpha r^{-1} d_t$ is stationary.

The empirical findings report that stock prices and dividends are non-stationary before differencing but stationary in first difference. Cointegration tests produce somewhat mixed results whereas this may due to the low power in tests. Overall, Diba and Grossman (1988) concludes that no bubbles in equity prices. However, this approach is soon criticized by Evans (1991), due to its limitation in testing one specific type of bubble. Evans (1991) reviews the bubble process with an emphasis on the following class of rational bubble, which is always positive but periodically collapsing,

$$B_{t+1} = (1+r) B_t \mu_{t+1} \; if \; B_t \leq \alpha,$$

$$B_{t+1} = [\delta + \pi^{-1}(1+r)\theta_{t+1} \times (B_t - (1+r)^{-1}\delta]\mu_{t+1} \; if B_t > \alpha.$$

where δ and α are positive parameters with $0 < \delta < (1+r)\alpha$; μ_{t+1} is an exogenous independently and identically distributed positive random variable with $E_t \mu_{t+1} = 1$; and θ_{t+1} is an exogenous independently and identically distributed Bernoulli process which takes the value 1 with probability π and 0 with probability $1 - \pi$, where $0 < \pi \leq 1$. In fact, Diba and Grossman (1988) already recognize the possibility of bubbles that can ‘periodically shrink' and West (1987) provides examples of strictly positive bubbles which are periodically collapsing. This process is straightforward that if $B_t \leq \alpha$, the bubbles will grow at a rate of $(1+r)$, but if $B_t > \alpha$, the bubble shifts into a phase in which it will grow at a faster average rate of $\pi^{-1}(1+r)$, as long as the grow continues until the bubble collapse, with probability $1-\pi$ every period. When the bubble bursts, it drops to a mean value of δ, then the process restarts. Also, by varying the value of δ, α, and π, one can change the frequency with which bubbles shift into another phase, the average length of time before collapse, and the scale of the bubble. To demonstrate the failure of unit-root and cointegration tests on testing this type of bubble, 200 simulated non-negative bubbles have been produced using the periodically collapsing model. Final results confirm that the periodically collapsing bubbles are not detectable by implementing standard unit-root tests, because the test cannot determine whether price is more explosive or less stationary than dividends. There are still some studies discussing the possibility of applying different methods to examine the existence of bubbles in markets; however, no one is proved to be better than the others while widely applied in real world until one recent study by Phillips, Wu and Yu (2011, PWY hereafter), which introduces another mechanism that provides a reliable way to date-stamp the origination and collapse of bubbles. The testing framework is based on recursive testing procedures, involving the recursive implementation of a right-side unit root and a sup-test to discover the explosive behaviour in order to overcome the pitfalls mentioned by Evans (1991).

2.2.2 PWY Strategy

Philips, et al. (2011) apply the augmented Dickey-Fuller test for a unit root against the alternative of an explosive root. That is, for each time series x_t (log stock price or log dividend), they estimate the following autoregressive specification by least squares,

$$x_t = \mu_x + \delta x_{t-1} + \sum_{J=1}^{J} \phi_J \, \Delta x_{t-j} + \varepsilon_{x,t}, \varepsilon_{x,t} \sim NID(0, \sigma_x^2). \tag{2.13}$$

for some given value of the lag parameter *J*, where *NID* is independent and normal distribution. In their empirical application, they use the significant tests to decide the lag order *J*, as suggested by Campbell and Perron (1991). The null hypothesis expresses $H_0: \delta = 1$ and the right-tailed alternative hypothesis is $H_1: \delta > 1$. In the PWY test, to improve the discriminatory power of the ADF test in detecting periodically collapsing bubbles, a recursive testing procedure is employed. In the forward recursive regressions, equation (2.13) is estimated repeatedly forward, using subsets of the sample data with increasing number of observations at each pass. In particular, supposing the rolling window regression sample starts from the r_1^{th} fraction of the total sample T and ends at the r_2^{th} fraction of the sample, where $r_2 = r_1 + r_w$ and r_w is the (fractional) window size of the regression. In the sup-ADF (PWY) test, the window size r_w expands from r_0 to 1, so that r_0 is the smallest sample window width fraction (initializing computation) and 1 is the largest window fraction (the total sample size in the recursion). The starting point of r_1 is fixed at 0, so the ending point of each sample (r_2) equals r_w, and changes from r_0 to 1. Let the corresponding *t*-statistic be denoted ADF_r, and, therefore, ADF_1 represents the test statistic employing the full sample. Under the null hypothesis,

$$ADF_r \Rightarrow \frac{\int_0^r \widetilde{W} dW}{\left(\int_0^r \widetilde{W}^2\right)^{\frac{1}{2}}}, \tag{2.14}$$

and

$$sup_{r\in[r_0,1]}\, ADF_r \Rightarrow sup_{r\in[r_0,1]}\, \frac{\int_0^r \widetilde{W} dW}{\left(\int_0^r \widetilde{W}^2\right)^{\frac{1}{2}}}, \tag{2.15}$$

where W is the standard Brownian motion and $\widetilde{W}(r) = W(r) - \int_0^1 W$ is demeaned Brownian motion. Test for a unit root against explosiveness can be implemented by comparison of $sup_r ADF_r$ with the right tailed critical values from $sup_{r\in[r_0,1]} \int_0^r \widetilde{W}\, dW /$ $\left(\int_0^r \widetilde{W}^2\right)^{1/2}$. To record the origin and termination of the bubble, they match the time-series of the recursive test statistic ADF_r, with $r \in [r_0, 1]$, against the right tailed critical values of the asymptotic distribution of the standard Dickey-Fuller t-statistic,

$$\hat{r}_e = inf_{r\in[r_0,1]} \left\{r: ADF_r > cv_r^{\beta_T}\right\},$$

$$\hat{r}_f = inf_{r\in[\hat{r}_e+\log(T)/T,1]} \left\{r: ADF_r < cv_r^{\beta_T}\right\}, \tag{2.16}$$

where $\hat{r}_e$ is the estimation of origination date and $\hat{r}_f$ is the estimation of collapsing dates. $cv_r^{\beta_T}$ is the right-sided critical value of ADF_r corresponding to a significance level of β_n.

Note that the dating strategy assumes that the duration of the bubble must exceed $\log(T)$, but here we set the condition that the duration of the bubble must exceed 2 months to exclude short-lived blips in the fitted autoregressive coefficient.

They finally confirm the existence of bubbles in NASDAQ and record their origination and collapse dates. However, their most recent study illustrates how the testing procedures and dating methods are influenced by the case of multiple bubbles and may fail to be consistent; thus, they develop a generalized version of the sup-ADF to solve this issue and introduce a new strategy to date-stamp bubbles.

2.2.3 PSY Strategy

The generalized sup-ADF (PSY) test still borrows the idea of repeatedly running the *ADF* testing regression on a sample sequence and the number of observations in each regression is $T_w = \lfloor Tr_w \rfloor$, where $\lfloor . \rfloor$ is the floor function (giving the integer part of the argument). However, the sample sequence is broader than that of the sup-ADF test and by only varying the ending point of regression r_2 from r_0 to 1, the generalized sup-ADF test also allows the starting point r_1 to vary within a feasible range from 0 to $r_2 - r_0$. The generalized sup-ADF testing statistic is defined as the largest *ADF* statistic over the feasible ranges of r_1 and r_2 and testing statistic is denoted by $GSADF(r_0)$,

$$GSADF(r_0) = \sup_{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}} \{ADF_{r_1}^{r_2}\}. \tag{2.17}$$

When the regression model consists an intercept and the null hypothesis a random walk with an asymptotically negligible drift, the limit distribution of the generalized sup-ADF testing statistic is,

$$\sup_{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}} \left\{ \frac{\frac{1}{2} r_w [W(r_2)^2 - W(r_1)^2 - r_w] - \int_{r_1}^{r_2} W(r)dr [W(r_2) - W(r_1)]}{r_w^{1/2} \left\{ r_w \int_{r_1}^{r_2} W(r)^2 dr - \left[\int_{r_1}^{r_2} W(r) dr \right]^2 \right\}^{1/2}} \right\}. \tag{2.18}$$

The proof of this proposition is similar to that of PWY and details are given in the technical paper PSY (2015b). The usual limit distribution of conventional *ADF* statistic is a special case of equation (2.18) with $r_1 = 0$ and $r_2 = r_w = 1$, while the limit distribution of the sup-ADF statistic is another special case of equation (2.18) where $r_1 = 0$ and $r_2 = r_w \in [r_0, 1]$. Besides, similar to the sup-ADF statistic, the asymptotic generalised sup-ADF distribution depends on the smallest window size of r_0. In our work, r_0 is chosen based on the total number of observations and we ensure that the size of r_0 is large enough to ensure adequate observations for initial estimation.

Their study also suggests a new date-stamping method to record the origination and termination dates of bubbles. Our work performs the same dating mechanism that uses a sup-ADF test on a backward expanding sample sequence, where the ending points of the samples are fixed at r_2, but the starting point changes from 0 to $r_2 - r_0$. The backward sup-ADF statistic is defined as the sup value of the *ADF* statistic sequence,

$$BSADF_{r_2}(r_0) = sup_{r_1 \in [0, r_2 - r_0]}\{BADF_{r_1}^{r_2}\}. \tag{2.19}$$

The origination date of a bubble is the first observation whose backward sup-ADF statistic exceeds its critical value and the collapsing date of a bubble is the first observation after $\lfloor T\hat{r}_e \rfloor + \delta \log(T)$ whose backward sup-ADF statistic falls below its critical value. It is assumed that the duration of the bubble exceeds $\delta \log(T)$, where δ is a frequency dependent parameter. However, in our work, we still set that the duration of the bubble must exceed 2 months, the same with the restriction applied in our PWY (2011). The origination and termination points of a bubble are estimated by following equations:

$$\hat{r}_e = inf_{r_2 \in [r_0, 1]}\left\{r_2 \colon BSADF_{r_2}(r_0) > scv_{r_2}^{\beta_T}\right\},$$

$$\hat{r}_f = inf_{r_2 \in [\hat{r}_e + \delta \log(T)/T, 1]}\left\{r_2 \colon BSADF_{r_2}(r_0) < scv_{r_2}^{\beta_T}\right\}, \tag{2.20}$$

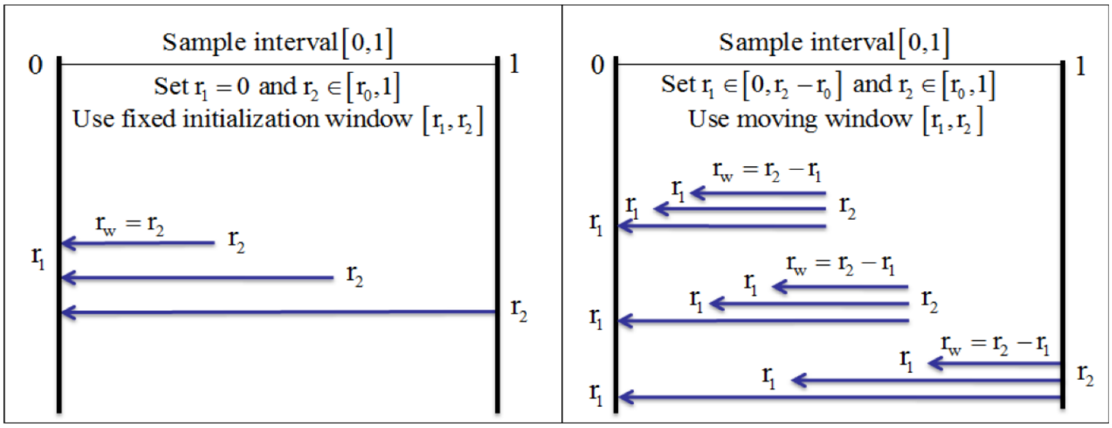
where $scv_{r_2}^{\beta_T}$ is the level of significance for a critical value of the sup-ADF statistic based on $\lfloor Tr_2 \rfloor$ observations. Analogously, the significance level β_T depends on the sample size T and it goes to zero as the sample size approaches infinity.

Overall, the sup-ADF test is based on repeated implementation of the ADF test for each testing window. The generalized sup-ADF test implements the backward sup-ADF test repeatedly for each testing window and makes inferences based on the sup value of the backward sup-ADF statistics sequence. Hence, the sup-ADF and generalized sup-ADF statistics can respectively be written as,

$$SADF(r_0) = sup_{r_2 \in [r_0, 1]}\{ADF_{r_2}\},$$

$$GSADF(r_0) = sup_{r_2 \in [r_0,1]}\{BSADF_{r_2}(r_0)\}.$$

Thus, the PWY date-stamping strategy corresponds to the sup-ADF test and the new strategy corresponds to the generalized sup-ADF test. The essential features of the two testing mechanisms are shown in the figure below, and further illustration of differences in hypotheses between PWY and PSY are presented in Appendix 2.1.



(a) The SADF test

(b) The GSADF test

2.3 Other Testing Mechanism

Other statistics also have been suggested to test for a structural break in the autoregressive parameter, while a majority of studies focus on a change from a non-stationary regime to a stationary regime or vice versa. Here we consider a few of them suggested in the literature. All testing procedures are based on the time-varying AR (1) model,

$$y_t = \rho_t y_{t-1} + \varepsilon_t,$$

where ε_t is a white noise process with $\mathrm{E}(\varepsilon_t) = 0$, $\mathrm{E}(\varepsilon_t^2) = \sigma^2$, and $y_0 = c < \infty$, in real casese, y_t can represent any time series in stock markets.

2.3.1 The Bhargava Statistic

To test the null hypothesis of a random walk against explosive alternatives, Bhargava (1986) proposed the locally most powerful invariant testing statistic,

$$B_0^* = \frac{\sum_{t=1}^{T}(y_t - y_{t-1})^2}{\sum_{t-1}^{T}(y_t - y_0)^2}.$$

Since Bhargava's (1986) alternative test statistic does not incorporate a structural break, Homm and Breitung (2012) introduce a modified version of the inverted test statistic,

$$B_\tau = \frac{1}{T-[\tau T]}\left(\frac{\sum_{t=[\tau T]+1}^{T}(y_t - y_{t-1})^2}{\sum_{[\tau T]+1}^{T}(y_t - y_{[\tau T]})^2}\right)^{-1} = \frac{1}{s_\tau^2 (T-[\tau T])^2}\sum_{t=[\tau T]+1}^{T}\left(y_t - y_{[\tau T]}\right)^2,$$

where $s_\tau^2 (T-[\tau T])^{-1}\sum_{t=[\tau T]+1}^{T}\left(y_t - y_{[\tau T]}\right)^2$ (T is the size of sample, τ is the fractional window size of the regression). To test for a change from *I* (1) to an explosive process in the interval $\tau \in [0,1-\tau_0]$, where $\tau_0 \in (0, 0.5)$, they consider the statistic,

$$supB(\tau_0) = Sup_{\tau\in[0,1-\tau_0]}B_\tau.$$

Note that this testing statistic is inverse to the original Bhargava (1986), thus the test rejects the null hypothesis for large values of $supB(\tau_0)$.

The asymptotic distribution of the test statistic under null hypothesis is not derived in the literature but simply follows from the continuous mapping theorem as,

$$supB(\tau_0) \Rightarrow sup_{\tau\in[0,1-\tau_0]}\left\{(1-\tau)^{-2}\int_\tau^1 (W(r)-W(\tau))^2 dr\right\},$$

where $\Rightarrow$ denotes weak convergence and W denotes standard Brownian motion on the interval [0, 1].

2.3.2 The Busetti-Taylor Statistic

Busetti and Taylor (2004) propose a statistic for testing the hypothesis that a time series is stationary against the alternative that it switches from a stationary to an *I* (1) process at an unknown breakpoint. Homm and Breitung (2012) also modify the statistic to test the null against the alternative,

$$supBT(\tau_0) = sup_{\tau\in[0,1-\tau_0]}BT_\tau, where\ BT_\tau = \frac{1}{s_0^2 (T-[\tau T])^2}\sum_{t=[\tau T]+1}^{T}(y_T - y_{t-1})^2.$$

The asymptotic distribution of $supBT$ can be derived,

$$sup_{\tau\in[0,1-\tau_0]}BT_\tau \Rightarrow\ BT_{\tau\in[0,1-\tau_0]}\left\{(1-\tau)^{-2}\int_\tau^1 W(1-r)^2\, dr\right\}.$$

2.3.3 The Kim Statistic

Another statistic for testing the *I* (0) null hypothesis against a change from *I* (0) to *I* (1) is proposed by Kim (2000). To transfer the statistic to the bubble testing framework, Homm and Breitung (2012) apply modifications similar to above testing procedures, which yield the following statistic,

$$supK(\tau_0) = sup_{\tau\in[0,1-\tau_0]}K_\tau \ with \ K_\tau = \frac{(T-[\tau T])^{-2}\sum_{t=[\tau T]+1}^{T}(y_t - y_{[\tau T]})^2}{[\tau T]^{-2}\sum_{t=1}^{[\tau T]}(y_t - y_0)^2}.$$

The test rejects for large values of $supK(\tau_0)$. The statistic K_τ is computed over the interval $[\tau_0, 1-\tau_0]$. It can be interpreted as the scaled ratio of the sum of squared forecast errors. The predication is obtained based on the assumption that the time series follows a random walk. y_0 is used to forecast $y_1, \ldots, y_{[\tau T]}$ $(denominator)$ and $y_{[\tau T]}$ is the forecast of $y_{[\tau T]+1}, \ldots$, y_T. The limiting distribution is obtained as,

$$sup_{\tau\in[0,1-\tau_0]}K_\tau \Rightarrow sup_{\tau\in[0,1-\tau_0]}\left\{\left(\frac{\tau}{1-\tau}\right)^2 \frac{\int_\tau^1 (W(r)-W(\tau))^2 dr}{\int_0^\tau W(r)^2 dr}\right\}.$$

2.3.4 A Chow-Type Unit Root Statistic for a Structural Break

The information that y_t is a random walk for $t = 1, \ldots, [\tau^* T]$ under both null hypothesis and alternative hypothesis can be incorporated in the test procedure by applying a Chow test for a structural break in the autoregressive parameter. Under the assumption that $\rho_t = 1$ for $t = 1, \ldots, [\tau T]$ and $\rho_t - 1 = \delta > 0$ for $t = [\tau T] + 1, \ldots, T,$ the model can be written as,

$$\Delta y_t = \delta\big(y_{t-1}\ \mathbb{1}\{t > [\tau T]\}\big) + \varepsilon_t,$$

where $\mathbb{1}\{\cdot\}$ is an indicator function that equals 1 when the statement in braces is true and equals 0, otherwise. Correspondingly, the null hypothesis of interest is $H_0: \delta = 0,$ which is tested against the alternative $H_0: \delta > 0.$ It is easy to see that the regression *t*-statistic for this null hypothesis is,

$$DFC_\tau = \frac{\sum_{[\tau T]+1}^{T} \Delta y y_{t-1}}{\tilde{\sigma_\tau}\sqrt{\sum_{t=[\tau T]+1}^{T} y_{t-1}^2}},$$

where

$$\tilde{\sigma}_\tau^2 = \frac{1}{T-2}\sum_{t=2}^{T}\big(\Delta y_t - \tilde{\delta}_\tau y_{t-1}\ \mathbb{1}\{t > [\tau T]\}\big)^2,$$

and $\tilde{\delta}_\tau$ denotes the OLS estimator of δ in the equation of Δy_t. The Chow-type *DF* statistic to test for a change from *I* (1) to explosive in the interval $\tau \in [0,1-\tau_0]$ can be written as,

$$supDFC(\tau_0) = sup_{\tau\in[0,1-\tau_0]}DFC_\tau.$$

The test rejects the large values of $supDFC(\tau_0)$. In fact, the test corresponds to a one-sided version of the sup-Wald test of Andrews (1993), where the supremum is taken over a sequence of *Wald* statistics. The asymptotic limit distribution is obtained as,

$$supDFC(\tau_0) \Rightarrow sup_{\tau\in[0,1-\tau_0]} \frac{\int_\tau^1 W(r)dW(r)}{\sqrt{\int_\tau^1 W(r)^2 dr}}.$$

Note that the limiting distribution is analogous to the one of PWY (2011). In finite samples, the null distribution for both the sup-DFC and the sup-DF statistics are affected by the initial value of the time series if the series is not demeaned or detrended. To overcome this issue, Homm and Breitung (2012) suggest computing the test statistics by using modified series $\{\tilde{y}_t\}_{t=1}^T$ with $\tilde{y}_t = y_t - y_0$.

2.3.5 Real-time Monitoring

The test statistics considered above are designed to detect speculative bubbles within a fixed historical dataset. As argued by Chu, Stinchcombe, and White (1996), such test may be highly misleading when applied to an increasing sample. This is due to the fact that structural break tests are constructed as a single test procedure, that is, the size of the test is controlled, provided that the sample is fixed, and the test procedure is applied only once to the same dataset but unable to discover whether the evidence for a speculative bubble has strengthened. To illustrate the problem involved, assume that an investor is interested to find out whether the stock price is subject to a speculative bubble. Applying above tests to a sample of the last 100 trading days, he or she is not able to reject the null hypothesis of no speculative bubbles. If the stock price continues to increase in the subsequent days, the investor is interested to find out whether the evidence of a speculative bubble has strengthened. However, repeating the tests for structural breaks when new observations become available eventually leads to a severe over-rejection of the null hypothesis due to multiple application of statistical tests.

Another practical issue is that the tests assume a single structural break from a random-walk regime to an explosive process. The monitoring procedures suggested below are able to sidestep the problems due to multiple breaks. Two typical monitoring procedures are broadly discussed in the literature: fluctuation monitoring procedure (FLUC) and cumulative sum monitoring procedure (CUSUM). As FLUC (recursive ADF strategy) has been briefly introduced, then here we just present CUSUM strategy. The CUSUM detector is denoted by $C_{r_0}^r$ and defined as,

$$C_{r_0}^r = \frac{1}{\hat{\sigma}_r}\sum_{j=\lfloor Tr_0\rfloor+1}^{\lfloor Tr\rfloor}\Delta y_j \ with\ \hat{\sigma}_r^2 = (\lfloor Tr\rfloor - 1)^{-1}\sum_{j=1}^{\lfloor Tr\rfloor}\left(\Delta y_j - \hat{\mu}_r\right)^2,$$

where $\lfloor Tr_0\rfloor$ is the training sample (r_0 represents the initial fraction); $\lfloor Tr\rfloor$ is the monitoring observation (r is the fractional size of monitoring sample); $\hat{\mu}_r$ is the mean of $\{\Delta y_1, \dots, \Delta y_{\lfloor Tr\rfloor}\}$, and $\mathrm{r} > r_0$. Under the null hypothesis of a pure random walk, it has the following asymptotic property,

$$\lim_{T\to\infty} P\left\{C_{r_0}^r > c_r\sqrt{\lfloor Tr\rfloor}\ for\ some\ r \in (r_0, 1]\right\} \le \frac{1}{2}\exp(-\kappa_\alpha/2),$$

where $c_r = \sqrt{\kappa_\alpha + \log(r/r_0)}$. For example, when the significance level $\alpha = 0.05$, $\kappa_{0.05}$ equals 4.6.

2.4 Testing Power Comparison

The testing procedures presented so far fall into two general categories: recursive *DF t*-statistics (FLUC) and tests based on scaled sum of forecast errors (CUSUM). In the literature on tests for a change in persistence, the varieties of Kim's (2000) and Busetti and Taylor's (2004) tests are also available to test the bubble scenario; however, Homm and Breitung (2012) prove that those procedures perform worse than the sup-DFC (recursive ADF test) in terms of power through the application of Monte Carlo simulations. They conclude that the PWY (2011) test is much more robust than all other tests in detecting periodically collapsing bubbles of the Evans (1991)'s type. Moreover, its dating strategy also works satisfactorily against other recursive procedures and is exclusively effective as a real-time bubble detection algorithm. Similarly, in the study of PSY (2015a, b), they confirm that the recursive ADF date-stamping strategy enjoys better power in discovering bubble episodes than the strategy of CUSUM.

Chapter 3 The Discovery of Bubbles in Global Markets

3.1 Introduction

It is now widely accepted that for both developed and developing countries, stock market bubbles have occurred in the past and it is likely that they will occur in the future. Furthermore, experience has shown that stock market bubbles pose a serious threat to global financial stability and to sustained economic growth. Formally, an asset price bubble is said to exist if the price of asset significantly exceeds the value that is justified by relevant fundamentals (its intrinsic value). The presence of stock market bubbles is characterized by explosive growth in the relevant stock market index. Those bubbles can be rational if they grow in expectation at the explosive rate 1+ r, where r is the rate of interest used by investors for discounting capital gains. Alternatively, a stock market bubble might exist that does not satisfy this criterion and is entirely driven by investors' irrational exuberance. Empirical observations suggest that stock market bubbles do not continue forever and that they eventually burst to a lower level, before growing again at some point in the future. In recent years, there has been a renewed interest in statistically modeling and detecting asset price bubbles. Recent research in econometrics has led to the development of robust methods for detecting the existence of asset price bubbles and for date-stamping the periods of growth and collapse.

The previous literature concentrates on the empirical discovery of bubbles in the US stock market but ignoring the importance of detecting bubbles in a broader context. The increasing interdependence of financial markets reveals the possibility that the presence of exuberance in one market might cause the behavioural change in another. Therefore, examination for the existence of the bubble is treated as the first step for investigating the nature and evolutionary process of the bubble in global markets. In addition, if the history has a habit of repeating itself, the study can be served as useful alerting mechanism for market participants as well as policymakers to build up counter measures to defend bubbles. The present chapter responds to those needs by providing the empirical examination in international markets where more than 40 stock markets are selected. Three econometric methods are applied: the conventional ADF test, PWY and PSY strategies. In general, we have found significant evidence of explosiveness for stock markets in Australia, Hong Kong, India, South Korea, and Thailand in Asia; Finland, France, Germany, Greece, Ireland, Netherlands, Spain, Sweden, Turkey, and the UK in Europe; Canada, the US, and Mexico in North and South America, and South Africa in Africa. For those indices where periods of explosive autoregressive behavior are identified, suggesting that asset price bubbles exist, the start and end dates obtained using the PWY and PSY date-stamping procedures strongly suggest that for some stock markets, bubbles do transfer to other stock markets. By showing those results, our study adds to the growing literature on the discovery of bubbles. Comparing with previous works which typically focus on just a small number of stock markets (very often, just the US), our analysis falls in to a much broader horizon, using data for 47 stock markets. Surprisingly, our results suggest that the contagion–effect might be functional when we observe several bubbles in the global markets during the same period, and such effect will be discussed further in the Chapter 4.

The plan of this chapter is as follows. The next section will have a brief introduction for model specifications. Section 3.3 describes the data. Section 3.4 presents our results and Section 3.5 concludes.

3.2 Models and Specifications

The starting point in the analysis of financial bubble is the asset pricing model,

$$P_t = \sum_{i=0}^{\infty} \left(\frac{1}{1+r_f}\right)^i E_t(D_{t+i} + U_{t+i}) + B_t, \tag{3.1}$$

$$\text{with } E_t(B_{t+1}) = (1+r_f)B_t,$$

where P_t is the price series in stock market. D_t is the payoff received from the asset (i.e. dividend); r_f is the risk-free interest rate; U_t represents the unobservable fundamentals; B_t stands for the bubble component. Here, follow Blanchard and Watson (1982), Diba and Grossman (1988), Phillips et al (2011) and Phillips et al (2015), we adopt the broader definition of bubble where it contains both run-up (boom) and run-down (crisis) periods. The quantity $p_t^f = P_t - B_t$ is often called the market fundamental and B_t satisfies the sub-martingale property. In the absence of bubbles ($B_t = 0$), the degree of non-stationarity is controlled by the character of dividend series and unobservable fundamentals. Basically, if bubble does not exist, stock prices are non-stationary in levels whilst stationary in first difference. However, if stock prices contain a bubble, then the process, differencing stock prices a finite number of times would not produce a stationary process. For example, if D_t is an I (1) process and U_t is either I (0) process, then the asset price is at most an I (1) process. On the other hand, given $E_t(B_{t+1}) = (1 + r_f)B_t$, asset prices will be explosive in the presence of bubbles. Therefore, when unobservable fundamentals are at most I (1) and D_t is stationary after differencing, empirical evidence of explosive behaviour in asset prices may be applied to conclude the existence of bubbles.

Equation (3.1) is not the only model used to interpret the bubble phenomena and there is continuing academic debate over how (or even why) to accommodate bubble term in asset pricing model and their relevance in empirical studies. For instance, Cochrane (2005) discusses an overlapping generation model that captures the interesting possibility of rational bubbles. Pastor and Veronesi (2006) explore the bubble phenomena in the NASDAQ market, arguing that the NASDAQ valuations are not necessarily irrational ex-ante as uncertainty about average profitability which increases the fundamental value of a firm, is abnormally high in the late 1990s. They reckon that the high uncertainty seems plausible because it matches not only the high level but also the high volatility of NASDAQ stock prices at that time. Although debate still exists, academics reach a great consensus that bubbles start from pricing errors relative to market fundamentals, or in another situation, Phillips and Yu (2011) show that the temporary explosiveness in asset prices could be the consequence of changes in discount rate. No matter what its origins are, explosive or mildly explosive behaviour in asset price is a primary indicator of market exuberance and this time series feature subjects to econometric testing.

A common issue that arises in unit-root test is the specification of the model used for estimation purpose, not least because of its potential impact on appropriate asymptotic distribution and the critical values used in testing. Unit root testing is a well-known example where intercepts, deterministic trends, or trend breaks all materially impact the limit theory. PSY (2015b) discuss the impact of hypothesis formulation and model specification on right-tailed unit-root test and eventually suggest a null random walk process with asymptotically negligible drift to capture the mild drift in price processes that are often empirically realistic over long historical periods. The prototypical model of this type has the following weak intercept form,

$$y_t = dT^{-\eta} + \theta y_{t-1} + \varepsilon_t, \varepsilon_t \sim NID(0, \sigma^2), \theta = 1, \tag{3.2}$$

where y_t represents a time series of stock price. *d* is a constant; *T* is the sample size; the parameter η is a localizing coefficient that controls the magnitude of the intercept and drift as $T \longrightarrow \infty$. Solving equation (3.2) gives $y_t = d\frac{t}{T^\eta} + \sum_{j=1}^{t} \varepsilon_j + y_0$ revealing the deterministic drift $dt/_{T^\eta}$. When $\eta > 0$, the drift is small relative to a linear trend; when $\eta > \frac{1}{2}$, the standardized output $T^{-1/2}{}_{y_t}$ behaves asymptotically like a Brownian motion with drift which suits many macroeconomic and financial time series. The null specification (3.2) includes the pure random walk null of PWY (2011) as a special case when $\eta \longrightarrow \infty$ and the order of magnitude of y_t is then identical to that of a pure random walk. The model is normally complemented with transient dynamics in order to conduct tests for exuberance, just as in standard ADF unit root testing against stationarity.

Our study basically contains three testing mechanisms: (i) the right-tailed unit-root test, (ii) PWY Strategy, and (iii) PSY Strategy, and compares their testing power in real cases. For original right-tailed unit-root test, the following autoregressive specification by least squares is estimated,

$$x_t = \mu_x + \delta x_{t-1} + \sum_{j=1}^{J} \phi_J \, \Delta x_{t-j} + \varepsilon_{x,t}, \varepsilon_{x,t} \sim NID(0, \sigma_x^2),$$

for some given value of the lag *J*, where x_t represents time series for log stock price or log dividend. *NID* denotes independent and normal distribution. The null hypothesis is $H_0: \delta = 1$ and the right-tailed alternative hypothesis is $H_1: \delta > 1$.

The sup-ADF test follows the testing procedures discussed in PWY (2011), repeatedly estimating the augmented Dickey-Fuller testing regression with increasing number of observations at each pass. In particular, suppose that the rolling window regression sample starts from the r_1^{th} fraction of the total sample (*T*) and ends at the r_2^{th} fraction of the sample, where $r_2 = r_1 + r_w$ and r_w is the (fractional) window size of the regression. In the sup-ADF test, the window size r_w expands from r_0 to 1, so that r_0 is the smallest sample window width fraction (initializing computation) and 1 is the largest window fraction (the total sample size in the recursion). The starting point of r_1 of the sample sequence is fixed at 0, so the ending point of each sample (r_2) equals r_w, and changes from r_0 to 1. Let the corresponding *t*-statistic be denoted ADF_r, and, therefore, ADF_1 represents the test statistic employing the full sample. Under the null hypothesis,

$$ADF_r \Longrightarrow \frac{\int_0^r \widetilde{W} dW}{\left(\int_0^r \widetilde{W}^2\right)^{1/2}},$$

and

$$sup_{r\in[r_0,1]} ADF_r \Longrightarrow sup_{r\in[r_0,1]} \frac{\int_0^r \widetilde{W} dW}{\left(\int_0^r \widetilde{W}^2\right)^{1/2}},$$

where W is the standard Brownian motion and $\widetilde{W}(r) = W(r) - \int_0^1 W$ is demeaned Brownian motion. To test for a unit root against explosiveness, $sup_r\, ADF_r$ testing statistic needs to compare with the right-tailed critical values from $sup_{r\in[r_0,1]} \int_0^r \widetilde{W}\, dW/\left(\int_0^r \widetilde{W}^2\right)^{1/2}$.

As discussed in the Introduction, regulators and policymakers concerned with practical policy implementation need to assess whether real time data provide evidence of financial exuberance – specifically whether any particular observation belongs to a bubble phase in the overall trajectory. The sup-ADF test provides a valid date-stamping framework by matching the time series of the recursive testing statistics ADF_r (with $r \in [r_0, 1]$) against the right-tailed critical values for the asymptotic distribution of the standard ADF t-statistic (i.e. information embodied in $I_{\lfloor Tr\rfloor} = \{y_1, y_2, y_3, \dots, y_{\lfloor Tr\rfloor}\}$). Since it is possible that the data $I_{\lfloor Tr\rfloor}$ may include one or more collapsing bubble episodes, the ADF test, like earlier unit root/cointegration-based tests for bubbles (e.g., Diba and Grossman, 1988), may result in finding *pseudo stationary* behaviour. The strategy recommended here is to perform a backward sup ADF test on $I_{\lfloor Tr\rfloor}$, to improve identification accuracy. Particularly, if r_e is the origination date and r_f is the termination date of bubbles in the data, the estimates of these dates are,

$$\hat{r}_e = inf_{r\in[r_0,1]}\left\{r\colon ADF_r > cv_r^{\beta_T}\right\} and$$

$$\hat{r}_f = inf_{r \in [\hat{r}_e + \log(T)/T, 1]} \left\{ r: ADF_r < cv_r^{\beta_T} \right\},$$

where $cv_s^{\beta_T}$ is the right-side critical value of ADF statistic corresponding to a significance level of β_T. The current work sets the significant level at 5% and the shortest duration of bubble should be no less than two months.

The generalized sup-ADF test, the most recent recursive procedures for practical implementation of testing explosive behaviour in asset price, proposes a generalized version of the sup-ADF test. It allows both starting points and ending points of the testing pass to vary and the testing statistic is defined as the largest ADF statistic over the feasible ranges of r_1 and r_2, then,

$$GSADF(r_0) = \sup_{\substack{r_2 \in [r_0, 1] \\ r_1 \in [0, r_2 - r_0]}} \left\{ ADF_{r_1}^{r_2} \right\}.$$

The new date-stamping strategy makes inferences on the explosiveness of observations based on the backward sup-ADF statistics where

$$\hat{r}_e = inf_{r_2 \in [r_0, 1]} \left\{ r_2: BSADF_{r_2}(r_0) > scv_{r_2}^{\beta_T} \right\} \text{ and}$$

$$\hat{r}_f = inf_{r_2 \in [\hat{r}_e + \delta \log(T)/T, 1]} \left\{ r_2: BSADF_{r_2}(r_0) < scv_{r_2}^{\beta_T} \right\},$$

where $\hat{r}_e$ stands for the estimation of origination date and $\hat{r}_f$ is the estimation of collapsing date. The $scv_s^{\beta_T}$ is the level of significance for a critical value of the sup-ADF statistic based on $\lfloor Tr_2 \rfloor$ observations, where $\lfloor . \rfloor$ is the floor function (giving the integer part of the argument). Again, in the generalized sup-ADF dating strategy, all significance level is set to 5% and all bubble periods should last at least for two months. Here we see that one advantage of applying PWY and PSY date-stamping strategies is that both of them clearly define not only boom periods where stock prices keep rising, but also crisis periods where stock prices keep falling down. These two strategies make it possible to study the entire bubble evolutionary process containing both run-up and run-down periods instead of only focusing on one of them.

3.3 Data Collection

This study collects the long historical time-series market indices in over 40 stock markets. In general, the testing samples are collected from five regions on monthly basis: Asia (16, including 2 markets from Australasia), EU (20), the US, America excluding the US (5), and Africa (1). The monthly stock price and dividend data in the US consist of three major market indices: Dow Jones Industrial Average (DJIA), NASDAQ, and S&P 500. In particular, S&P 500 and its dividend sequence are collected from Robert Shiller's website, while DJIA and NASDAQ indices are obtained from DataStream.[3] The major local stock indices in Europe are collected in the UK, France, Germany, Norway, Netherlands, Switzerland, Russia, and so on. For Russia, FTSE Russia Dollar and FTSE Russia Ruble are both included in our testing sample, as the former contains much more observations. In addition, this study uses FTSE Euro First 80E index as an indicator of the whole EU markets, since it represents the 60 largest companies ranked by market capitalization in the FTSE Developed Europe Index and 20 additional companies selected for their size and sector representation. The Asian market proxies contain a majority of the local stock market indices, such as the Chinese A-Share index, Hong Kong Hang Seng index, and Korea SE KOSPI 200, etc. FTSE Bura Malaysia and FTSE Malaysia as well as FTSE Japan and Japan Tokmacap have been chosen as market proxies for Japan and Malaysia, respectively. Table 3.1 shows that all market index returns (except for the S&P 500 index) are collected from DataStream with the same ending date of December 2015 but various starting dates from January 1871 to June 2000.

<Table 3.1>

3.4 Empirical Application

3.4.1 The Conventional unit-root Testing Results

The first testing mechanism applied is the conventional right-tailed unit-root test. Instead of testing explosiveness in both index and dividend sequence, price-dividend ratio is employed to reflect asset prices in relation to fundamentals based on the pricing equation (3.1). Table 3.1 presents the testing results for each market. From Table 3.1, we observe that no testing results are significant at 10 percent level except for Greece. Greek price-dividend ratio is significant at 1 percent level as its ADF testing statistic is approximately 3.147, exceeding its 1 percent right-tailed ADF critical value (3.147 > 0.524) and indicating strong evidence that speculative

[3] The Data link for Robert Shiller's Website: http://www.econ.yale.edu/~shiller/data.htm.

bubble exists in Greek stock market. However, no evidence supports the hypothesis that explosive behaviour is present in other equity markets, particularly for those well-known exuberance episodes. For example, testing results of DJIA, S&P 500, and NASDAQ are –1.490, –1.489, and –1.734 respectively, and none of them are significant at 10 percent level. Similar to the US, no bubble phenomenon has been discovered in Japan, since two Japanese market indices have respective testing results of –1.322 (FTSE Japan) and –2.045 (Japan TOPIX), which are not significant at 10 percent level.

One potential concern of our ADF test results is that they may not reflect the truth, as Evan (1991) proves that periodically collapsing bubbles which are very realistic in the real world, are not detectable by using the conventional unit-root test because they appear to be stationary even though they are explosive in the relevant case. Therefore, to overcome this issue, two additional testing procedures are carried out and testing results are presented in the following sections.

3.4.2 The Sup-ADF and Generalized Sup-ADF Critical Values

Additional empirical analysis concerns with the solution of low testing power in traditional method, especially when multiple bubbles with periodically collapsing behaviour are present overtime. In this section, sup-ADF and generalized sup-ADF tests are applied for each of our sample. Lag order k of zero has been chosen in our mean testing equation, because PSY (2015a, b) prove that this measure can avoid size distortion and further improve the power of both sup-ADF and generalized sup-ADF tests. Critical values for these two tests are obtained from Monte Carlo simulation with 1,000 replications based on actual sample size. Table 3.2 display the critical values of sup-ADF and generalized sup-ADF critical values, where we use the US as an example.

<Table 3.2>

From Table 3.2, we can see that the critical values of generalized sup-ADF are normally larger than those of the sup-ADF values. As a case in point, for S&P 500, when the sample size T is 1,740 and window size equals 92, the 95 percent critical value of the generalized sup-ADF is 2.42 while that of the sup-ADF critical value is 1.55. Similarly, for NASDAQ, its generalized sup-ADF critical value is 2.26, which is bigger than its sup-ADF critical value of

1.502.

3.4.3 *The Sup-ADF Testing Results*

The last two columns in Table 3.1 present the sup-ADF and the generalized sup-ADF statistics in each sample market. The sup-ADF statistics (PWY) developed by Phillips et al. (2011) provide significant evidence of explosiveness in the following sample markets: Australia, Hong Kong, India, South Korea and Thailand in Asia; Finland, France, Germany, Greece, Ireland, Netherlands, Spain, Sweden, Turkey, and the UK in Europe; Canada and Mexico in America excluding the US, South Africa in Africa; and the US. Note that the testing results of three US market indices are all significant at the 1% level with sup-ADF statistics of 3.84 (p-value < 0.01; DJIA), 12.48 (p-value < 0.01; NASDAQ) and 3.443 (p-value < 0.01; S&P 500), consistently indicating strong evidence of bubble existence in the US stock market. However, the PWY testing statistics for Japan offer mixed results. Testing result obtained from the FTSE Japan is insignificant (–1.07; p-value > 0.10), suggesting no bubbles in the Japanese market; however, test result for the Japan TOPIX is highly significant at the 1% level (2.463; p-value < 0.01), providing substantial evidence for the presence of bubbles. This discrepancy could be due to the number of observations in FTSE Japan being smaller compared to the Japan TOPIX, which reduces the power of the sup-ADF test (the sample of FTSE Japan drops the first three years data of Japan TOPIX which tends to be very volatile and has significant impact on the results). After we controlling the size of Japan TOPIX (manually setting the sample size of Japan TOPIX being equal to FTSE Japan), the significant testing result of Japan TOPIX is gone (see in Table 3.1). We also run our test procedures on the FTSE Euro First 80E, which represents the overall European market. We find statistically significant results at the 1% level (2.376; p-value < 0.01), again offering evidence to support the existence of bubbles over the time period considered.

3.4.4 *The Generalized Sup-ADF Testing Results*

To ensure the robustness of our results, we apply the generalized sup-ADF test to our data. For a majority of stock markets considered, samples cover long-time intervals that have high possibility of containing multiple bubbles. The last column of Table 3.1 provides the PSY test results for each market, showing that explosive behavior is a common and widespread phenomenon in the global markets considered. For example, the results for all three US market indices are significant at the 1% level, showing strong evidence for sub-explosive periods in the US stock market. Similarly, for a majority of stock markets in the Europe, Asia, and America excluding the US, the PSY tests demonstrate the presence of bubbles. For instance, the generalized sup-ADF statistics of Belgium, Denmark, and Italy are 2.16 (p-value < 0.10), 2.119 (p-value < 0.10), and 2.037 (p-value < 0.10), respectively, significant at the 10% level.

Compared with the PWY, the PSY test suggests that more markets experience bubbles, highlighting the superior discriminatory power of this test statistic relative to the PWY when there are multiple bubbles. Taking Malaysia as an example, the Malaysia KLCI in Asia, its PSY testing statistic is significant at the 5% level (2.636; p-value < 0.05), while the PWY result shows statistically insignificance (0.193; p-value > 0.10). Moreover, some of the PSY testing statistics support bubble existence in stronger sense. For instance, the PSY statistic of Hong Kong is 3.522 (p-value < 0.01) is significant at the 1% level, but its PWY statistic of 1.776 (p-value < 0.05) is only significant at the 5% level. Although the sup-ADF and generalized sup-ADF testing statistics provide robust findings for bubble existence, another potential concern raises the question of how to locate the origin and collapse dates of those explosive episodes. Here in this chapter, we employ date-stamping strategies proposed by Phillips et al. (2011) and Phillips et al. (2015a, b) to record these dates.

3.4.5 The Sup-ADF Dating Results

Panel A of Table 3.3 reports the PWY date-stamping results for each of our sample market. It shows that for many markets, bubble periods appear to persist for months, or even years. For example, S&P 500 index has explosive sub-periods for quite long periods, e.g., from May 1879 to May 1880 and from July 1997 to June 2002 (Dotcom bubble). Similarly, the DJIA and NASDAQ indices are found to be explosive in the 1980s (e.g., 1983M03-1984M02 and 1986M02-1987M11 for DJIA; 1983M05-1984M06 and 1984M08-1990M04 for NASDAQ) and in the Dotcom bubble period (e.g., 1995M06-2000M12 for DJIA and 1993M09-2001M04 for NASDAQ). In the Europe and America excluding the US, dating results show explosive sub-periods in the 1980s and 1990s. For example, the UK has explosive periods from 1981 to

1987 and 1993 to 2002, whilst the periods for Canada is found to be explosive from 1983 to 1987 and 1993 to 2010. Note that our analysis also focuses on discovering bubbles for the whole European market, and we find explosive behavior from the middle of 1997 to the end of 2000. In the Asian markets, we date the explosive behavior as follows: South Korea (e.g., 1994M01-1995M01, 1999M04-1999M10, and 1999M11-2000M04), Thailand (e.g., 1986M10-1987M11, 1988M02-1988M11, 1989M01-1990M09, and 1998M11-2000M02), and Japan (e.g., 1986M06-1986M11, 1986M12-1987M12, 1988M03-1988M09, and 1988M12-1990M03). All PWY testing figures are presented in Figures 3.1.

<Table 3.3>

<Figures 3.1>

3.4.6 The Generalized Sup-ADF Dating Results

The Panel B of Table 3.3 provides the detailed starting and ending dates of the explosive regimes detected by the PSY strategy. For example, the exuberant sub-periods for the S&P 500 index include the late 19th century (e.g., 1879M07-1880M05), the early 20th century (e.g., 1917M09-1918M05), the Great Depression (e.g., 1928M09-1929M11), the post-war bubbles in the 1950s (e.g., 1955M04-1956M08 and 1958M11-1959M09), the black Monday in October 1987 (e.g., 1987M01-1987M10), and the Dotcom bubble period (e.g., 1995M12-1996M07 and 1996M09-2001M09). For the DJIA and NASDAQ indices we obtain approximately the same results in the 1980s and 1990s, while for the NASDAQ index, we also date-stamp the period of the subprime mortgage crisis in 2008 (e.g., 2008M10-2009M03). From this point, we see that indeed, the PSY date-stamping strategy is able to identify more bubble periods (either run-up or run-down periods) than PWY. This is consistent with the limit theory provided by Phillips, et al (2015), that under the hypothesis of multiple bubbles (the key outcomes are revealed from the case of single bubble episode) and rate condition of $\frac{1}{cv^{\beta_T}} + \frac{cv^{\beta_T}}{T^{1/2}\delta_T^{r-r_e}} \to 0, as\ T \to \infty$ (cv^{β_T} is the critical value *T* is the sample size, $r - r_e$ represents the remaining dates after the first bubble occurred, $\delta_T = 1 + cT^{-\alpha}$ with $c > 0$ and $\alpha \in (0,1)$), the ADF detector provides consistent estimates $(\hat{r}_{1e}, \hat{r}_{1f}) \xrightarrow{p} (r_{1e}, r_{1f})$ of the origination and termination of the first bubble, but does not detect the second bubble when the duration of the first bubble exceeds that of the second or shorter than the second bubble. Then under rate condition of $\frac{1}{cv^{\beta_T}} + \frac{cv^{\beta_T}}{T^{1-\alpha/2}} \to 0, as\ T \to \infty$, the PWY still consistently estimates the first bubble but discovers the second bubble with a delay that misdates the bubble. Alternatively, for PSY strategy, under the hypothesis of multiple bubbles and rate condition of $\frac{1}{cv^{\beta_T}} + \frac{cv^{\beta_T}}{T^{1/2}\delta_T^{r-r_e}} \to 0, as\ T \to \infty$, sequential application of the ADF detector will provides consistent estimates $(\hat{r}_{1e}, \hat{r}_{1f}, \hat{r}_{2e}, \hat{r}_{2f}) \xrightarrow{p} (r_{1e}, r_{1f}, r_{2e}, r_{2f})$ of the origination and termination of the first and second bubbles. Note that for both PWY and PSY, the theoretical hypothesis of multiple bubbles considers either run-up and run-down periods for a bubble and allows the model switches between a martingale mechanism, a single mildly explosive episode, collapse, and subsequent renewal of martingale behaviour. Such measure allows the strategy to capture any collapsing period appeared in the data sequence, for example, in our case, the subprime mortgage crisis in 2008. For more details, please see Appendix 2.1.

For America excluding the US, the PSY test results show that the index for Colombia experiences explosive behavior from 2004 to 2006 (e.g., 2004M11-2005M03 and 2005M06-2006M05). In Europe, explosive behavior is detected over the following dates: the UK (e.g., 1971M10-1972M04, 1997M06-1997M10, and 1997M11-2000M07), Germany (e.g., 1982M12-1984M05, 1985M05-1986M07, and 1997M06-1997M10), Italy (e.g., 1993M06-1993M10, 1994M03-1994M10, and 2008M12-2009M04), and Belgium (e.g., 2008M10-2009M06). In particular, Panel B of Table 3.3 shows that, similar to the US, the whole Europe index experiences a difficult time in 2008 and 2009 (e.g., 2008M09-2009M04), due to the spillover of the subprime mortgage crisis from the US to Europe.

The Asian results illustrate the impact of the Asian financial crisis occurred in the middle and late of 1990s. For example, the South Korea and Hong Kong stock market bubbles grow and collapse in the middle and late 1990s (e.g., 1994M01-1995M01, 1999M05-1999M10, 1999M11-2000M03 for South Korea; 1987M06-1987M10 and 1993M10-1994M02 for Hong Kong). The indices for Japan, India, and Hong Kong also have similar behavior to the US indices in 2008, while the Chinese stock market experiences exuberance in 2008 and 2015 (e.g., 2007M01-2007M06, 2008M01-2008M12, and 2015M04-2015M06). Note that for both the PWY and PSY tests, the duration of the exuberance episodes detected are no less than two months. All PSY testing figures are presented in the Figures 3.2.

<Figures 3.2>

3.4.7 Further Discussions

This chapter attempts to support the literature from the empirical perspective by confirming evidence of bubble existence in a broad context without using subjective method. Here in this chapter, we adopt a broader definition of bubble that a bubble contains both run-up and run-down periods which enable us to study the entire bubble evolutionary process. In early studies, economic professions reject the hypothesis that bubbles are present in the stock market, but such conclusion has been proved to be biased, as the testing method cannot recognize explosive sub-periods if bubbles are periodically collapsing. To overcome such difficulty, recent studies develop new testing procedures by implementing recursive procedures to generate sup- and generalized sup-testing statistics, both of which are easy to use in practical cases. In general, our findings reject conclusions reached by Diba and Grossman (1988) and Evans (1991), who have proved no bubbles in the market, while provide significant evidence that, indeed, such bubbles commonly exist in the global context. We confirm massive exuberance episodes in the US, consistent with the PWY (2011) and PSY (2015a, b), but we further extend findings to other regions, such as the Europe and Asia, offering convincing evidence for the existence of bubbles in those areas, particularly for the periods that publics fail to recognize bubbles. Our empirical estimates match relatively well with the general dateline of crisis putting forward in the public intuition about those financial bubble episodes. For example, our results stamp the concatenation events occurred after the Japanese housing bubble in the late 1980s, followed by the Dotcom bubble in the US, which originally began in 1995 then expanded to the UK in 1997. In the US, the bubble finally collapsed in March 2001 and subsequently, in July 2001, the bubble in the UK exploded as well. Similar transmission mechanism has been confirmed in the 2008 financial crisis, which is originally triggered by the collapse in subprime mortgages in the US and then quickly moved to the other continents, particularly to the mainland of Europe since we observe several market recessions followed up by the crisis in the US.

We have observed some mixed results when we apply different market indices for a single market. For instance, the PWY testing statistics for FTSE Japan is insignificant (–1.07; *p*-value > 0.10), suggesting no bubbles in the Japanese market; however, test result for the Japan TOPIX is highly significant at the 1% level (2.463; *p*-value < 0.01), providing substantial evidence for the presence of bubbles. This discrepancy could be due to the number of observations in FTSE Japan being smaller compared to the Japan TOPIX, which reduces the power of the sup-ADF test. This hypothesis has been proved after we controlling the size of Japan TOPIX (manually setting the sample size of Japan TOPIX being equal to FTSE Japan), the significant testing result of Japan TOPIX is gone. Another example of this discrepancy is the market indices of United States. We can clearly observe that the date-stamping results of United States for PSY offer distinct dates of bubbles: Dow Jones Industrial Average (DJIA) fails to recognize the collapsing period in 2008 while NASDAQ index successfully stamps it. Despite the fact that they have different sample size, another reason behind such difference could be the distinct nature between market indices – the DJIA represents well-established and well-known firms in the US market, while the NASDAQ consists of high-tech and growth firms. The literature has also suggested that NASDAQ normally has higher average returns than DJIA and the higher returns in NASDAQ are associated with higher volatilities (see Chiang, Yu and Wu, 2009). Such feature may cause the NASDAQ to be more volatile than DJIA in recent decades since high-tech stocks have received more attention after the late of 20th century Therefore, the mismatch between bubble dates between DJIA and NASDAQ may due to the fact that NASDAQ is more sensitive and overreact to positive or negative shocks than DJIA.

However, we can see from Table 3.3 and Figures 3.2 that not all markets are subject to the bubble phenomena, that is, the bubble episode may still be an independent event in the global markets. Taking Spain and Switzerland as an example, we confirm the collapsing period of 1993-2000 in Spain but fail to recognize the same period in Switzerland. Such non-overlapping period shows that the financial crisis happened in Spain might not be present for the equity market of Switzerland, which refuses the hypothesis of transmission. Several potential interpretations may be applied to explain such mismatch. First, there might be explosive behavior during that period, but such an increase in the relevant stock market index cannot be confirmed as a bubble, based on the formal definition of an asset price bubble.

Recalling the definition of a bubble used is that the observed asset price significantly exceeds its market fundamental component, and the growth of the price is explosive. If both price and market fundamental are explosive during the same period, or in other words, the growth of the asset price is supported by a similar rise in relevant fundamentals, we cannot recognize such phenomenon as an asset price bubble (rational or irrational), and that might be the reason why we have observed bubbles in Spain but failed to confirm the same phenomenon in Switzerland because either there is truly no shooting up in asset prices in Switzerland when Spain is experiencing exuberance, or there is a surge in asset prices but such rises are supported by fundamentals (both price and dividend are shooting up). Therefore, technically, our procedures do not recognize the price surge in Switzerland as a bubble.

We have also considered another potential explanation: market itself may not be sensitive to the bubble transmission since it has a market barrier to prevent the transmission, or in other words, the interdependence between those markets is insufficient to allow bubble transmission. The literature suggests that factors such as listed firms, political risk, liquidity risk, poor corporate governance or inefficient markets may generate implicit barriers to important institutional investors and lead to market barriers (see e.g., Chua, Eun and Lai, 2007; Bekaert, Harvey, Lundblad and Siegel, 2011), and such market segmentation could protect markets from contamination.

3.5 Conclusion

In this chapter, we use a large number of datasets to discover the existence of bubbles and date-stamp their originations and collapses. From our testing results, we can observe that the conventional unit-root method fails to discover bubbles appearing to be stationary, even though they are explosive in the relevant case. However, such issue has been solved by implementing unit-root test recursively forward, and obtained results are opposite to the findings of Evans (1991). Overall, our results are consistent with the conclusion made by PWY (2011) and PSY (2015a, b), who confirm the existence of bubble in the US; but we further extend their research and find strong evidence in other regions outside the US, and that greatly supports our hypothesis in terms of university in bubble existence. Moreover, by comparing the testing power between selected strategies, we suggest that the generalized sup-

ADF strategy enjoys the superior discriminatory power than the others if multiple bubbles are present.

Our dates are matched against the onset dates of the great depression, the post-war bubbles, the subprime mortgage crisis as well as the other specific sequential bubble episodes in the mainland Europe and Asia. It is worth to note that, from our date-stamping results, either in western or eastern markets, the phenomenon originated in one market highly possibly move selectively into the other equity markets, creating bubbles that subsequently burst and cause severe impacts on the real economy. We suggest several potential interpretations to explain the story, but the lack of empirical evidence supports our hypotheses.

This chapter has not attempted to identify the explicit or implicit linkage between those bubble episodes. Identification of such relationship will involve more accurate formulation of alternative models and suitable determination techniques. Therefore, the following chapter will concentrate on this aspect with the purpose of investigating the bubble evolutionary process.

Table 3.1: Traditional ADF, PWY and PSY testing results with detailed information about the data

Markets	Sources	Starting dates	No. of observations	ADF	PWY	PSY
Asia						
Australia (AU)	FTSE Australia	1986M02	355	–2.561	1.740[b]	4.265[a]
China (CN)	China A-DS Market	1994M05	259	–2.608	0.149	4.098[a]
Hong Kong (HK)	Hang Seng Index	1980M10	421	–2.404	1.776[b]	3.522[a]
India (IN)	NIFTY 500	1996M01	238	–0.701	2.513[a]	3.425[a]
Indonesia (ID)	FTSE Indonesia	1996M07	233	–1.610	1.040	1.040
Israel (IL)	FTSE Israel	1993M12	264	–7.007	–2.892	0.076
Japan (JP)	FTSE Japan	1986M02	357	–1.322	–1.070	1.226
Japan TOPIX (JP)	TOPIX	1983M02	394	–2.045	2.463[a]	2.510[b]
Japan TOPIX (Restricted)	TOPIX	1986M02	357	1.187	-0.743	1.188
Malaysia (MY)	FTSE Malaysia	1993M12	263	–3.167	–0.581	0.273
Malaysia *KLCI* (MY)	FTSE Bursa Malaysia	1986M01	359	–3.641	0.193	2.636[b]
New Zealand (NZ)	FTSE New Zealand	1986M02	355	–2.291	–0.809	1.565
Philippine (PH)	Philippine SE I (PSEi)	1988M01	335	–2.868	–0.506	1.120
Singapore (SG)	FTSE Singapore	1986M02	357	–2.792	–0.428	1.063
South Korea (KR)	Korea SE KOSPI 200	1990M01	311	–2.121	2.226[a]	2.226[b]
Taiwan (TW)	Taiwan SE Weighted TAIEX	1989M07	316	–2.606	–1.398	0.462
Thailand (TH)	Bangkok S.E.T.	1976M01	479	–2.532	5.812[a]	7.789[a]
Europe						
Belgium (BE)	BEL 20	1990M02	310	–2.275	0.851	2.160[c]
Czech Republic (CZ)	Prague SE PX	1994M04	260	–3.634	–2.161	1.254
Denmark (DK)	FTSE Denmark	1986M02	357	–2.498	2.120[a]	2.119[c]
Finland (FI)	FTSE Finland	1988M01	335	–2.503	4.212[a]	5.009[a]
France (FR)	France CAC 40	1988M01	334	–3.010	0.441	0.898
Germany (DE)	DAX 30	1973M01	514	–2.130	3.276[a]	5.314[a]
Greece (GR)	FTSE Greece	1998M05	211	3.147[a]	11.610[a]	11.610[a]
Hungary (HU)	FTSE Hungary	1997M10	212	–3.309	–0.981	0.501
Ireland (IE)	FTSE Ireland	1986M02	358	–2.024	1.487[b]	5.263[a]
Italy (IT)	FTSE Italy	1986M02	359	–2.288	0.771	2.037[c]
Netherlands (NL)	AEX Netherlands	1983M01	394	–2.038	2.697[a]	3.996[a]
Norway (NO)	FTSE Norway	1986M02	358	–3.181	–0.095	–0.095
Poland (PL)	FTSE Poland	1994M04	260	–10.540	–5.087	0.754
Portugal (PT)	FTSE Portugal	1998M05	211	–3.943	–1.320	1.547
Russia (RU)	FTSE Russia	2003M09	147	–2.561	0.714	1.086
Russia Dollar (RU)	FTSE Dollar	2000M06	186	–2.535	–0.576	0.878
Spain (ES)	IBEX 35	1987M03	345	–2.140	3.470[a]	3.725[a]
Sweden (SE)	OMX Stockholm 30	1986M01	358	–2.046	2.667[a]	3.796[a]
Switzerland (CH)	Swiss Market (SMI)	1988M07	328	–2.199	0.685	1.574
Turkey (TR)	BIST National 100	1988M02	333	–1.544	7.199[a]	7.199[a]
United Kingdom (UK)	FTSE All Share	1965M01	610	–0.974	3.610[a]	3.610[a]
European Area (EU)	FTSE Euro First 80 E	1993M12	264	–1.730	2.376[a]	2.613[b]
USA						
Dow Jones	Dow Jones Index	1978M02	456	–1.490	3.840[a]	3.848[a]
NASDAQ	NASDAQ Index	1973M01	516	–1.734	12.48[a]	12.48[a]
S&P 500	S&P Index	1871M01	1737	–1.489	3.443[a]	4.207[a]
America excluding USA						
Brazil (BR)	FTSE Brazil	1994M11	253	–3.206	–2.244	1.619
Canada (CA)	S&P/TSX Composite Index	1973M06	509	–1.491	3.930[a]	3.936[a]
Chile (CL)	FTSE Chile	1993M12	264	–31.757	–13.694	1.226
Colombia (CO)	FTSE Colombia	1993M12	264	–3.309	–1.715	4.076[a]
Mexico (MX)	Mexico IPC	1989M03	320	–2.920	5.539[a]	5.643[a]
Africa						
South Africa (ZA)	FTSE South Africa	1986M02	358	–0.721	1.347[c]	1.618

This table reports the details of our data selection including markets, sources, testing periods, and number of observations contained in each sample market. The ending dates of all series are set to December 2015, along with various starting dates ranging from January 1871 to June 2000. This study employs monthly data on the index level (referred to as the price) and the associated dividend index for 47 stock market indices from over 40 countries in six continents/regions: Asia (14), Australasia (2), Europe (22), North and South America (8), and Africa (1). For simplicity, we category the 47 stock markets into five groups: Asia including Australasia (16), Europe (22), the US (3), North and South America excluding the US (for brevity, referred to as America excluding the US) (5), and Africa (1). This data is used to compute the price-dividend ratio for each index. The sup-ADF statistics of PWY tests and the generalized sup-ADF statistics of PSY tests in each sample market are presented in the last two columns. [a], [b], and [c] represent the 1%, 5%, and 10% level of significance, respectively. Japan Tokmacap represents the TOPIX medium capitalization index from Japanese stock exchange. Japan TOPIX (restricted) represents the sample which we manually set the size being equal to FTSE Japan (controlling for size). FTSE Bursa Malaysia *KLCI* consists 30 largest companies in FBMEMAS (FTSE Bursa Malaysia Emas Index) by full market capitalization. The European Area uses the FTSEEUROFIRST 80 E Index as the dataset to testing whether speculative bubbles exist in the European region.

Table 3.2: Critical values of sup-ADF and generalized sup-ADF methods

	DJIA		NASDAQ		S&P 500	
	T=455; window size: 43		T=516; window size: 46		T=1740; window size: 92	
	SADF	GSADF	SADF	GSADF	SADF	GSADF
90%	1.222	1.978	1.174	2.002	1.324	2.195
95%	1.487	2.263	1.502	2.26	1.55	2.416
99%	2.109	2.681	2.049	2.659	2.014	2.957

Table 3.3: PWY and PSY date-stamping results

	Panel A: PWY	Panel B: PSY
Asia		
Australia (AU)	1990M01-1990M05, 1993M09-1994M05	1990M01-1990M04, 1993M10-1994M05, 2003M08-2004M06
China (CN)	N/A	2007M01-2007M06, 2008M01-2008M12, 2015M04-2015M06
Hong Kong (HK)	N/A	1987M06-1987M10, 1993M10-1994M02, 2007M09-2007M12
India (IN)	2000M01-2000M04, 2007M10-2008M02	1999M12-2000M04, 2007M10-2008M02
Japan Tokmacap (JP)	1986M06-1986M11, 1986M12-1987M12, 1988M03-1988M09, 1988M12-1990M03	1986M06-1986M11, 1986M12-1987M12, 1989M02-1989M06, 2008M11-2009M04
Malaysia *KLCI* (MY)	N/A	1993M11-1994M03
South Korea (KR)	1994M01-1995M01, 1999M04-1999M10, 1999M11-2000M04	1994M01-1995M01, 1999M05-1999M10, 1999M11-2000M03
Thailand (TH)	1986M10-1987M11, 1988M02-1988M11, 1989M01-1990M09, 1998M11-2000M02	1983M04-1984M02, 1986M09-1987M11, 1988M03-1988M09, 1989M04-1990M08, 1999M02-2000M02
Europe		
Belgium (BE)	N/A	2008M10-2009M06
Denmark (DK)	1989M03-1990M04, 1993M07-1994M05	1989M03-1990M04, 1993M08-1994M04, 2000M10-2001M01
Finland (FI)	1993M04-1994M03	1993M03-1994M03, 1999M11-2000M03, 2008M09-2009M04
Germany (DE)	1983M01-1984M06, 1984M12-1987M01, 1997M01-1998M08, 1998M12-1999M03	1982M12-1984M05, 1985M05-1986M07, 1997M06-1997M10
Greece (GR)	2013M04-2013M07, 2014M02-2015M12	2013M04-2013M07, 2014M03-2015M12
Ireland (IE)	1998M02-1998M08, 2011M12-2012M07, 2013M02-2013M12	1997M12-1998M08, 1998M12-1999M05, 2008M06-2009M03, 2013M03-2013M12
Italy (IT)	1993M06-1993M10, 1994M03-1994M10, 2008M12-2009M04	1993M06-1993M10, 1994M03-1994M10, 2008M12-2009M04
Netherlands (NL)	1997M05-1998M09, 2000M07-2000M10	1993M11-1994M04, 1997M02-1998M09, 2008M11-2009M04
Spain (ES)	1996M12-1998M09, 1998M12-1999M04, 1999M12-2000M06	1993M11-1994M04, 1996M12-1997M11, 1997M12-1998M09, 2000M02-2000M05
Sweden (SE)	1993M07-1994M10, 1994M11-1995M03, 1999M12-2000M04	1993M04-1994M07, 1999M12-2000M04
Turkey (TR)	1993M05-1994M03, 1994M11-1996M04, 1996M12-1997M05, 1997M10-1998M09, 1999M01-1999M06, 1999M09-2000M12, 2001M12-2002M04, 2003M10-2004M05	1993M05-1994M03, 1994M11-1996M04, 1996M12-1997M05, 1997M10-1998M08, 1999M11-2000M12, 2003M10-2004M05
United Kingdom (UK)	1971M12-1973M02, 1981M04-1981M10, 1981M12-1982M07, 1982M09-1987M11, 1993M08-1994M07, 1995M05-2002M07	1971M10-1972M10, 1982M11-1987M11, 1997M11-2001M07
European Area (EU)	1997M06-1997M10, 1997M12-1998M08, 1999M10-2000M11	1997M01-1997M04, 1997M06-1997M10, 2008M10-2009M04
U.S.		
Dow Jones	1983M03-1984M02, 1986M02-1987M11, 1995M06-2000M12	1983M02-1984M03, 1986M01-1986M10,1986M11-1987M11, 1995M12-1998M09, 1998M11-2000M07

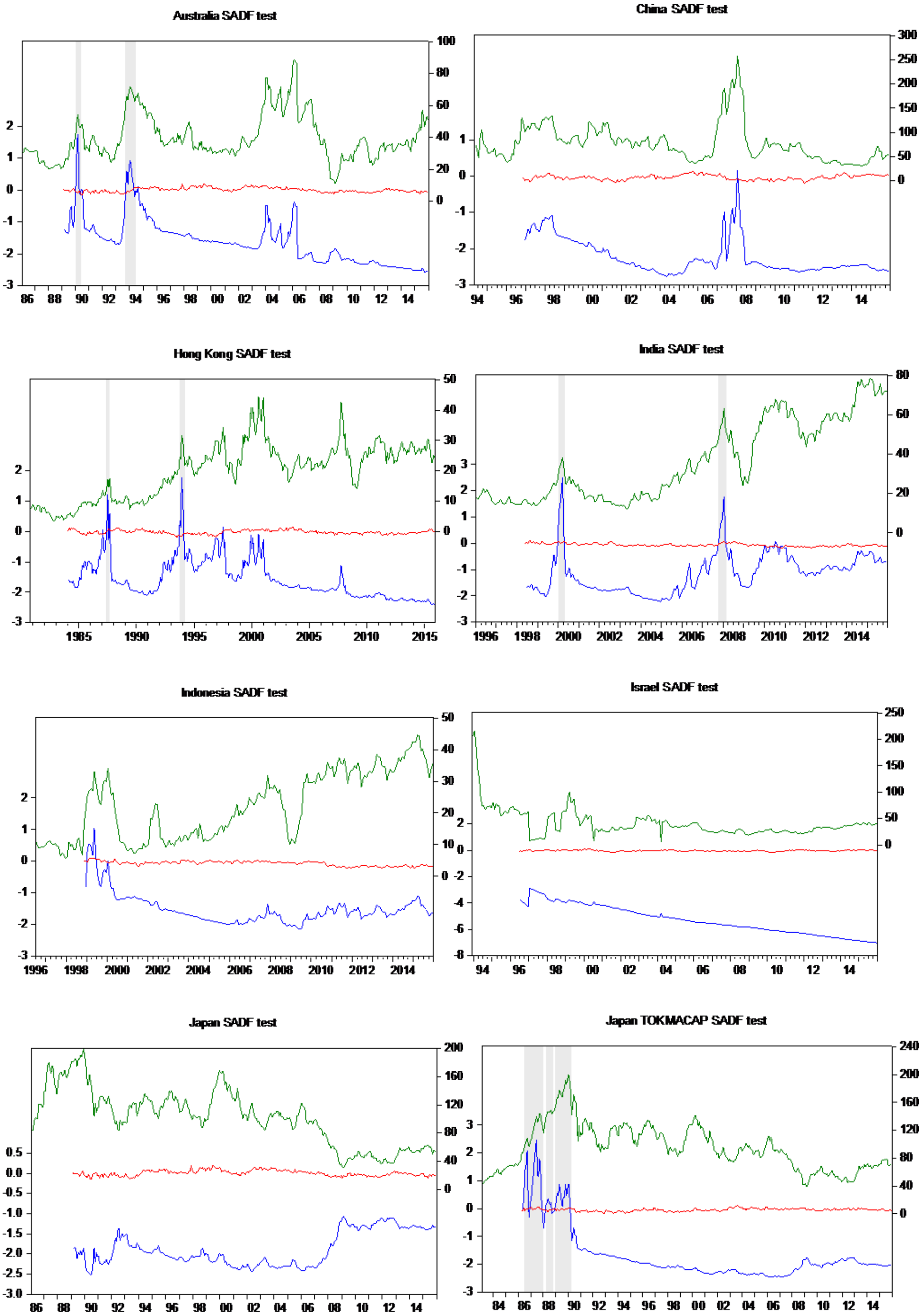
Continued

Table 3.3 Continued	**Panel A: PWY**	**Panel B: PSY**
NASDAQ	1983M05-1984M06, 1984M08-1990M04, 1993M09-2001M04	1983M04-1984M06, 1985M11-1987M11, 1995M05-2001M03, 2008M11-2009M04
S&P 500	1879M05-1880M05, 1997M07-2002M06	1879M07-1880M05, 1917M09-1918M05, 1928M09-1929M11, 1955M04-1956M08, 1958M11-1959M09, 1987M01-1987M10, 1995M12-1996M07, 1996M09-2001M09
America ex. U.S.		
Canada (CA)	1980M08-1981M02, 1981M03-1981M07, 1983M02-1984M05, 1985M01-1987M10, 1993M03-1998M08, 1998M10-2001M03	1983M04-1984M02, 1985M11-1987M10, 1993M04-1994M06, 1996M03-1998M08, 1999M03-2001M02
Colombia (CO)	N/A	2004M11-2005M03, 2005M06-2006M05
Mexico (MX)	1993M05-1994M12	1992M02-1992M06, 1993M05-1995M01, 2006M01-2006M05

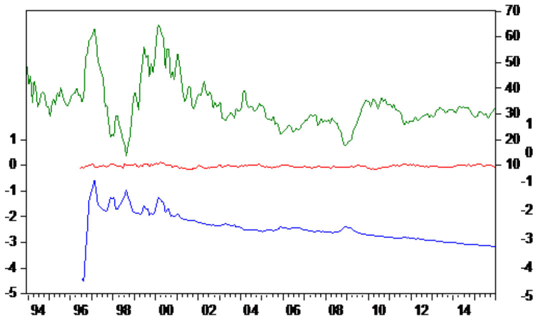
This table provides date-stamping results for the PWY and PSY dating mechanism. The PWY date-stamping method estimates the origin and collapse date of speculative bubbles by matching the time series of the recursive test sequence ADF_r against the right-tailed critical values of the asymptotic distribution of the standard Dickey-Fuller t-statistic. The origination date of a bubble is calculated as the first chronological observation whose ADF statistic exceeds the critical value of ADF_r, and the estimated termination date of a bubble is the first chronological observation whose ADF statistic goes below the critical value of ADF_r. For the PSY, the origination date of a bubble is the first observation whose backward sup-ADF statistic exceeds the critical value of the backward sup-ADF statistic and the collapsing date of a bubble is first observation whose backward sup-ADF statistic falls below the critical value of the backward sup-ADF statistic. The current paper adopts the 5% significant level in both the PWY and PSY dating mechanism.

Figure 3.1: Testing figures of PWY

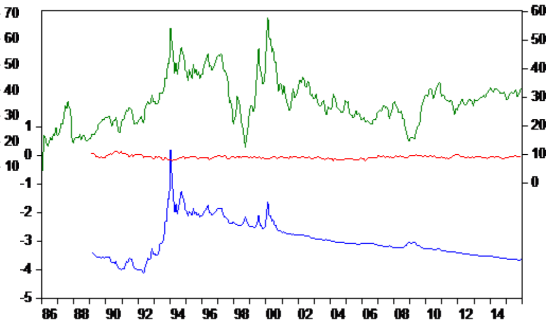
Figures below generally show the movement of SADF testing statistics comparing with the 95% SADF critical value sequence, which were obtained from Monte-Carlo simulations with 1000 replications. The figure denoted by Japan represents the FTSE Japan testing figure, and the figure denoted by Malaysia shows the FTSE Malaysia result. The European Area uses the FTSEEUROFIRST 80 E Index as the dataset to demonstrate whether speculative bubbles exist in the European region. The red-line represents the 95% SADF critical value sequence, the green-line (right-axis) is the corresponding price-dividend ratio movement noted by the figure title, and the blue-line (left-axis) is the corresponding movement of SADF testing statistics.



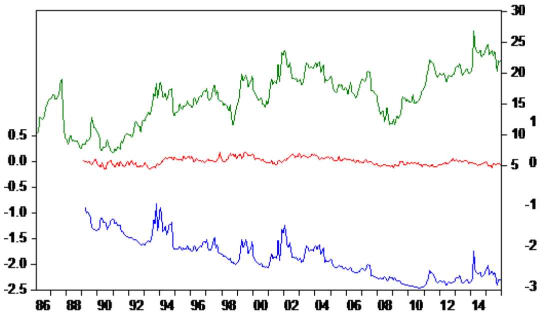
Malaysia SADF test



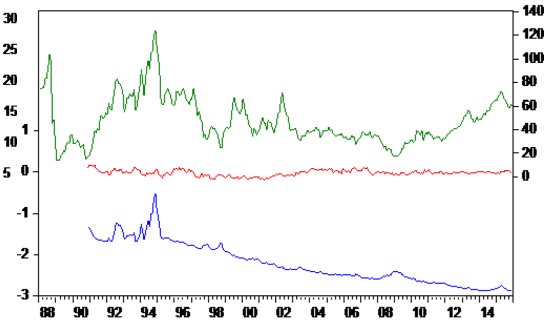
Malaysia KLCI SADF test



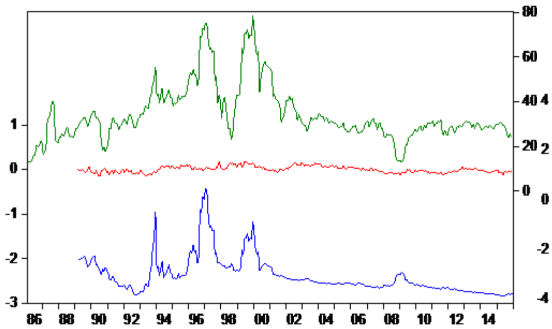
New Zealand SADF test



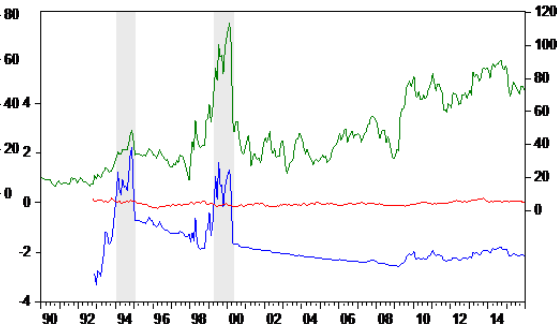
Philippine SADF test



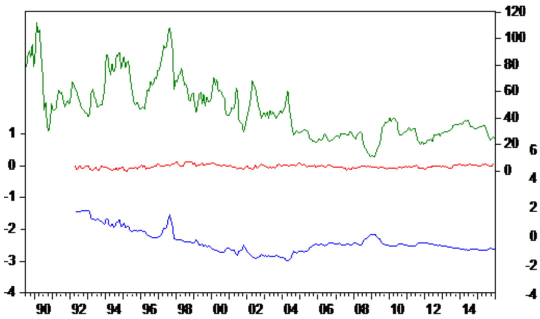
Singapore SADF test



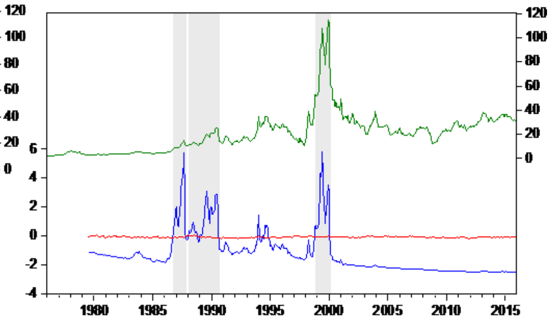
South Korea SADF test



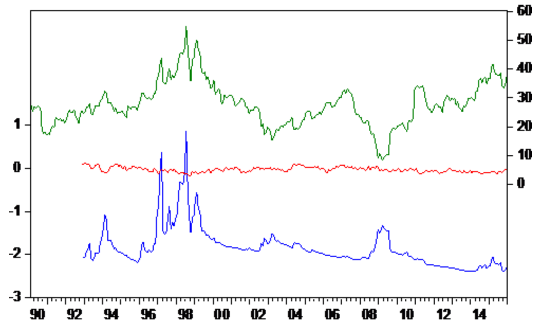
Taiwan SADF test



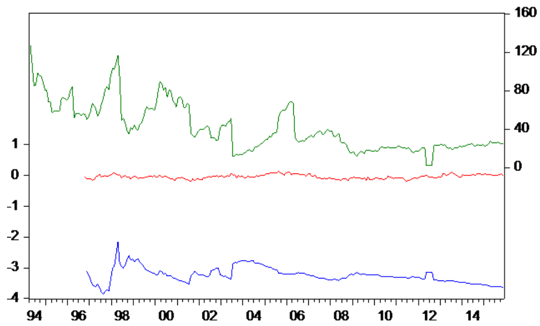
Thailand SADF test



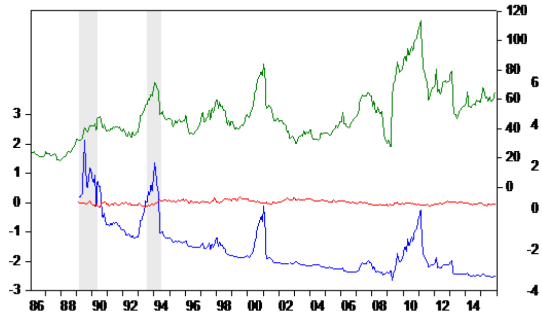
Belgium SADF test



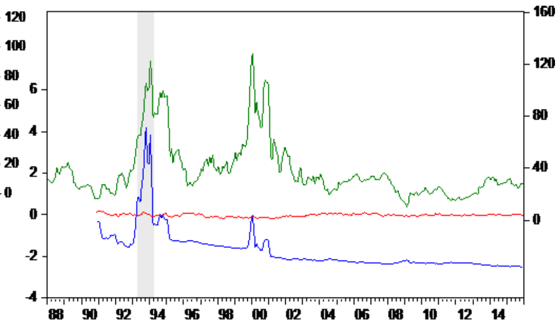
CZECH Republic SADF test



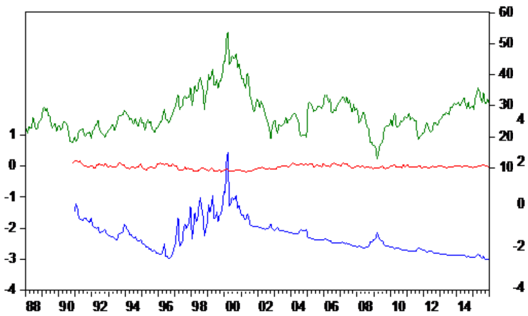
Denmark SADF test



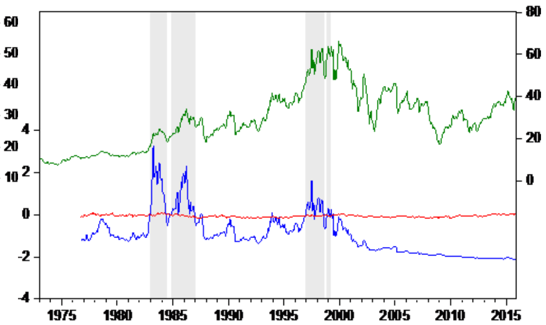
Finland SADF test



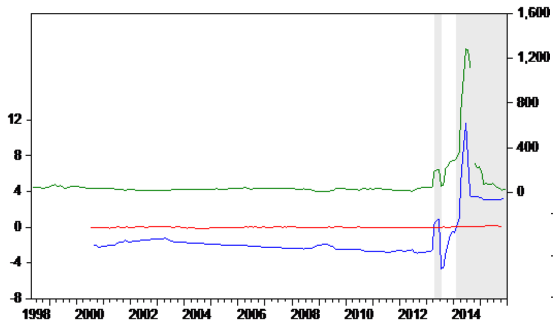
France SADF test



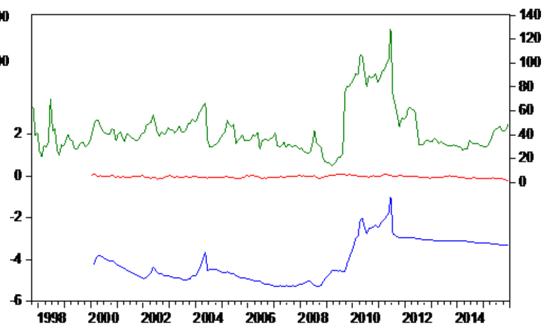
Germany SADF test

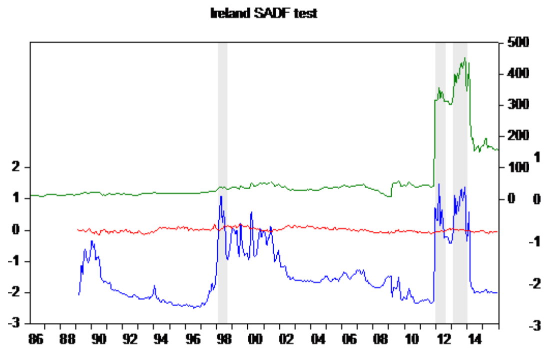


Greece SADF test



Hungary SADF test




Ireland SADF test
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500 400 300 200 100 0
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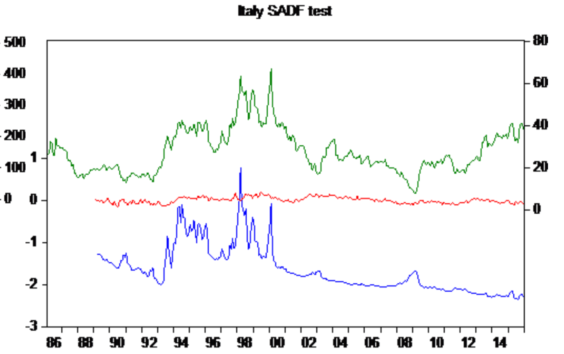
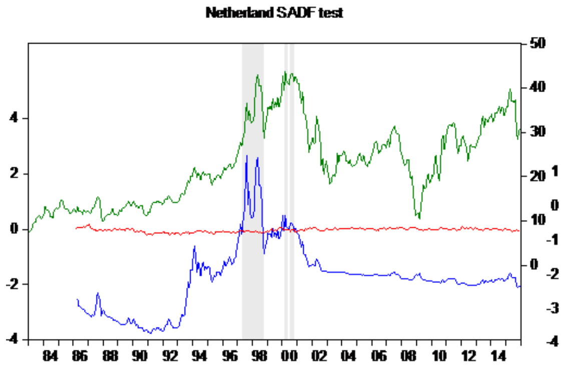

Italy SADF test
1 0 -1 -2 -3
80 60 40 20 0
86 88 90 92 94 96 98 00 02 04 06 08 10 12 14


Netherland SADF test
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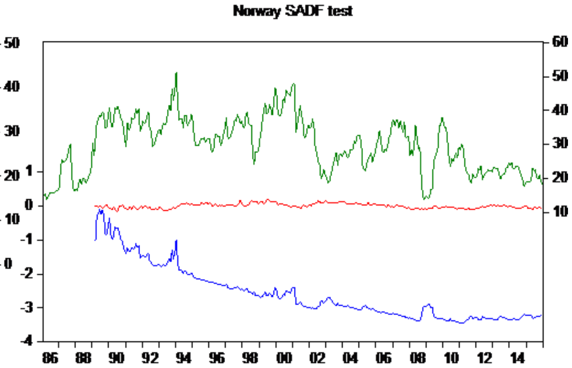
50 40 30 20 10 0
84 86 88 90 92 94 96 98 00 02 04 06 08 10 12 14


Norway SADF test
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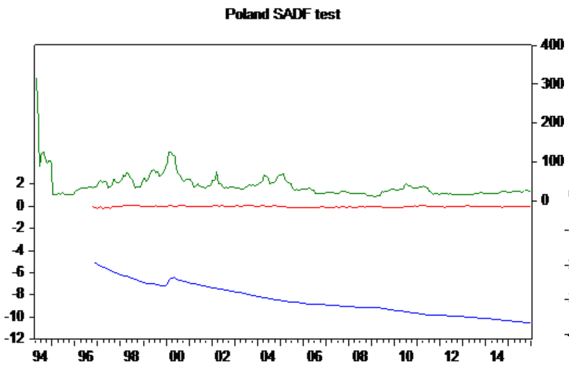
86 88 90 92 94 96 98 00 02 04 06 08 10 12 14


Poland SADF test
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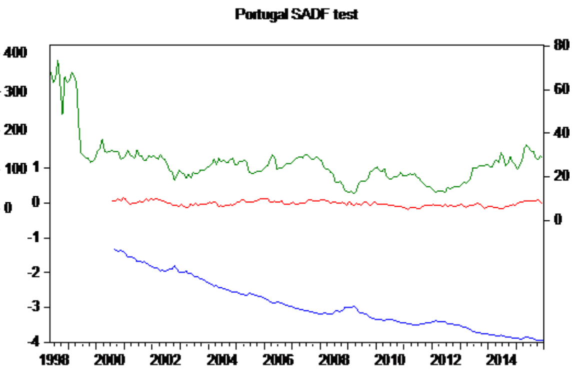
400 300 200 100 0
94 96 98 00 02 04 06 08 10 12 14


Portugal SADF test
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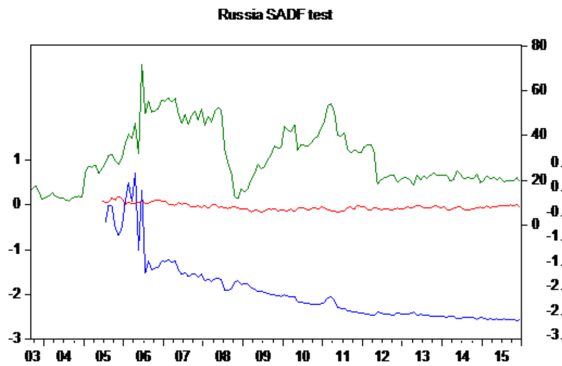
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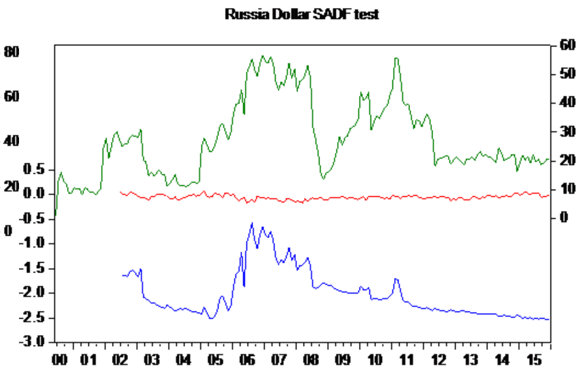
Russia Dollar SADF test
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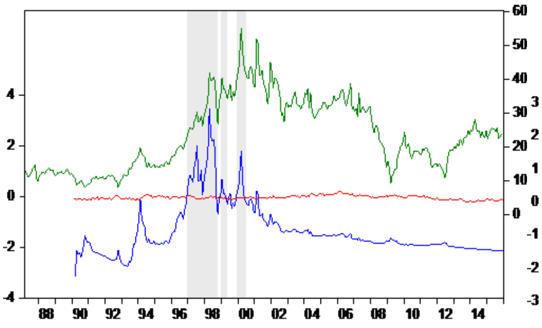
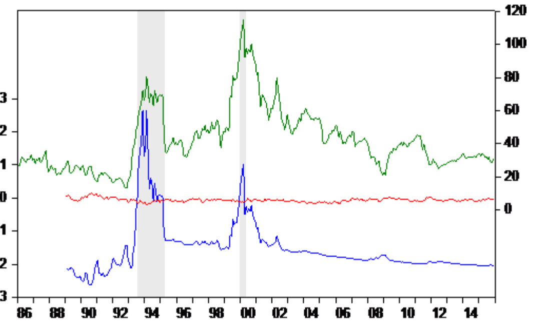
00 01 02 03 04 05 06 07 08 09 10 11 12 13 14 15

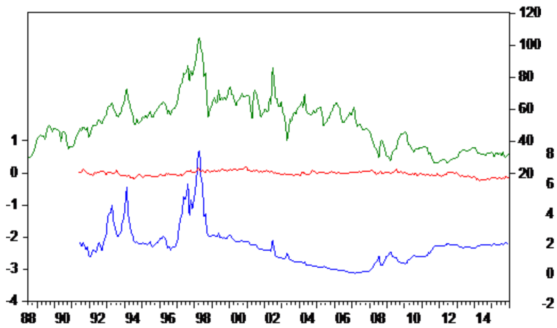
Spain SADF test



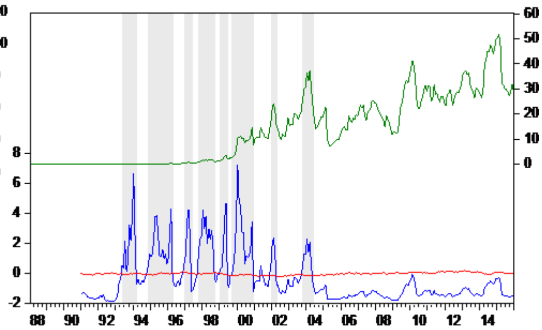
Sweden SADF test



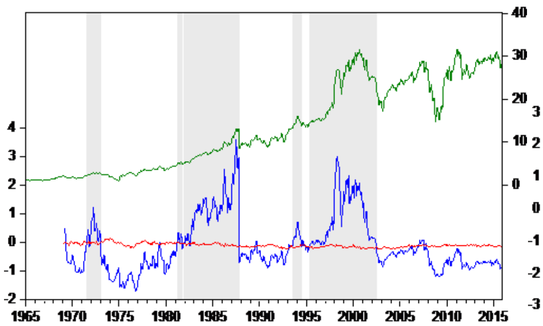
Switzerland SADF test



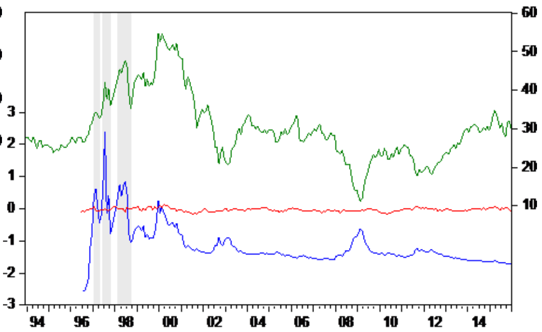
Turkey SADF test



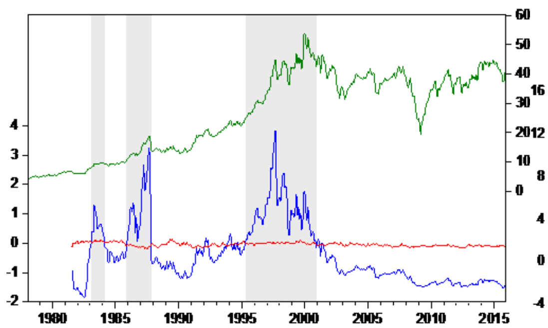
UK SADF test



European Area SADF test



Dow Jones SADF test



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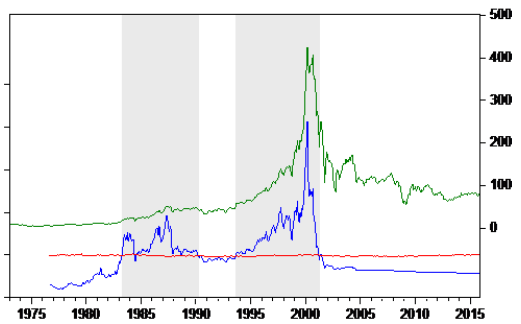
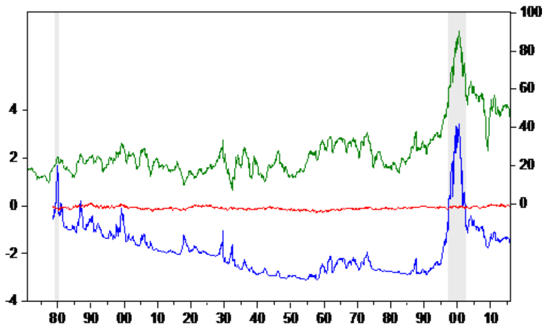
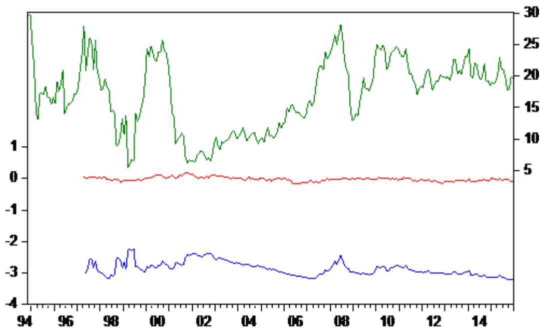


S&P SADF test



Brazil SADF test



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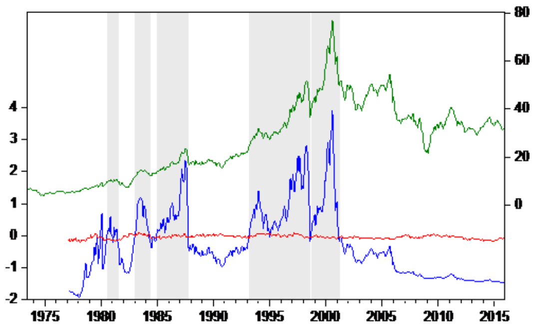
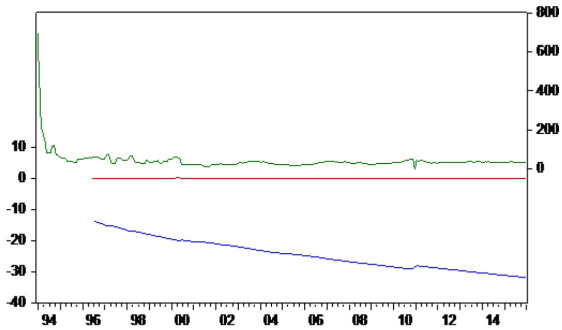
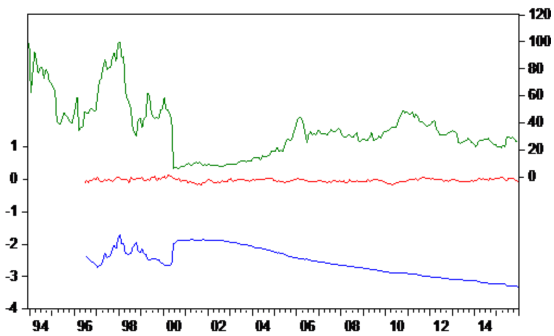


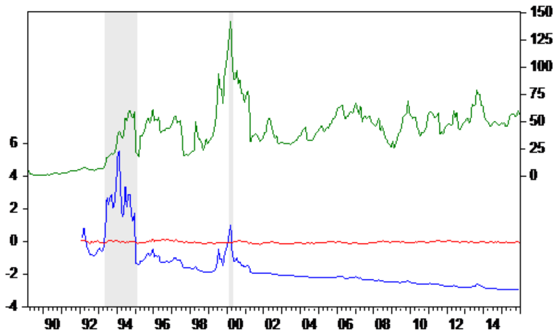
Chile SADF test



Colombia SADF test



Mexico SADF test



South Africa SADF test

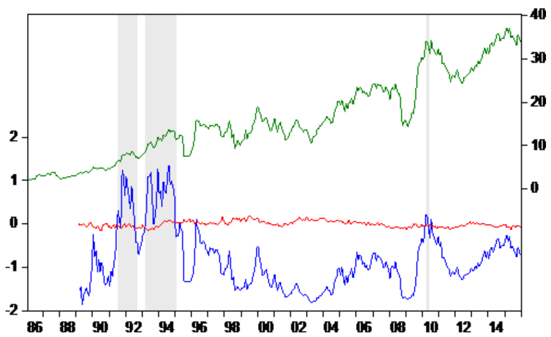
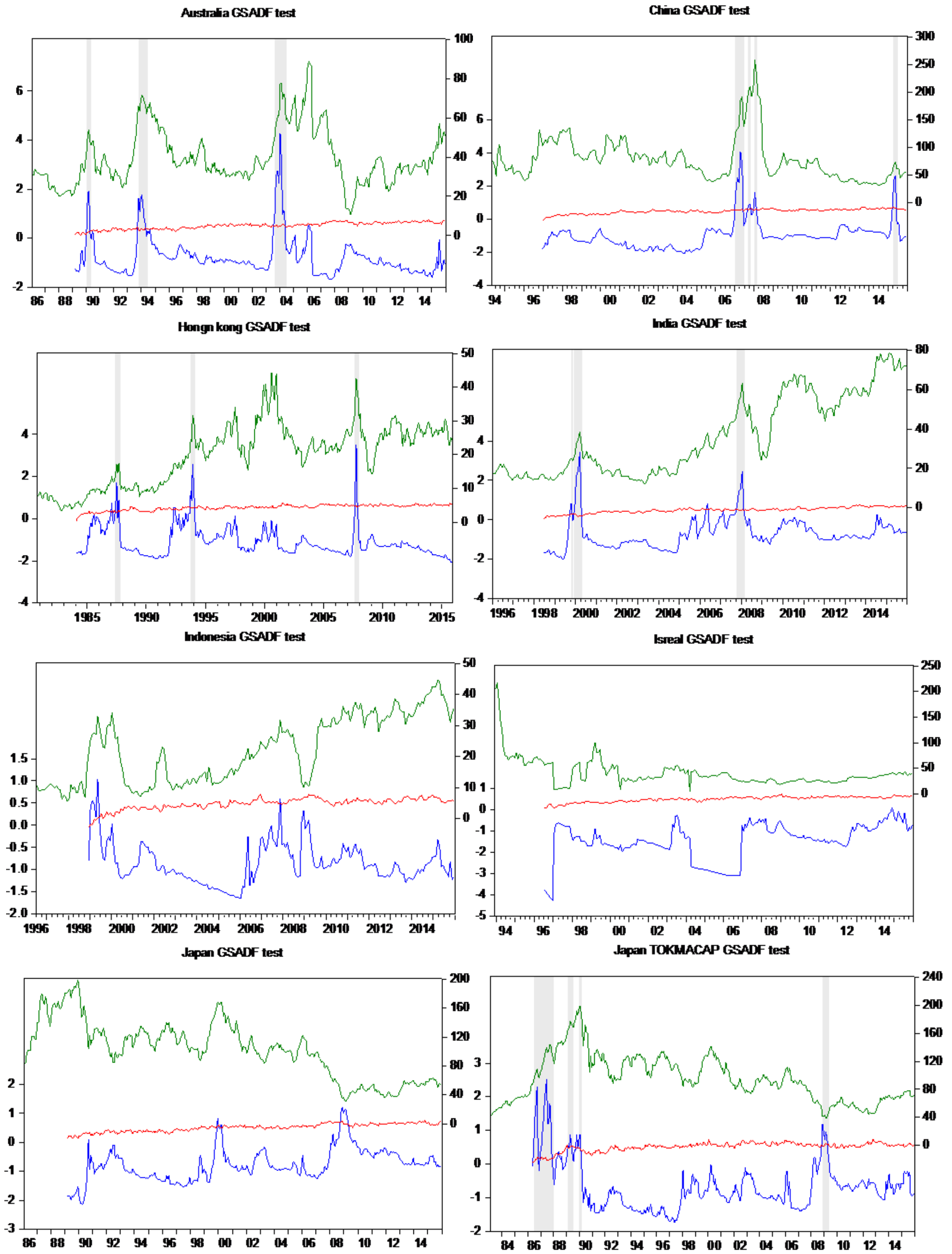
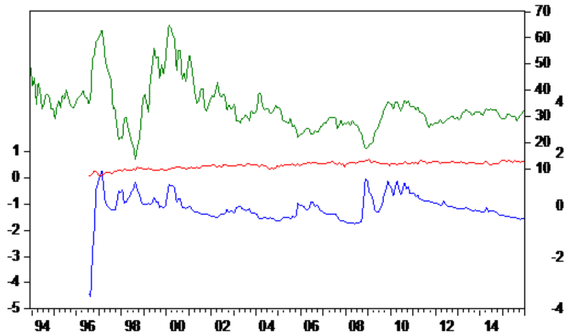


Figure 3.2: Testing figures of PSY.

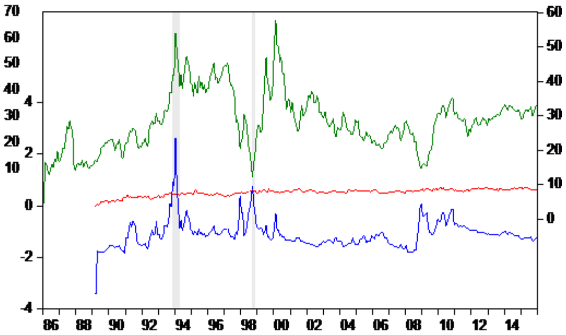
Figures below generally show the movement of GSADF testing statistics comparing with the 95% GSADF critical value sequence, which were obtained from Monte-Carlo simulations with 1000 replications. The figure denoted by Japan represents the FTSE Japan testing figure, and the figure denoted by Malaysia shows the FTSE Malaysia result. The European Area uses the FTSEEUROFIRST 80 E Index as the dataset to demonstrate whether speculative bubbles exist in the European region. The red-line represents the 95% GSADF critical value sequence, the green-line (right-axis) is the corresponding price-dividend ratio movement denoted by the figure title, and the blue-line (left-axis) is the corresponding movement of GSADF testing statistics.



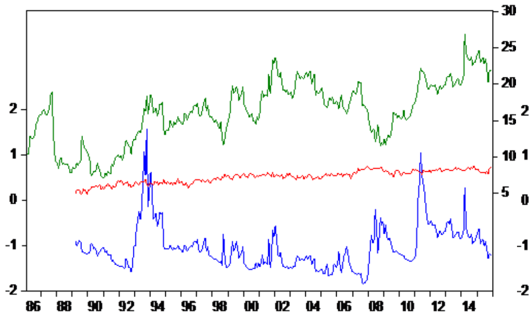
Malaysia GSADF test



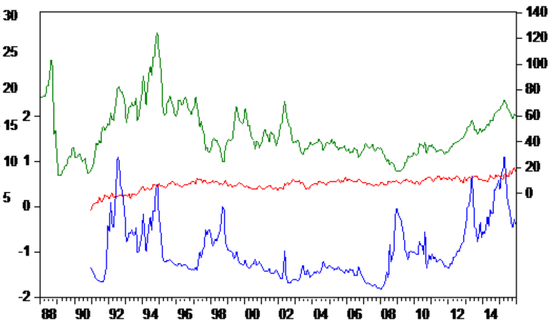
Malaysia KLCI GSADF test



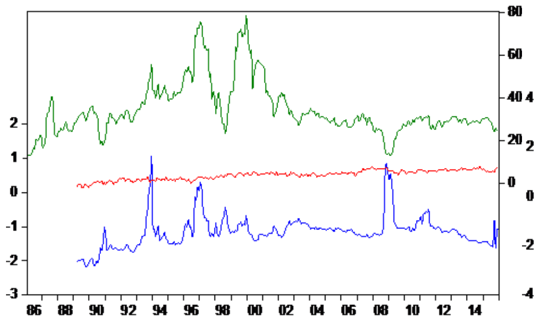
New Zealand GSADF test



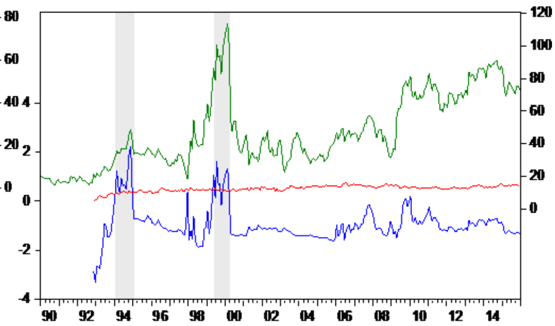
Philippine GSADF test



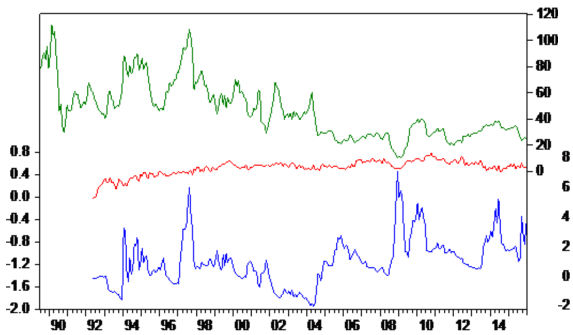
Singapore GSADF test



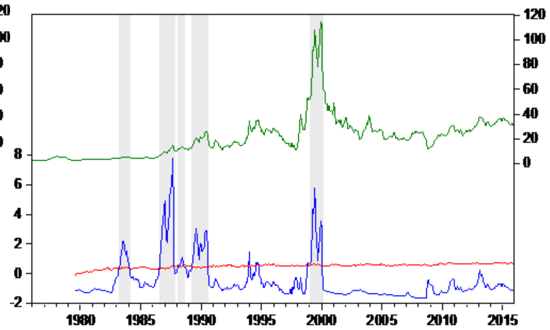
South Korea GSADF test



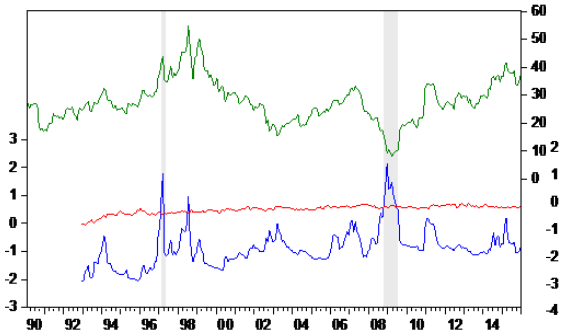
Taiwan GSADF test



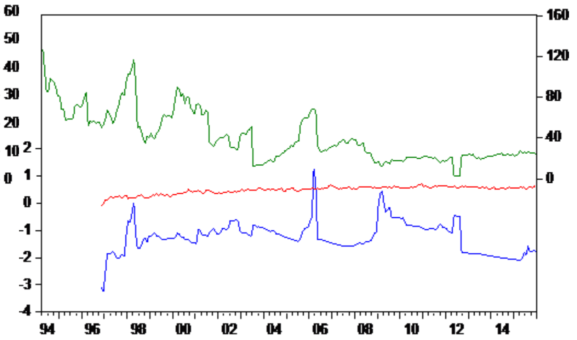
Thailand GSADF test



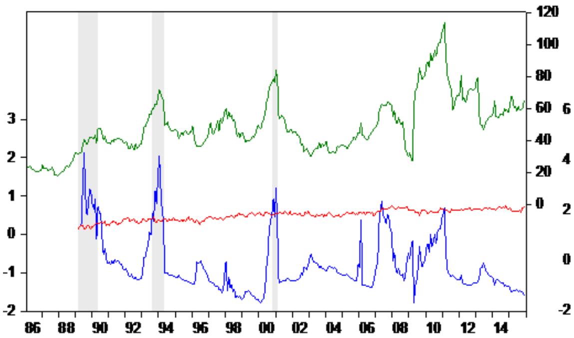
Belgium GSADF test



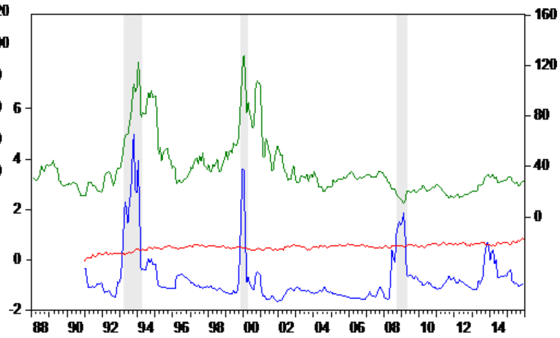
CZECH Republic GSADF test



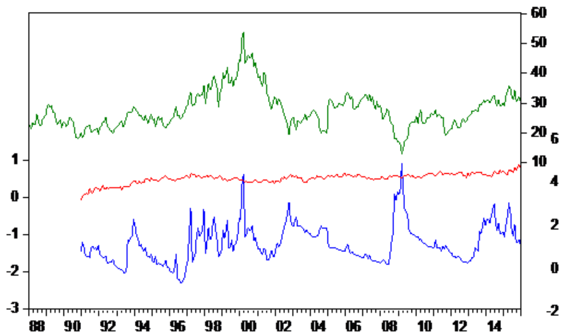
Denmark GSADF test



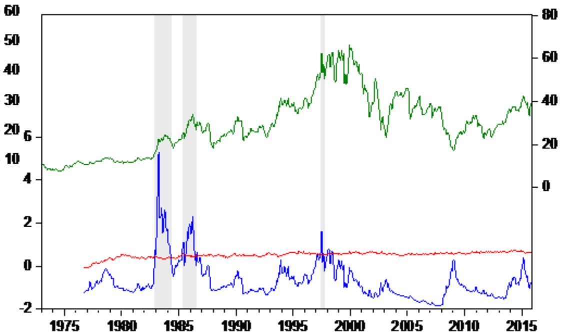
Finland GSADF test



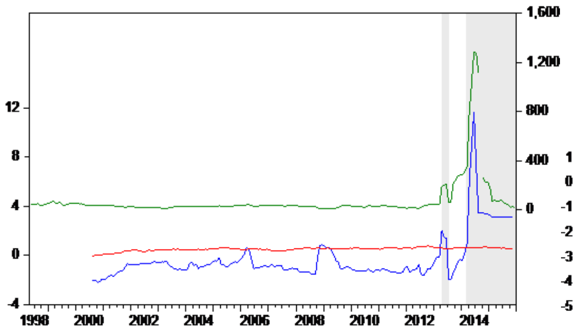
France GSADF test



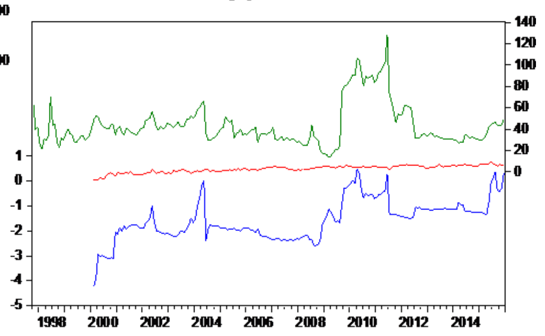
Germany GSADF test



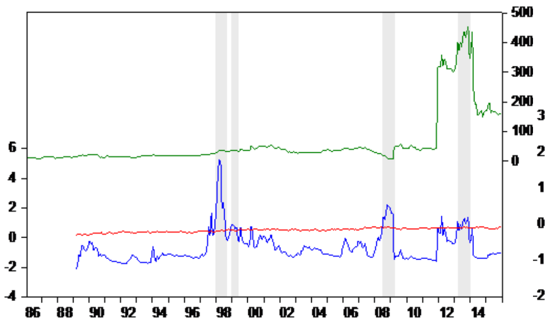
Greece GSADF test



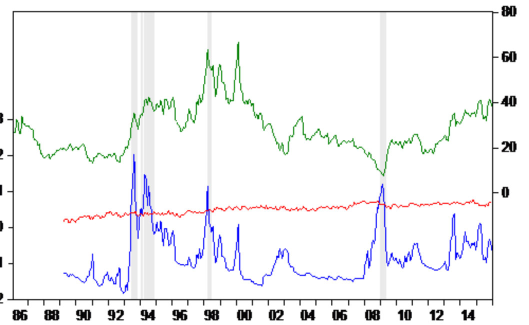
Hungary GSADF test



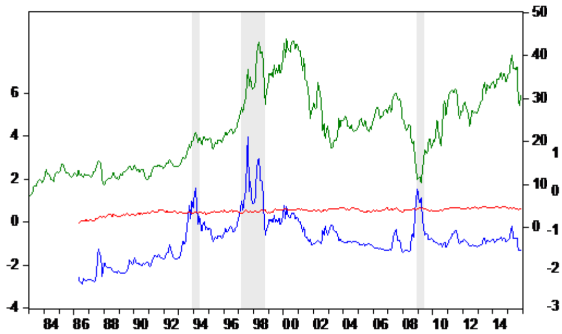
Ireland GSADF test



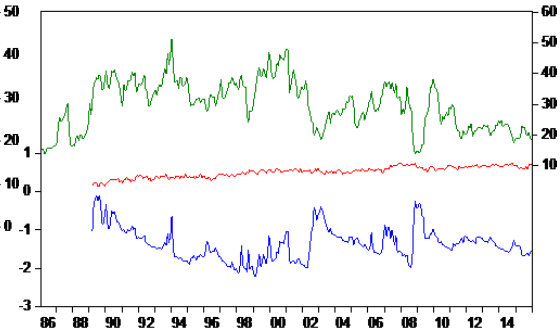
Italy GSADF test



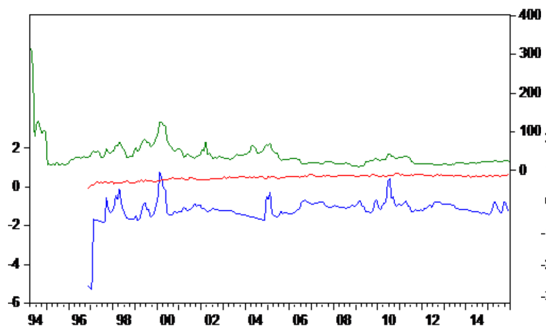
Netherland GSADF test



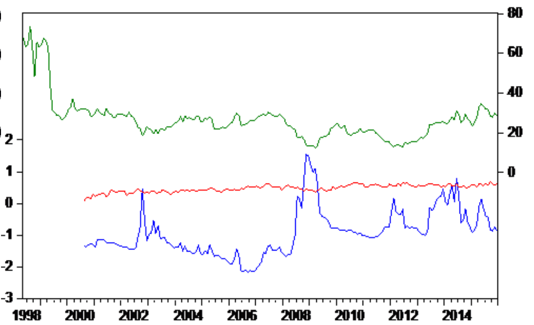
Norway GSADF test



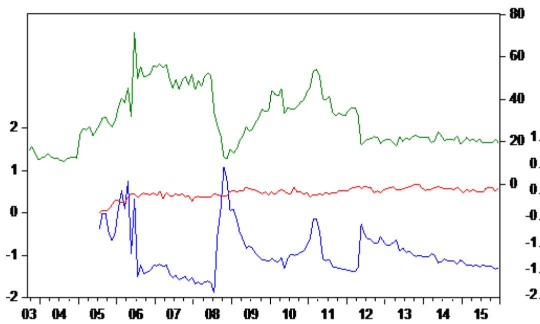
Poland GSADF test



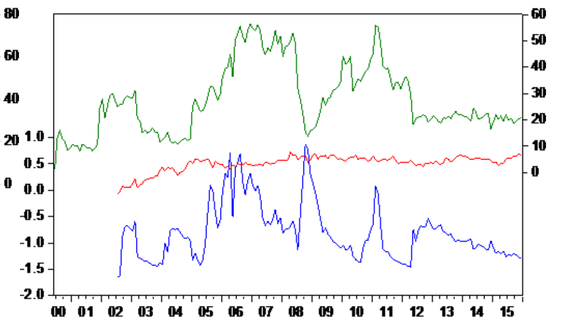
Portugal GSADF test



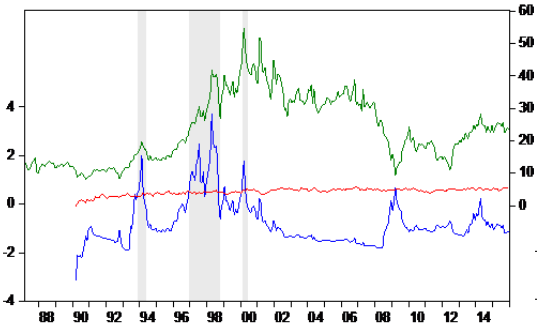
Russia GSADF test



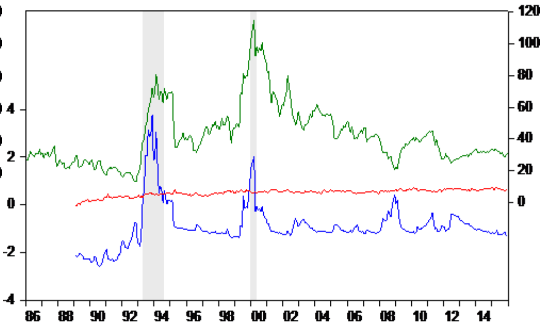
Russia Dollar GSADF test



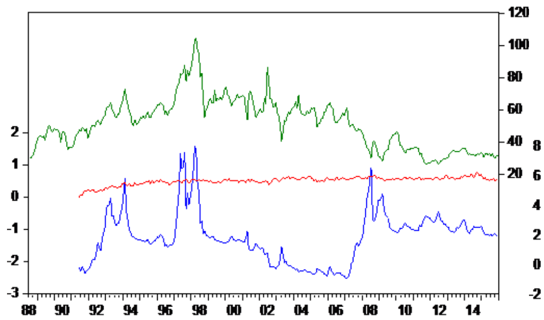
Spain GSADF test



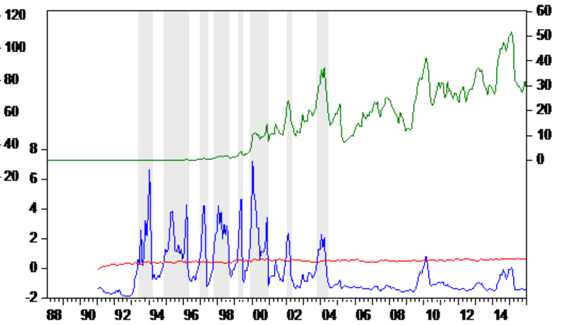
Sweden GSADF test



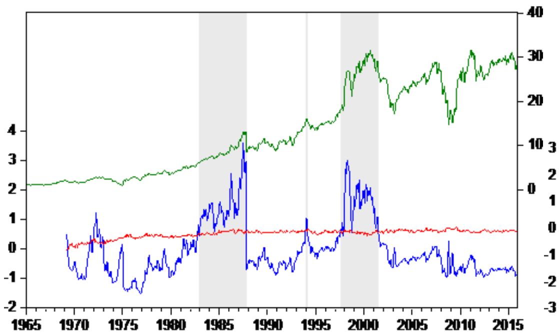
Switzerland GSADF test



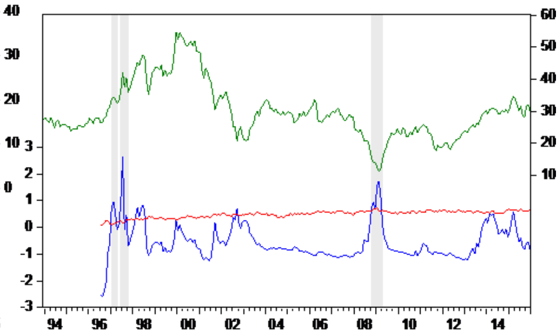
Turkey GSADF test



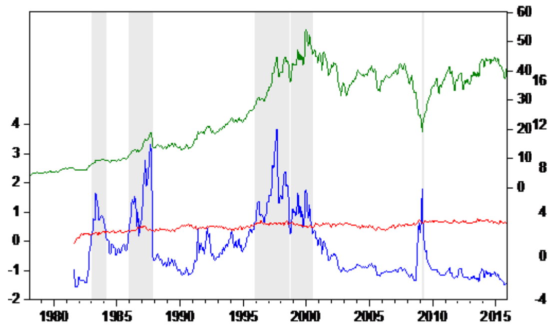
UK GSADF test



European Area GSADF test



Dow Jones GSADF test



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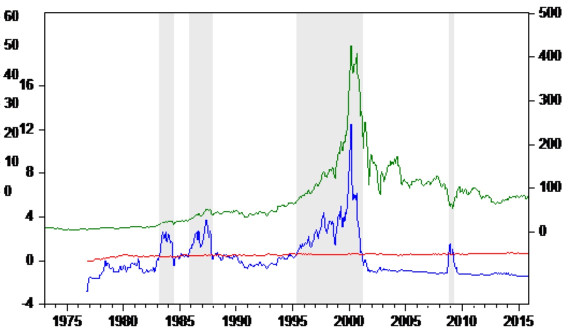
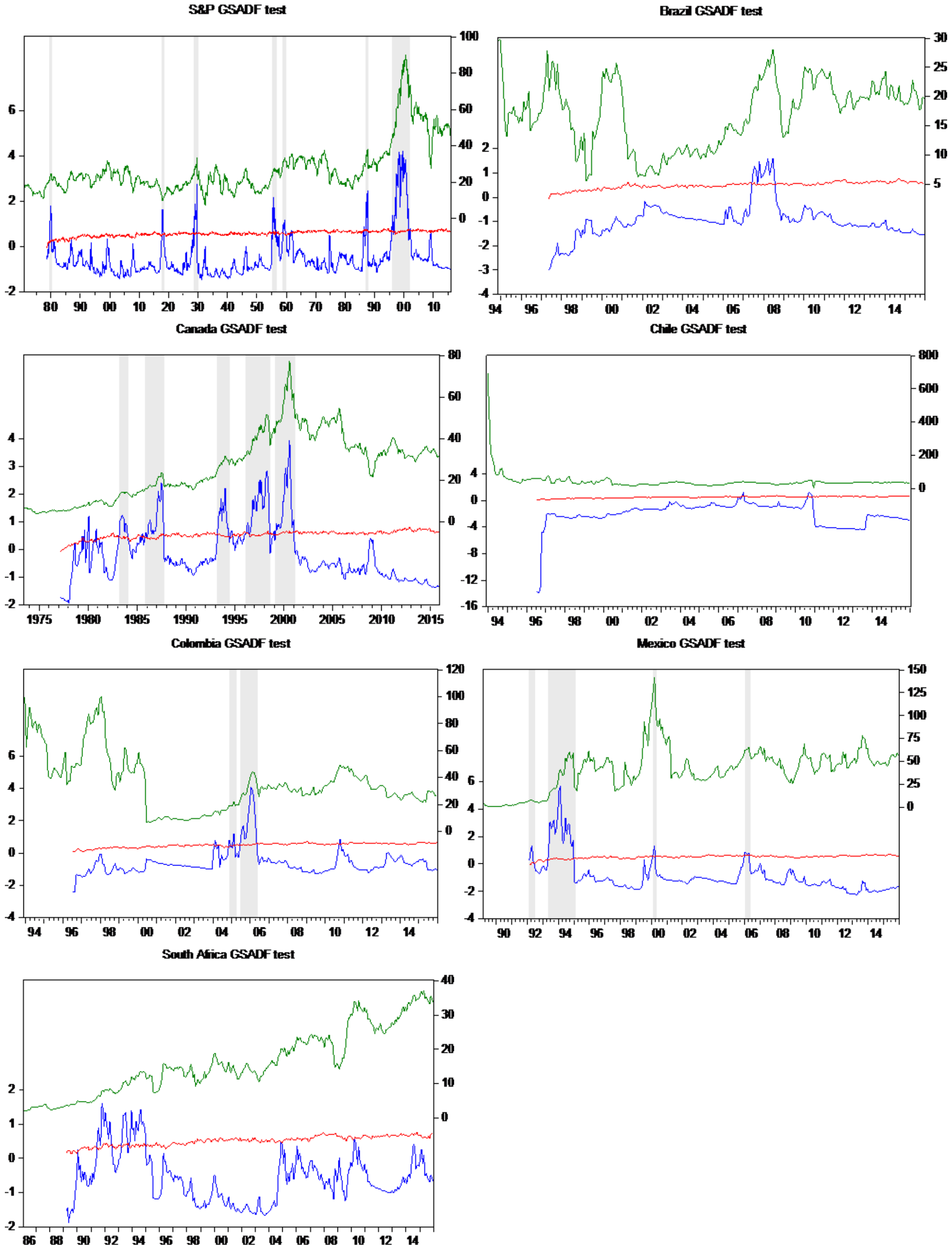



S&P GSADF test
Brazil GSADF test
Canada GSADF test
Chile GSADF test
Colombia GSADF test
Mexico GSADF test
South Africa GSADF test

Chapter 4 Do Bubbles migrate in the Global Markets?

4.1 Introduction

In recent decades, equity markets have suffered several financial crises which originated in one economy and then, after a short period of time, spread to the other markets. A substantial body of literature attributes the episode to bubbles, and focuses on the mechanisms of modeling, the methods of measuring their extent, and analyses on investors' psychology during the periods of market bubbles. However, the history of thought in stock markets has shown a surprising lack of consensus about a very fundamental question: what ultimately causes all those fluctuations in the price of assets, such as corporate stocks, commodities, or real estates? One might think that so basic a question would long ago have been confidently answered; however, it seems that the answer is not so easily found.

The recent financial exuberance provides a rich environment for empirical research. The most urgent ongoing question relates to the matters of fiscal, monetary, and regulatory policies for securing financial stability and buttressing real economic activity. Beyond these immediate policy issues are underlying questions in relation to bubble detection and evolutionary course. To answer those questions, we employ a unique testing framework including both return and volatility analyses to examine the bubble transmission mechanism across the international stock markets. The initial step is closely related to date-stamping method (see e.g., Phillips et al., 2015a, b) which extensively relies on forward recursive regressions coupled with sequential right-sided unit-root tests, and it aims to characterize the phenomenon, identify individual event, and sequence the timeline. In the following steps, we begin with developing several hypotheses for the bubble transmission process, and then implement two: (i) return (VAR tests) and (ii) volatility (AG-DCC) analyses to examine the key features. Basically, we believe that the transmission is due to the increased linkage between markets where the bubble is originated, and such concept directly corresponds to the definition of contagion. Indeed, our empirical results confirm the relationship between bubble movement and contagion at the very beginning of bubble periods and display the possibility that some equity markets are more sensitive to bubble transmission. We discuss the implications of our empirical findings in Section 4.11, but further studies are required to shed additional light on transmission channels.

The present chapter contributes to the literature in various ways. Firstly, our study greatly relates to the growing literature on financial bubbles and specifically for those focusing on bubble evolutionary process. The examination on linkage between market bubbles and financial contagion aims to discover the possible reason of bubble transmission with the purpose of assisting policymakers to gain important insight for the timing and channels of transmission. Secondly, we adopt a unique testing framework including both return and volatility analyses. Specifically, the VAR results unfold the information about which country is more likely to be affected if others experience market bubbles, while the results obtained through multivariate GARCH models enable practitioners to have deeper knowledge for the correlation dynamics, helping them maximize portfolio return but reducing the relevant risk. Finally, comparing with previous works which typically focus on just a small number of stock markets (very often, just the US stock market), our analysis falls into a much broader horizon, using data for 47 stock markets.

The outline of this chapter is as follows. Section 4.2 outlines the steps taken in this chapter, whilst in Section 4.3, we introduce our hypotheses about bubble transmission mechanism based on global stock markets. In Sections 4.4, 4.5, and 4.6, we review the relevant literature for transmission, financial contagion, and testing techniques. In Sections 4.7 and 4.8, we provide details about our data and our empirical design. Section 4.9 reports relevant empirical findings and Section 4.10 shows the details of robustness analysis. Then, in Section 4.11, we further discuss our results and finally Section 4.12 concludes.

4.2 Outline of Methodologies

To discover what happens in the global markets when bubbles are present, we set up a unique testing framework by the following steps:

Step 1: We borrow the PSY testing results from Chapter 3 to identify dates of bubbles and establish respective dummies (as bubble indicator) for each market.

Step 2: With the purpose of identifying transmission vector, VAR models with bubble indicators are specified for bivariate analysis.

Step 3: AG-DCC model is further applied to figure out correlation dynamics in both bubble and non-bubble periods for selected 10 equity markets.

4.3 Hypothesis

The establishment of exuberance timeline provides an opportunity to observe how bubble originates in one market and then evolves into a global financial crisis. Table 4.1 gives a brief chronology of bubble episodes for three major stock markets – the US, the UK and Japan – from the early of 1980s to the start of 2000s based on the PSY test results.[4]

<Table 4.1>

This timeline suggests that the potential linkage may be present among these markets when one or more of them experience a market bubble. More importantly, we find that, after aggregating global market bubbles, there are basically two types of bubble transmission process: (i) a bubble spills over to another market when it starts to collapse, and (ii) a bubble migrates to another market before that bubble bursts. Table 4.1 provides great examples in terms of the first and second types of bubble transmission. We can see that the Dotcom bubble appearing subsequently to the collapse of Japanese housing bubble can refer to the first type of transmission; meanwhile, the presence of the market exuberance in the United Kingdom before the collapse of Dotcom bubble gives another empirical example for the second type of transmission process.

All these episodes show a potential timeline of market bubble phenomena that can be subject to empirical evaluation. To formally define the bubble expansion among the global markets, we borrow the theoretical framework proposed by Caballero, Farhi, and Gourinchas (2008; CFG model hereafter) who partially explains the spillover of bubbles between markets, and several hypotheses involving successive bubble creations and collapses are suggested. However, in this chapter, we modify their hypotheses and apply them on the global stock markets. Basically, the CFG model links together global financial asset scarcity, global imbalances, the real estate bubble, and the environment without monetary factors. The model assumes that the economy has two countries: U and M, and features two goods: X and Z. An

[4] A total of 24 markets are confirmed with exuberance phenomenon, while Table 4.1 only selects three of them to depict the timeline of bubble episodes.

important part of the CFG framework is a sequence of hypotheses relating to different stages of bubble evolution, which we generally review as follows. Country U is interpreted as the US and country M as the emerging market economies and commodity producers. Good X is a non-storable good, a fraction of which can be capitalized, and is produced by both countries. Good Z is a storable commodity produced only by country M. A presumption in the model is that there exists a global imbalance at t_0. The imbalance can be interpreted as arising from continuing capital flows from emerging markets to the US since the US runs a growing trade deficit with emergent economies, which in turn rely more heavily on export driven growth.

In real world, despite emerging economies' great growth potential, their corporate and government sectors may not generate the financial instruments to provide residents with adequate store of value. Poor investor protection, means that the corporate sector is unable to capitalize future earnings and provide stores of value to the economy. Fiscal and sovereign-default concerns also limit the ability of the government to issue reliable debt. These factors lead to the 'financial repression' that, for instance, McKinnon (1973) has argued to be a prominent aspect of emerging market's financial systems. Finally, where possible, agents actively seek high-quality stores of value abroad by purchasing developed economies' safe assets, leading to significant capital outflows. This process has also been critically discussed in the literature. For example, Caballero and Krishnamurthy (2006) has developed a simple overlapping generations model and discussed the consequence of inadequate quantity of high quality domestic financial instruments in emerging markets. Their model shows that rational bubbles are beneficial from the scarcity of investment opportunity because they provide extra stores of value.

For CFG model, one fundamental assumption is that the bubble bursts at $t = 0$, leaving market participants (both local and foreign) to search for alternative stores of value. In the first stage, a flight-to-quality reaction migrates the bubble to 'good' assets and therefore, the price of commodities (notably Z) jumps, which leads to a significant wealth transfer from U to M. In the second stage, under the assumption that the financial asset crisis and wealth transfer precipitates a severe growth slowdown, the excess demand for the good asset is destroyed, resulting in a decrease in inventory of good Z, and a collapse of bubble in commodity prices.

Accordingly, this model can describe events in which asset bubble merged and subsequently collapsed, creating a sequence of bubble effects in one market after another. For example, when the first bubble is crashed and the value of investment falls substantially, liquidity flows into other markets, creating bubbles in other financial markets (equity, commodities, or oil markets). The deepening financial crisis then sharply slows down economic growth, which in turn destroys the subsequent bubbles. Overall, the CFG model introduces the possibility of bubble migration under a theoretical context, interpreting the process either from one country to another or from a specific market (equity) to the others (commodity). One important feature emphasized by the model is wealth transfer when investors realize the potential exploration in risk when bubble bursts. This leads to the significant change in correlation, which directly corresponds to the concept of financial contagion, and this empirical implication can be directly tested through the VAR framework.

In our study, we modify the CFG model to allow two types of transmission mechanisms: the transmission appears before the first bubble burst, and the transmission happens after the first bubble collapsed. The distinction reveals two directions of change in correlation: the positive increase in correlation, which corresponds to the first type of transmission mechanism, and the negative increase in correlation that directly belongs to the second type. We will explain our hypotheses in detail below.

In our hypothesis, we recognize two types of bubble evolutionary process and describe the first model below.

Hypothesis 1: *A price bubble arises and grows in one equity market and then collapses as the bubble broke.*

Hypothesis 1: represents the first phase of bubble evolution, while in the next phase, bubble erupts and funds flow selectively to assets in other equity markets with lower perceived risk or greater opportunity (wealth transfer), leading to a significant negative increase in linkage between those markets. In consequence, bubble emerged in certain equity markets is due to the significantly negative increase in cross-market linkage after the first bubble collapsed (see Hypothesis 2).

Hypothesis 2: *Following the burst of first bubble, new bubble is emerged in the selected* *equity markets.*

In the last phase, investors are aware of the high risk and associated credit crunch happened when the first bubble burst. The recognition of global recessionary effects triggers bubble collapse in the other markets.

Hypothesis 3: *Bubbles in other equity markets collapse as the global economic implications of the crisis become apparent.*

The first type of bubble transmission describes how the bubble emerged in one market could evolve within the global markets, whereas in real cases, another possibility exists that bubble transmission follows a different mechanism. In our second model, we introduce a different hypothesis to interpret the bubble transmission process.

Hypothesis 4: *The asset bubble emerged in one equity market while the bubble quickly migrates to the other equity markets before the first bubble collapses.*

Unlike Hypotheses 1 and 2, Hypothesis 4 assumes that the bubble migrates to the other equity markets before the first bubble broke, since market participants seek to balance their market portfolios but still, the funds withdraw from the original market are not sufficient to trigger the collapse of the initial bubble, or in another situation, market participants invest extra funds in other markets to chase the concept that generates the first bubble. However, subsequently, the realized risk for the initial bubble becomes extremely high, resulting in further wealth transfer from the market where the first bubble developed to the other markets with the lower risk. Finally, the first bubble collapses, forcing the investment transferring selectively to assets in other equity markets and boosting following bubbles' growth rate. Hypothesis 5 summarizes the above phenomenon:

Hypothesis 5: *The bubble originated in the first market collapses and such collapse boosts the growth rate of exuberance in the other equity markets.*

Eventually, market participants realize the serious impact caused by the financial exuberance while the recognition of global recessionary effects precipitates a collapse in the other stock price bubbles.

Hypothesis 6: *Bubbles in other equity markets collapsed as the global economic implications* *of the crisis become apparent.*

Overall, Hypotheses 1 to 6 are consistent with the event timeline provided in Table 4.1. Furthermore, they reveal that market participants always seek to balance their investment portfolios during the bubble expansion period, especially when the market risk becomes high. Such behavior will lead to an increased linkage across markets, and we believe this is a key characteristic that drives the bubble transmission. We notice that this empirical implication directly corresponds to the concept of financial contagion, and thus, we translate our task into a simpler version, that is, focusing on the discovery of financial contagion during the bubble periods. Furthermore, it is important to target the timing and channels of contagion and it can offer an opportunity to have a better understanding in bubble transmission mechanism. Although the channels of spillover have been extensively reviewed in the literature, their empirical discussion on bubble transmission are still lacking. The following three sections provide a short review for financial contagion and its empirical implications.

4.4 Three Major Channels

The literature on contagion in financial markets is far too extensive to review fully in this section. Dornbusch, Park, and Claessens (2000), and Kaminsky, Reinhart, and Vegh (2003), however, provide excellent surveys. Dornbusch et al. (2000) discuss the possibility that shocks to an individual country may affect other countries on the regional basis and similarly, Kaminsky et al. (2003) provide a view that the fast and furious contagion, which represents that the financial events in one country have triggered an immediate adverse chain reaction in other countries, can lead to a subsequent surge in capital flows and involve a leveraged common creditor. Following Dornbusch et al. (2000), Kaminsky et al. (2003), Bae, Karolyi, and Stulz (2003), Longstaff (2010) and many others, the current chapter adopts a working definition of contagion: an episode in which a significant change (positively or negatively) in cross-market linkages arises after a shock occurs in one market. The literature identifies at least three major channels by which contagion effects can be propagated through different financial markets.

The first channel can be named as the correlated-information channel. In this mechanism, a shock to one financial market signals economic news that is directly or indirectly relevant for security prices in other markets. Note that this could be consistent with the revelation of information for economic factors that affect multiple markets. For instance, Dornbusch et al. (2000) report that weak countries' economic fundamentals, macro-similarities and exposures to certain type of financial agents and associated transmission channels are found to increase the risk of spillovers. They adopt the idea of contagion as the spread of market disturbances, a process observed through co-movements in exchange rates, stock prices, sovereign spreads, and capital flows, while such contagion can occur for different reasons and conceptually be divided into two categories based on the literature. The first category focuses on cross-market spillover resulting from the normal interdependence among economies. The interdependence means that shocks, whether of a global or local nature, will be transmitted across countries because of their real and financial linkages and this form of crisis propagation is named as 'fundamentals-based contagion' by Calvo and Reinhart (1996). The other category involves a financial crisis which cannot be connected to observed changes in macroeconomic or other fundamentals and is solely the consequence of the behavior of market participants. Under this definition, contagion will be present when there is co-movement that cannot be interpreted on the basis of fundamentals (shocks, or interdependence is not present or controlled for). Several testing categories are emphasized in the study: correlation of asset prices, conditional probabilities of currency crisis, changes in volatility, and co-movements of capital flows. They conclude that these empirical tests have assisted to identify the type of links and other macroeconomic conditions which can make a country vulnerable to contagion during the crisis period, although less is known on the importance of microeconomic conditions and institutional factors in propagating shocks. It thus helps to discover those countries which are at risk of contagion and the general policy interventions which can reduce risks.

Another balance-sheet contagion described by Kiyotaki and Moore (2002) also demonstrates the importance of correlated-information channel by showing that the losses in one market could translate into declines in the equity of other firms holding the distressed assets. They classify the balance-sheet contagion into two branches: (i) the indirect balance-sheet contagion, which is caused by leverage effect (the firm's outstanding debt obligation is the results of its past borrowing) and will lead to sector specific shocks to spread out across sectors, even when firms are not directly linked through production, and (ii) the direct balance-sheet contagion that shocks to the liquidity of some firms may result in a chain reaction in which the other firms also get into financial difficulties if these firms are credit-constrained. Both mechanisms emphasize that the information channel is a crucial part within the expansion process because market participants will normally react to the information received from different sources and change their trading behavior based on those shocks while leading to the chain effect across markets that boosts the financial contagion. Similarly, an earlier study by King and Wadhwanni (1990) introduces a model presenting that the similar drop in all equity markets occurs as a result of attempts by rational agents to infer information from price changes in other markets. They examine a rational expectations price equilibrium together with model contagion as the outcome of rational attempts to use imperfect information about the events relevant to equity values. Since investors have access to different sets of information, they can infer valuable information from price changes in other markets.

Overall, a common implication throughout the correlated-information literature is that contagion occurs rapidly through the price-discovery process, and thus, this channel should result in immediate price effects in the markets influenced by the distress event, especially when these markets are more liquid than the market in which the original shock occurs. Importantly, this implication of the correlated-information contagion mechanism can be directly tested using a VAR framework, while this is the basic rationale adopted in this chapter to implement our empirical examination.

The second channel can be termed the liquidity channel. In this mechanism, a shock to one financial market might cause a decrease in the overall liquidity of all financial markets and therefore, affecting market participant's behavior and asset prices. A typical study of Allen and Gale (2000), which suggests the financial contagion as an equilibrium phenomenon, presents a model in which banks have cross holdings of deposits across regions. In their model, to focus on the role of one particular channel for financial contagion, they exclude other propagation mechanisms that may be crucial for a complete understanding of financial contagion. Similarly, Kodres and Pritsker (2002) introduce a model in which contagion occurs as losses in one market force economic agents to either liquidate leveraged positions or to rebalance their portfolios in response. Through their transmission channel, investors transmit idiosyncratic shocks from one market to others by adjusting their portfolios' exposures to shared macroeconomic risks. The pattern and severity of financial contagion depends on markets' sensitivities to shared macroeconomic risk factors, and on the amount of information asymmetry in each market. Brunnermeier and Pedersen (2009) argue that agents who experience losses in one market may find their ability to obtain funding impaired, which would then lead to declines in the liquidity of the other financial assets in the markets. They suggest a model that links an asset's market liquidity (i.e., the ease with which it is traded) and traders' funding liquidity (i.e., the ease with which they can obtain funding). By showing under certain conditions, margins are destabilizing, and market liquidity and funding liquidity are mutually reinforcing, resulting in liquidity spirals.

In sum, the key implication of the liquidity-related channel of contagion is that a distress event may be associated with following declines in the availability of credit and increases in trading behavior in other markets.

The third channel can be designated as the risk-premium channel. In this mechanism, financial shocks in one market may influence the willingness of market participants to bear risk in any market. Therefore, asset prices in all markets may be affected as equilibrium risk premia adjusted in response. For example, Vayanos (2004) proposes a theoretical dynamic equilibrium model of a multi-asset market with stochastic volatility and transaction costs. Their key assumption is that investors are fund managers, subject to withdrawals when fund performance drops below a threshold, while such investor modeling generates a preference for liquidity that is time-varying and increasing with volatility. They show that during volatile times, the probability that performance falls below an exogenous threshold increases, and withdrawals become more likely. This reduces the manager's willingness to hold illiquid assets and raises the liquidity premia. One of empirical implications provided by their model relates to the role of liquidity, both as an asset characteristic and as a risk factor, in explaining cross-sectional expected returns. Similarly, Acharya and Pedersen (2005) discuss this empirical implication based on their simple theoretical framework that illustrates several channels through which liquidity risk can affect asset prices. The framework in its simplest form reveals that the CAPM applies for returns net of illiquidity costs and implies that investors should worry about a security's performance and tradability both in market downturns and when liquidity "dries up". The model further shows that a positive shock to illiquidity, if persistent, are associated with low contemporaneous returns and high predicted future returns.

A key implication of those time variations in risk premia is that return shocks to the distressed security may be predictive for the following returns of other assets due to the reason that the change of risk premium for an asset also has an impact on the distribution of future asset returns. In turn, this feedback effect can induce predictability into the time series of realized asset returns.

The above contagion channels all have different implications for the behavior of asset prices across markets when a negative shock occurs. However, it is important to be aware of the possibility that different channels are dependent on and affect each other since contagion is present. Taking financial crisis of 2007 to 2008 as an example, we can observe an obvious relationship between credit risk and liquidity because in fact, a significant factor during the period of 2007 may have been credit-risk-induced illiquidity as investors were keen to take positions in complex mortgage-related securities. Alternatively, an important factor in the global financial crisis of late 2008 may have been illiquidity-induced credit risk as major financial institutions confronted default, since they were unable to liquidate positions and collateralize their liabilities.

4.5 VAR Framework

Vector Autoregressive model is a widely accepted econometric model that is used to capture the linear interdependency among multiple time series. All variables in a VAR enter the model in a same way that each variable has an equation interpreting its evolution based on its own lags and the lags of other model variables. VAR enjoys the merit that it does not require as much knowledge about the forces influencing a variable as structural models with simultaneous equation, the only prior knowledge required is a list of variables which can be hypothesized to affect each other inter-temporally.

A p-th order VAR, denoted VAR(p), is,

$$y_t = \alpha + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + e_t, \tag{4.1}$$

where the p-periods back observation y_{t-p} is called the p-th lag of y; α is a $k \times 1$ vector of constants; A_p is a time-invariant $k \times k$ matrix and e_t is a $k \times 1$ vector of error terms satisfying,

(i) $E(e_t) = 0$,

(ii) $E\left(e_t e_t^{'}\right) = \Omega$ The contemporaneous covariance matrix of error terms is Ω (a $k \times k$ positive-semidefinite matrix), and

(iii) $E\left(e_t e_{t-k}^{'}\right) = 0$ for any non-zero *k*.

In studying the nature of contagion in financial markets, it is helpful to have two key elements. First, we must be able to identify an event window for the bubble periods. Second, we must be able to identify a vector of contagion which can then be used to test for changes in linkages across markets associated with the bubble episodes. The bubble periods stamped in Chapter 3 provide a nearly perfect example of a potential contagion event where both of these elements are present. In particular, during the exuberance periods, we can initially observe the sharp increase in the price-dividend ratio since market participants put their investment in the equity market when bubble is present while subsequently, the ratio will be back to its original level because of the bubble collapse. Therefore, price-dividend ratio of equity market index can be viewed as the prime vector of contagion.

In conclusion, to explore the empirical implications between financial contagion and bubble transmission, the approach will be used to test whether there is an increase in the cross-market linkage between one and the other stock markets when bubbles are present. This approach is motivated by the standard definition in the literature of contagion as a change in the linkages between markets is followed by distress events. The VAR framework is our primary choice and it allows us to discover the respective linkage between global equity markets over the relevant bubble periods recorded through date-stamping mechanism.

4.6 Multivariate GARCH Model

The majority of studies concern the contagion based on bivariate analysis, and the most popular approach is through studying correlations between returns among different markets. For instance, Longstaff (2010) conducts an empirical investigation into the pricing of subprime asset-backed collateralized debt obligations as well as their contagion effects with other markets. He adopts the widely accepted working definition and states channels causing the contagion in order to pin down the reason of applying VAR framework. Their results are substantial, supporting the hypothesis that financial contagion is propagated primarily through liquidity and risk-premium channels, rather than through a correlated-information channel. However, a number of academic studies argue that the standard analysis of cross-market correlations is biased because of the issue of heteroscedasticity. One typical study is Forbes and Rigobon (2002), who reveal that the unadjusted correlation coefficient is conditional on market movements over the sample period, so that during a period of turmoil when equity market volatility increases, standard estimates of cross-market correlations will be biased upward. Other studies attempt to model the volatility transmission mechanism to avoid inconsistent estimation issues (see e.g., Engle and Kroner, 1995; Engle, 2002). Academics support the superior power of the dynamic conditional correlation approach with respect to the correlation coefficient of Forbes and Rigobon (2002) because with the dynamic conditional correlation model there is no need to explicitly and arbitrarily divide the sample into subsamples. Prior to giving a brief introduction in volatility transmission, we will provide a general review for ARCH family models.

4.6.1 The ARCH Model

Autoregressive conditional heteroscedasticity (ARCH) is the condition that one or more data points in a series for which the variance of the current error term or innovation is a function of the actual sizes of the previous time periods' error terms. In the real world, uncertainty or randomness is commonly observed for financial time series data where the assumptions of normality, independence, and homoscedasticity do not always hold that limit the application of AR, MA, ARMA, and ARIMA models. Therefore, ARCH model is proposed by Engle (1982) with the volatility clustering effect in the modelling process.

To model a time series (y_t) using an ARCH process, considering the distribution of y_t is normal with a mean equal to $x_t\beta$ plus a random component h_t. From equations below, the distribution of y_t in the information set ψ_{t-1} is a linear combination of the vector and a coefficient vector $\beta = (\beta_1, \beta_2, \dots, \beta_n)'$.

$$y_t|\psi_{t-1} \sim N(x_t\beta, h_t),$$

$$h_t = h(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-p}, \alpha),$$

$$\varepsilon_t = z_t\sqrt{h_t},$$

$$y_t = x_t\beta + \varepsilon_t,$$

where z_t is a strong white noise process, β is a consistent.

The process of z_t is scaled by h_t, the conditional variance, which in turn is a function of past squared residual returns. In the ARCH(q) process,

$$h_t = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2, \tag{4.2}$$

where the condition $\omega > 0$ and $\alpha_j \geq 0$ are set to ensure strictly positive variance.

Traditional econometric models assume a constant one-period forecast variance but autoregressive conditional heteroscedastic processes are designed to generalize this implausible assumption. These are mean zero, serially uncorrelated processes with non-constant variances conditional on the past, but constant unconditional variances. For such processes, the recent past provides information in terms of the one-period forecast variance.

The ARCH regression model has a variety of characteristics which make it attractive for econometric applications. The typical one is the ability to capture the effect of clustering. Previous literature documents that large and small errors tend to cluster together (in contiguous time periods) while this analysis immediately suggests the usefulness of ARCH model where the underlying forecast variance might change over time and is predicted by past forecast errors. A second example is discovered in monetary theory and the theory of finance. Their simplest assumptions suggest that portfolios of financial assets are held as functions of the expected means and variances of the rates of return. Any movement in asset demand must be associated with changes in expected means and variances of the return. If the mean is assumed to follow a standard regression or time-series model, the variance is constrained to be constant over time. The adoption of an exogenous variable to interpret changes in variances is usually not appropriate. A third interpretation is that the ARCH regression model is an approximation to a more complex regression which has non-ARCH disturbances. The ARCH specification might then be picking up the effect of variables omitted from the estimated model and the existence of an ARCH effect (clustering effect) would be explained as evidence of misspecification, either by omitted variables or through structural change. If this is the case, ARCH could be a better approximation to reality than making standard assumptions in terms of the disturbances, but attempting to find the omitted variable or determine the nature of the structural change.

4.6.2 The GARCH Model

For high order ARCH(q) process, it is more parsimonious to model volatility as a Generalised ARCH model (GARCH (p, q) model) by Bollerslev (1986), where additional dependencies are allowed on p lags of past h_t,

$$h_t = \omega + \sum_{i=1}^{p} \beta_i h_{t-i} + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \tag{4.3}$$

and $\omega > 0$, β and α are estimated coefficients.

The unconditional variance for higher orders of GARCH equals,

$$\sigma^2 = \frac{\omega}{1-\sum_{i=1}^{p} \beta_i - \sum_{j=1}^{q} \alpha_j}. \tag{4.4}$$

The GARCH (p, q) model is covariance stationary if and only if $\sum_{i=1}^{p} \beta_i + \sum_{j=1}^{q} \alpha_j < 1$.

The GARCH (1,1) model is widely adopted in the literature where,

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1},$$

and its unconditional variance is,

$$\sigma^2 = \frac{\omega}{1-\alpha-\beta}. \tag{4.5}$$

While conventional time series and econometric models operate under an assumption of constant variance, the ARCH process developed in Engle (1982) allows the conditional variance to change over time as a function of past information, leaving the unconditional variance constant. This type of moving behaviour has proven useful in modelling a couple of different economic phenomena. For example, the inflation rate, which has been widely discussed in Engle (1982), Engle (1983), as well as Engle and Kraft (1983), is recognized that its uncertainty tends to change over time. Models for the term structure using an estimate of the conditional variance as a proxy for the risk premium are given in Engle, Lilien, and Robins (1987). Common to most of the above applications, however, is the introduction of a rather arbitrary linear declining lag structure in the conditional variance equation to take account of the long memory typically discovered in empirical studies, since estimating a completely free lag distribution often leads to violation of the non-negativity constraints. Therefore, Bollerslev (1986) introduces a new, more general class of processes that allows for a much more flexible lag structure, the generalized Autoregressive Conditional Heteroskedastic (GARCH), while such extension bears much resemblance to the extension of the standard time series AR process to the general ARMA process, and permits a more parsimonious description in many situations. In addition, an empirical example explaining the uncertainty of the inflation rate is presented in this study, aiming to show that a simple GARCH model provides a marginally better fit and more plausible learning mechanism than the ARCH model with an eighth-order linear declining lag structure.

4.6.3 The Absolute Value GARCH(AVGARCH) Model

Taylor (1986) proposes a GARCH model, which is not radically different from the conventional GARCH model but only takes the absolute value in the model specification of past error terms:

$$h_t^{1/2} = \omega + \alpha|\varepsilon_{t-1}| + \beta h_{t-1}^{1/2}. \tag{4.6}$$

4.6.4 The EGARCH Model

The simple GARACH models have been applied in modelling the relation between conditional variance and asset risk premia but these models have at least three major disadvantages in asset pricing applications: (i) academics have found a negative correlation between current returns and future returns volatility, while GARCH models reject this by assumption. (ii) GARCH models impose parameter restrictions that are often violated by estimated coefficients and that may unduly restrict the dynamics of the conditional variance process. (iii) it is difficult to interpret whether shocks to conditional variance persist in GARCH models as the usual norms measuring persistence often do not agree. To solve above issues, Nelson (1991) introduces the EGARCH model which considers the threshold effects and specifies the asymmetry in GARCH models.

$$\ln(h_t) = \omega + \alpha\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \gamma\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta\ln{(h_{t-1})}. \tag{4.7}$$

4.6.5 *The GJR-GARCH Model*

Glosten, Jagannathan, and Runkle (1993) find support for a negative relation between conditional expected monthly return and conditional variance of monthly return, using a GJR-GARCH model modified by allowing seasonal patterns as well as asymmetry in volatility. The GJR-GARCH (1,1) model is noted as,

$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma I[\varepsilon_{t-1} < 0]\varepsilon_{t-1}^2 + \beta h_{t-1}. \tag{4.8}$$

4.6.6 *The TGARCH Model*

Zakoian (1994) introduces another GARCH model which takes threshold effects into account, the TGARCH model. The model is similar to the GJR model, but different only because of the standard deviation, instead of the variance, in the specification,

$$h_t^{1/2} = \omega + \alpha|\varepsilon_{t-1}| + \gamma I[\varepsilon_{t-1} < 0]|\varepsilon_{t-1}| + \beta h_{t-1}^{1/2}. \tag{4.9}$$

4.6.7 *The Multivariate ARCH Family Model*

The multivariate GARCH models are specified as,

$$r_t = \epsilon_t,$$

$$\epsilon_t | I_{t-1} \sim N(0, H_t),$$

$$H_t = g(H_{t-1}, H_{t-2}, \dots, \epsilon_{t-1}, \epsilon_{t-2}),$$

where r_t is a $(n \times 1)$ vector of asset returns at time *t*, H_t is the covariance matrix of *n* asset returns at time *t*. The lagged conditional covariance matrices are modelled by the function of $g(.)$ and this covariance matrices can be functioned in a variety of ways. One of the most popular multivariate GARCH specifications is the Baba, Engle, Kraft, and Kroner (BEKK) model proposed by Engle and Kroner (1995), with permitted interactions among variances but as it requires $\left(\frac{n(n+1)}{2}\right) + n^2(q+p)$ parameters to be estimated, the optimization process becomes extremely complex and unstable when the dimensions of the model increase.

4.6.8 *The CCC Model*

Bollerslev (1990) suggests a simple multivariate conditional heteroskedastic time series model with time-varying conditional variances and covariance but constant conditional correlations. Let y_t denotes the $N \times 1$ time-series vector of interest with time-varying conditional covariance matrix H_t,

$$y_t = E(y_t|\psi_{t-1}) + \epsilon_t,$$

$$Var(\epsilon_t|\psi_{t-1}) = H_t,$$

where ψ_{t-1} is the σ-field generated by all the available information up through time $t-1$; H_t is almost surely positive definite for all *t*.

Also, let $h_{i,j,t}$ denotes the i,j^{th} element in H_t; $y_{i,t}$ and $\epsilon_{i,t}$ denote the i^{th} element in y_t and ϵ_t, respectively. Then a natural scale invariant measure of the coherence between $y_{i,t}$ and $y_{j,t}$ evaluated at time $t-1$ is given by the conditional correlation $\rho_{i,j,t} = h_{i,j,t}/\sqrt{(h_{i,i,t}h_{j,j,t}}$, where $-1 \leq \rho_{i,j,t} \leq 1$ for all *t*. In some applications the time-varying conditional covariance might be taken as proportional to the square root of the product of the corresponding two conditional variances,

$$h_{i,j,t} = \rho_{i,j}(h_{i,i,t}h_{j,j,t})^{1/2}, \qquad j = 1, \dots, N, i = j+1, \dots, N,$$

leaving the conditional correlations constant through time. The term $h_{i,i,t}$ is obtained from the univariate GARCH (*p*, *q*) model,

$$h_{i,i,t}{}^2 = \omega_{i,0} + \sum_{j=1}^{q} \alpha_{i,j}\epsilon^2_{(i,i),t-j} + \sum_{k=1}^{p} \beta_{i,k}h^2_{(i,i),t-k}.$$

The CCC model enjoys the feature of simplified estimation and inference procedures. To show this, each of the conditional variances is rewritten as,

$$h_{i,i,t} \equiv \omega_i\sigma^2_{i,t}, i = 1, \dots, N,$$

with ω_i a positive time invariant scalar and $\sigma^2_{i,t} > 0$ for all *t*. Given $h_{i,j,t} = \rho_{i,j}(h_{i,i,t}h_{j,j,t})^{1/2}$ and $h_{i,i,t} \equiv \omega_i\sigma^2_{i,t}$, the full conditional covariance matrix H_t can be portioned as,

$$H_t = D_t \Gamma D_t, \tag{4.10}$$

where D_t is the $N \times N$ stochastic diagonal matrix with elements $\sigma_{1,t}, \dots, \sigma_{N,t}$ and Γ is an

$N \times N$ time invariant matrix with typical element $\rho_{i,j}\sqrt{(\omega_i \omega_j}$. Now it follows that H_t will be positively definite for all *t* if and only if each of the *N* conditional variances are well defined and Γ is positively definite. These conditions are easy to impose and verify compared to many alternative parameterizations for the time-varying covariance matrix.

4.6.9 The DCC Model

Multivariate GARCH models are normally applied to estimate time-varying correlations that are linear in squares and cross products of the data. Engle (2002) suggests a new class of multivariate models called dynamic conditional correlation models which are not linear but can often be estimated very simply with univariate or two step methods based on the likelihood function. Basically, it first estimates a series of univariate GARCH models, which yield GARCH parameters and residuals; then it uses these residuals to estimate the conditional correlation. The DCC model can be formulated as the following statistical specification,

$$r_t|\Im_{t-1} \sim N(0, D_t R_t D_t),$$

$$D_t^2 = diag\{\omega_i\} + diag\{K_i\} \circ r_{t-1}r_{t-1}{'} + diag\{\lambda_i\} \circ D_{t-1}^2, \tag{4.11}$$

$$\varepsilon_t = D_t^{-1} r_t, \tag{4.12}$$

$$Q_t = S \circ \left(\iota\iota' - A - B\right) + A \circ \varepsilon_{t-1}\varepsilon_{t-1}{'} + B \circ Q_{t-1}, \tag{4.13}$$

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}, \tag{4.14}$$

Where r_t be a $k \times 1$ vector of asset returns, $\Im_{t-1}$ is the time $t-1$ information set, A, and B are $k \times k$ parameter matrices, S is the unconditional correlation matrix of epsilons, ι is a vector of ones and $\circ$ is the Hadamard product of two identically sized matrices which is computed simply by element by element multiplication. The assumption of normality in the first equation gives rise to a likelihood function. Without this assumption, the estimator will still have the QML interpretation. The second equation simply expresses the assumption that each of the series follows a univariate GARCH process. Nothing would change if this were generalized.

4.6.10 The Asymmetric Generalized DCC Model

Since the literature has provided convincing evidence that asymmetries commonly exist in many stock markets (see e.g., Kroner and Ng, 1998; Bekaert and Wu, 2000; Scruggs and Glabadanidis, 2003), Cappiello, Engle and Sheppard (2006) propose a new generalized autoregressive conditionally heteroskedastic process: the asymmetric generalized dynamic conditional correlation (AG-DCC) model. The AG-DCC model is evolved from DCC-GARCH model of Engle (2002) by introducing two modifications: it allows for series-specific news impact and smoothing parameters and permits conditional asymmetries not only in GARCH process but also in correlation dynamics. The general idea still based on the DCC model let r_t be a $k \times 1$ vector of asset returns, which is assumed to be conditionally normal with mean zero and covariance matrix H_t,

$$r_t|\Im_{t-1} \sim N(0, D_t R_t D_t), \tag{4.15}$$

where $\Im_{t-1}$ is the time $t-1$ information set; D_t is the $k \times k$ diagonal matrix of time-varying standard deviations from univariate GARCH models with $\sqrt{h_{i,t}}$ on the ith diagonal; P_t is the time-varying correlation matrix. Once the univariate volatility models are estimated, the standardized residuals, $\varepsilon_{i,t} = r_{i,t}/\sqrt{h_{i,t}}$, are used to estimate the correlation parameters. The evolution of the correlation in the AG-DCC model is given by,

$$Q_t = (\bar{P} - A'\bar{P}A - B'\bar{P}B - G'\bar{N}G) + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'n_{t-1}n'_{t-1}G + B'Q_{t-1}B, \tag{4.16}$$

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1}, \tag{4.17}$$

where A, B, and G are $k \times k$ parameter matrices; $n_t = I[\varepsilon_t < 0] \circ \varepsilon_t$ ($I[\cdot]$ is a $k \times 1$ indicator function which takes on value 1 if the argument is true and 0 otherwise, while '∘' indicates the Hadamard product); $\bar{N} = E[n_t n'_t]$ and $\bar{P} = E[\varepsilon_t \varepsilon'_t]$. $Q_t^* = [q_{iit}^*] = \lfloor \sqrt{q_{iit}} \rfloor$ is a diagonal matrix with the square root of the ith diagonal element of Q_t on its ith diagonal position.

4.7 Data Collection

This chapter continually uses the datasets collected in Chapter 3. To test the hypothesis of whether exuberance promotes the equity market contagion, discovering the booming and collapsing periods should be the initial step. The main sample is collected from six regions:

Asia (14), Australasia (2), Europe (22), the US (3), North and South America excluding the US (8), and Africa (1). For simplicity, we group the stock markets into five groups: Asia (including Australasia) (16), Europe (22), the US (3), North and South America excluding the US (for brevity, referred to as America excluding the US) (5), and Africa (1). This data is used to compute the price/dividend ratio for each index. All datasets except The US are collected through DataStream on monthly basis with earliest starting date of January 1871 to latest starting date of June 2000, constituting observations range from 147 to 1,737. All ending dates are set to December 2015 to ensure all datasets up-to-date. Data sources are chosen based on sequence availability to guarantee that each sample has both market index and dividend series.

4.8 Empirical Design

4.8.1 The VAR Test

In studying the nature of contagion during the bubble periods, it is important to notify two key elements. The first element relates to the identification of possible exuberance period which contains the positive or negative shocks. PSY (2015a, b) provide us with a reliable dating mechanism to identify exuberance episodes within a long sample period. Second, vectors of contagion need to be defined and then can be used to test for changes in linkage across markets. In this thesis, price-dividend ratios, rather than price itself, is used as a measure of vectors. There are two main reasons: (i) we adopt the price-dividend ratio to revel the cause-and-effect relationship between the bubble and market contagion because it follows the logic to use the same variable which we have selected in Step 1, (ii) it is reasonable since the ratio actually reflects the asset price in relation to its fundamentals according to asset pricing equation of Shiller (1981), whereas market return does not reveal such relationship and cannot be used to define bubble phenomenon. To test whether the exuberance results in return spillover from one equity market to another, we estimate the following bivariate VAR equations:

$$Y_{i,t} = \alpha + \sum_{k=1}^{4} \delta_{i,t-k} Y_{i,t-k} + \sum_{k=1}^{4} \beta_{j,t-k} Y_{j,t-k} + \sum_{k=1}^{4} \gamma_{j,t-k} D_{j,t-k} Y_{j,t-k} + \varepsilon_{i,t}, \quad (4.18)$$

for each of the dependent variables, where $Y_{i,t}$ and $Y_{j,t}$ are the returns of price-dividend ratios for major stock market indices; the four-lag structure in latter part of the equation is selected based on the consideration of delay in transmission. We set the lag structure to 4 rather than applying BIC order selection criteria because our datasets have different sample size and the use of BIC order selection criteria may result in different lag structures that distort the comparability of our testing results. $D_{j,t-k}$ is set according to the date-stamping results and equals to 1 when bubbles are present, and 0 otherwise. Note that we primarily use the PSY date-stamping results in our VAR and following testing procedures. The VAR model given by equation (4.18) is estimated using ordinary least squares (OLS) for all pairs of indices in our sample, and to correct any issues that could violate the standard assumptions of regression analysis, we use the Newey-West approach to provide consistent estimates. We primarily carry out the *t*-test to test null that whether $\beta_k s = 0$ and $\gamma_k s = 0$, and *F*-tests that whether $\beta_k s$ and $\gamma_k s$ are jointly zero ($\beta_1 = \beta_2 = \beta_3 = \beta_4 = \gamma_1 = \gamma_2 = \gamma_3 = \gamma_4,\ p_1$) and whether $\gamma_k s$ are jointly zero ($\gamma_1 = \gamma_2 = \gamma_3 = \gamma_4,\ p_2$). The estimated model provides useful information on the extent to which a bubble in stock market *j* influences the conditional mean linkage between stock market *j* and stock market *i*.

4.8.2 The Volatility Correlation Test

The second approach used to investigate the contagion-effect and correlation dynamics involves the estimation of AG-DCC models with the purpose of checking robustness and observing the dynamic movement for correlation within the period of bubble episodes. After accommodating the significant change by our VAR model, we further apply the AG-DCC model to disclose the movement of correlation (increase or decrease) within respective bubble periods. Similar to our VAR framework, we apply the return of price-dividend ratio in all of our AG-DCC estimation procedures. The AG-DCC model is evolved from DCC-GARCH model of Engle (2002) by introducing two modifications: asset-specific correlation evolution parameters and conditional asymmetries in correlation. To accomplish our research objective, we use the price dividend ratio of market indices and then calculate their returns. Let r_t be a $k \times 1$ vector of asset returns, which is assumed to be conditionally normal with mean zero and covariance matrix H_t:

$$r_t | \xi_{t-1} \sim N(0, H_t),$$

where ξ_{t-1} is the time $t-1$ information set. H_t can be decomposed as follows:

$$H_t = D_t P_t D_t,$$

where D_t is the $k \times k$ diagonal matrix of time-varying standard deviations from univariate GARCH models with $\sqrt{h_{i,t}}$ on the ith diagonal; P_t is the time-varying correlation matrix.

The DCC model is designed to allow for three-stage estimation of the conditional covariance matrix where any univariate GARCH process that is covariance stationary and assumes normally distributed errors can be used to model the variances. In the first stage, univariate volatility models are estimated for each of the assets while in the second stage, asset returns which are transformed by their estimated standard deviations are used to estimate the intercept parameters of the conditional correlation. The final stage conditions on the correlation intercept parameters to estimate the coefficients governing the dynamics of correlation. All results obtained through the three-stage estimation procedures assume that the univariate GARCH model is correctly specified. If the models are not well specified, then the correlation estimates will no longer be consistent. Thus, to reduce the risk that the univariate models will lead to inconsistent correlation estimates, we apply the model selection procedure to select the correct univariate models for each of our sample. In addition, Bayesian information criterion (BIC) are employed to select the univariate volatility specifications. Although other information criteria are available, the use of BIC is appropriate as it leads to the correct model specification (see Cappiello, et al., 2006). We include a variety of models in the specification search, all with one lag of the innovation and one lag of volatility.[5]

The simplest models are GARCH and AVGARCH, followed by EGARCH, TGARCH and GJR-GARCH, which all allow for threshold effects whereas employ different powers of the variance in the evolution equation. Once the univariate volatility models are estimated, the standardized residual, $\varepsilon_{i,t} = r_{i,t}/\sqrt{h_{i,t}}$, is used to estimate the correlation parameters. The evolution of the correlation in the asymmetric generalized DCC model (see Cappiello, et al., 2006) is given by,

$$Q_t = (\bar{P} - A'\bar{P}A - B'\bar{P}B - G'\bar{N}G) + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'n_{t-1}n'_{t-1}G + B'Q_{t-1}B,$$

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1},$$

[5] The detailed specifications for each GARCH model will be presented in Table 4.6.

where A, B, and G are $k \times k$ parameter matrices; $n_t = I[\varepsilon_t < 0] \circ \varepsilon_t$ ($I[\cdot]$ is a $k \times 1$ indicator function which takes on value 1 if the argument is true and 0 otherwise; '$\circ$' indicates the Hadamard product); $\bar{N} = E[n_t n_t']$ and $\bar{P} = E[\varepsilon_t \varepsilon_t']$; $Q_t^* = [q_{iit}^*] = \lfloor \sqrt{q_{iit}} \rfloor$ is a diagonal matrix with the square root of the ith diagonal element of Q_t on its ith diagonal position.

4.9 Empirical Findings

4.9.1 Testing and Date-stamping Results

We borrow testing and date-stamping results from the Chapter 3. Table 4.2 shows the testing results by applying PSY (2015a, b). Generally, all testing results show that explosive behavior is a common phenomenon in the global markets. Three US market indices (DJIA, NASDAQ and S&P 500) are significant at 1% level, showing strong evidence that these market indices have explosive sub-periods. Similarly, most of the stock markets in the Europe, Asia, and America excluding US evidence the presence of bubbles. For example, the generalized sup-ADF statistics of Belgium, Denmark, Italy are 2.16, 2.119, and 2.037, respectively, all exceeding their respective ten percent right-tailed critical values (2.16 > 1.908, 2.119 > 1.955, and 2.037 > 1.955). Table 4.2 provides the detailed testing results including sources and the number of observations for each market in our sample.

<Table 4.2>

Additionally, date-stamping results are primarily used in this chapter to set up the testing window for both VAR and AG-DCC models. Here, we adopt the PSY date-stamping results, considering the merits of this method when testing periods are relatively long with high possibility that contains multiple bubbles. Table 4.3 displays the PSY date-stamping results for each market discovered with exuberance. The exuberant sub-periods for S&P 500 include the late 19th century (e.g., 1879M07-1880M05), the early 20th century (e.g., 1917M09-1918M05), the great depression episode (e.g., 1928M09-1929M11), the post-war bubbles in fifties (e.g., 1955M04-1956M08, and 1958M11-1959M09), the black Monday in October 1987 (e.g., 1987M01-1987M10), and the Dotcom bubble (e.g., 1995M12-1996M07 and 1996M09-2001M09). DJIA and NASDAQ obtain approximately the same results in eighties and nineties, but NASDAQ further finds the subprime mortgage crisis in 2008 (e.g., 2008M10-2009M03). For America excluding US, the PSY test results show that the index for

Colombia experiences explosive behavior from 2004 to 2006 (e.g., 2004M11-2005M03 and 2005M06-2006M05). In Europe, explosive behavior is detected over the following dates: the UK (e.g., 1971M10-1972M04, 1997M06-1997M10, and 1997M11-2000M07), Germany (e.g., 1982M12-1984M05, 1985M05-1986M07, and 1997M06-1997M10), Italy (e.g., 1993M06-1993M10, 1994M03-1994M10, and 2008M12-2009M04), and Belgium (e.g., 2008M10-2009M06). Asian market results prove the widely influence of Asian financial crisis: The South Korea and Hong Kong encounter market grow and collapse in the middle and late 1990s (e.g., 1994M01-1995M01, 1999M05-1999M10, and 1999M11-2000M03 for South Korea; 1987M06-1987M10 and 1993M10-1994M02 for Hong Kong). The indices for Japan, India, and Hong Kong also have similar behavior to the US indices in 2008, whilst the Chinese stock market experiences its exuberance periods in 2008 and 2015 (e.g., 2007M01-2007M06 and 2008M01-2008M12, and 2015M04-2014M06). Note that for above results, the duration of the exuberance episodes detected are no less than two months.

<Table 4.3>

4.9.2 The Overall VAR Results

Table 4.4 summarizes the whole VAR estimation results (20 stock markets which are subject to bubble episodes confirmed by PSY date-stamping strategy in the previous section), while Table 4.5 reports the Newey-West t-statistics for corresponding γ_k coefficients in equation (4.18) in selected 10 major stock markets (e.g., Australia, China, Hong Kong, Japan, Thailand, Germany, Netherlands, the UK, the US (NASDAQ), and adding the whole EU as one separate market). Table 4.5 also reports the p-values for the F-tests that whether $\beta_k = \gamma_k = 0$ (p_1) and whether $\gamma_k = 0$ (p_2). These F-tests can be viewed as a test of the hypothesis that returns in one market granger-cause subsequent changes in returns from the other markets within their relevant exuberance periods. These testing results allow us to determine whether there is a significant change in correlation when bubbles are present. Moreover, for significant estimated coefficients, we have observed that they obtain positive or negative in signs. For example, in Panel B (China), all of the significant coefficients for the Japan price-dividend ratios are negative in sign, indicating that a positive shock to the Japanese stock market translates into a decline in Chinese price-dividend ratio when Japanese stock market experiences a bubble. In contrast, in Panel S (United States), the significant coefficients for price-dividend ratios of EU are positive in sign, strongly pointing out that a positive shock to the EU market will translates into an increase in the stock market of United States. Although the signs of estimated coefficients disclose information in terms of correlation dynamics; however, since this correlation movement is not continuous, we therefore utilize AG-DCC model to provide a continuous and complete picture for correlation dynamics within the bubble periods.

<Table 4.4>

Table 4.4 shows that there is an apparent pattern of significant change in linkage within the exuberance period among a majority of stock markets. In particular, the *t*-statistics of both β_k and γ_k for some markets are significant, providing the sign of persistent spillovers are enhanced during their bubble periods. For example, in Panel T (Canada), the coefficients of the UK have significant β_3 with *t*-statistics of 1.757 at 10 percent level, and γ_2, γ_3, γ_4 with respective statistics of 1.798, –1.844, and –2.327, corresponding to 10 percent and 5 percent significance level separately. Similarly, the *t*-statistics of β_k for a number of markets are insignificant, but some of their corresponding γ_k coefficients are significant, still suggesting that bubbles in these markets lead to spillovers. For instance, in Panel O (Spain), none of the Japan's β_k coefficients are significant; however, it has significant γ_1 and γ_4 with testing statistics of 3.956 and 5.179, all highly significant at 1 percent level. In contrast, few testing results in Table 4.4 exhibit a pattern where β_k is significant, but none of the γ_k coefficients are significant, concluding that the bubble does not promote the market contagion, although these markets are interdependent. Examples include Finland in Panel J when South Korea is experiencing bubbles; the coefficients of β_2 and β_3 in South Korea are significant at 5 percent and 10 percent, with respective testing statistics of 2.453 and 1.958, whereas all of its γ_k coefficients are insignificant at 10 percent level. Finally, only a small number of the *t*-statistics for both β_k and γ_k are insignificant in our testing results.

4.9.3 The VAR results for 10 Major Markets

Table 4.5 (Panels A to J) report our detailed *t*-statistics together with the *F*-test results in 10 major markets. Panels A and B contain the respective VAR results for Australia and China.

For Australia, the t-statistics of Hong Kong, Japan, and Germany show that when market bubbles are present in these markets, returns in these markets have greater forecasting power to ratio returns in the Australian stock market. Their F-statistics confirm this finding since all of them are significant at least at the 10% level. However, we fail to reach similar conclusion for the UK since although its F-statistics are significant, none of its t-statistics are significant. For China, we find that ratio returns in Australia, Thailand, Europe, and the US have no forecast ability to returns in the Chinese stock market, given their insignificant F-statistics. In contrast, Japan, Hong Kong, Germany, and the UK have increased spillover effect among their respective exuberance periods, as both of their t-statistics and F-statistics are significant.

<Table 4.5>

Panels C and D summarize the t-statistics and p-values of F-statistics for Hong Kong and Japan, respectively. Both the t-statistics and F-statistics of China show very little information in forecasting returns from Hong Kong. Similar patterns have also been spotted for Japan, Thailand, the UK, and the US. Differently, the significant F-statistics for Australia and Germany suggest that the increased linkages between these markets and Hong Kong exist, especially within their respective market bubble periods. For Japan, our t-statistics show that Australia, Hong Kong, and the UK have closer relationship with Japan during their sub-explosive periods. Similarly, F-statistics of these markets are all significant, further supporting our findings.

Panels E and F report the respective testing results of Thailand and Germany. Surprisingly, for Thailand, none of ratio returns have significant predictive power to Thailand based on their p-values. For Germany, the insignificant F-statistics for Australia, China, Hong Kong, Netherlands, and the US indicate ratio returns in these markets have no causality for ratio returns in Germany, regardless of whether bubbles are present in those markets. In contrast, the causality of Japan and UK are significantly increased during their exuberance periods; their F-statistics for p_1 and p_2 are significant at the 5% level.

Panels G and H show the VAR results for Netherlands and the UK, respectively. For Netherlands, Australia, Japan, Hong Kong, Thailand, Germany, the UK, and Europe are able to forecast stock ratio returns in Netherlands during normal times. In particular, ratio returns in Japan, Thailand, Germany, the UK, and Europe become highly predictive for ratio returns in Netherlands when bubbles exist in these markets. Similarly, Japan, Hong Kong, Germany, and the UK are highly interdependent, whilst little evidence is shown within the bubble periods of Japan, Hong Kong, and Germany. Alternatively, bubbles in Australia, Thailand, and Europe have significant impacts on the UK stock market, because those bubbles lead to dramatic increase in correlation between those markets.

Finally, Panels I and J show the evidence for Europe and the US, respectively. We find that bubbles in Japan, Hong Kong, Germany, and the UK promote a rise in linkages between those markets and European regional market. However, there is little evidence of any lead-lag relations between Australia, China, Netherlands, the US, and Europe in any periods. When estimating equation (4.18) for the US, we find no evidence for spillover effects of any substance for China and Netherlands. In contrast, both *t*-statistics and *F*-statistics for Australia, Japan, Germany, and the UK support the hypothesis that exuberance promotes the contagion between these markets and the US. Other markets, such as Hong Kong, Thailand, and Europe, are interdependent with the US, while these relations are not enhanced when we observe bubbles in those markets.

To sum up, our VAR results provide strong support for our hypothesis that there is a significant change in linkage during the majority of bubble periods, and such significant change may lead to contagion that promotes the bubble transmission.

4.9.4 Volatility Correlation

To further display the correlation movement during the bubble periods which have been targeted by our VAR results, we now run the AG-DCC model. The first stage of establishing DCC model consists of building univariate GARCH specifications to each of the 10-ratio return series and selects the best fitting one based on the BIC. Note that there are other information selection criterion but here we choose to apply the BIC. Table 4.6 shows the specifications of the GARCH processes with detailed information about their estimated parameters. Six of the 10 models selected for the stock ratio returns include a significant asymmetric term: China, Hong Kong, Japan, Thailand, United Kingdom and United States. Asymmetry is introduced in the form of threshold effects, but in different powers of the variance in the evolution equation. In particular, four equity-ratio return series are fitted in EGARCH form (China, Thailand, United Kingdom and United States) and the remaining two apply TGARCH parameterization (Hong Kong and Japan).

<Table 4.6>

The univariate models estimated through the first stage are applied in the following stages to obtain the results for conditional correlation across stock markets. Empirical examples of these correlation estimates are presented for several interesting series. Figure 4.1 illustrates the estimated correlation between China, Japan, the UK, the US, and Europe, separately. The dynamic correlation between China and the US does not exhibit a clear increased movement during the Dotcom exuberance period; however, an obvious negative spike can be observed in the year of 2008 when the Chinese stock market experienced a shooting up whereas the US stock market is in a crisis period (however, it does not recognized as contagion by our VAR results). Alternatively, the correlation between Japan and the US has an increased tendency when the US experienced exuberance during the late of 1980s and 1990s (it does not confirmed as contagion by our VAR results), and their average correlation reveals the existence of interdependence because of their relatively high correlation (0.30 to 0.35, also confirmed by our VAR results). Similarly, the third correlation graph of Europe and the US supports the hypothesis that the correlation fluctuates dramatically when bubble is present. Obviously, from the figure, we have seen an increase in correlation starting from the middle of Dotcom bubble, whilst such rise soon disappears at the early of 2000 but the correlation rises again after the bubble collapsed. Note that, the result distinguishes two sub-periods: (i) the first contagion appears when the bubble in the US is growing, and (ii) the second contagion appears after the bubble burst. Moreover, when looking at the latter part of the graph (the global financial crisis in 2008), we observe a clear tendency of negative increase in correlation from 0.3 to –0.3 which directly proves that the collapse of the housing bubble in the US leads to the adverse movement between the stock markets of Europe and the US. Although their results show an excellent example corresponding to our hypotheses, their movements of correlation do not result in contagion based on our VAR results. Now turning to the last graph of the UK and US. It reveals the strong linkage between two markets, since we observe that their correlation is relatively high and stable, around 0.4 among the entire sample. However, there is only one time point in exception, that is, the late of 80s when the US's stock market experiences a well-known dramatic drop called Black Monday, we can see the correlation negatively shoots up to almost –1 within a few months, and quickly recovers to the normal level afterwards.

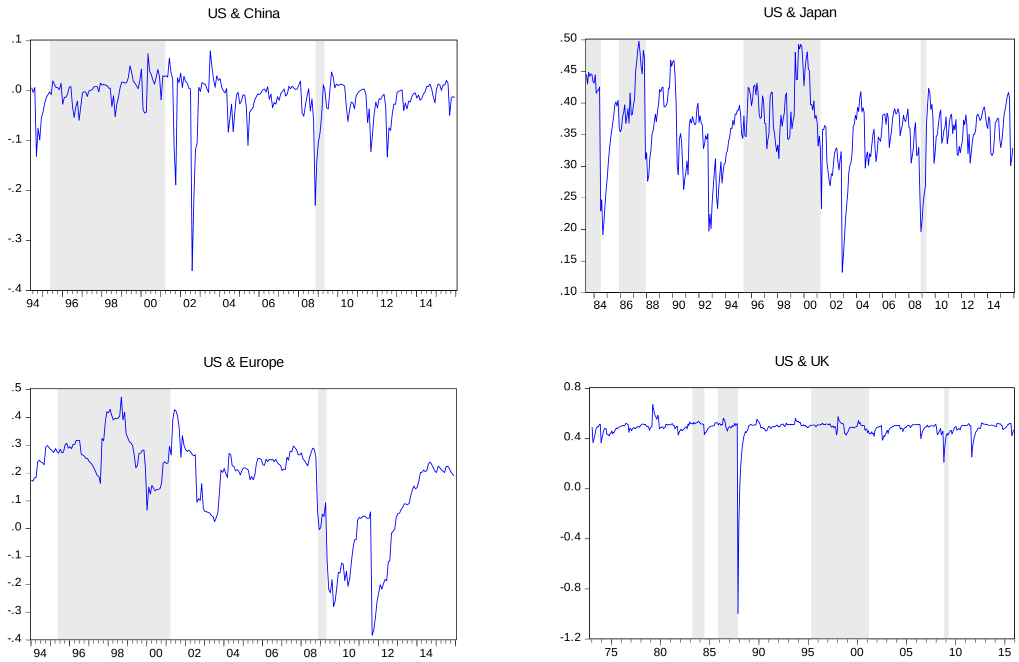
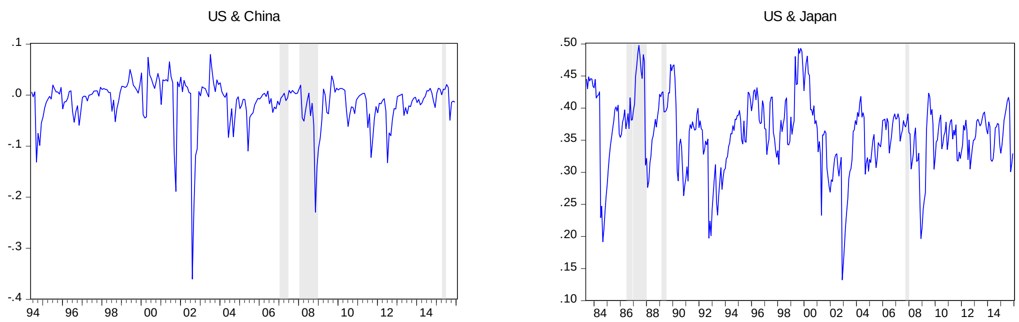


Figure 4.1: Plots of the conditional correlation of stock returns for China, Japan, European Area, and the UK with the US. The shaded area represents the bubble periods in the US.



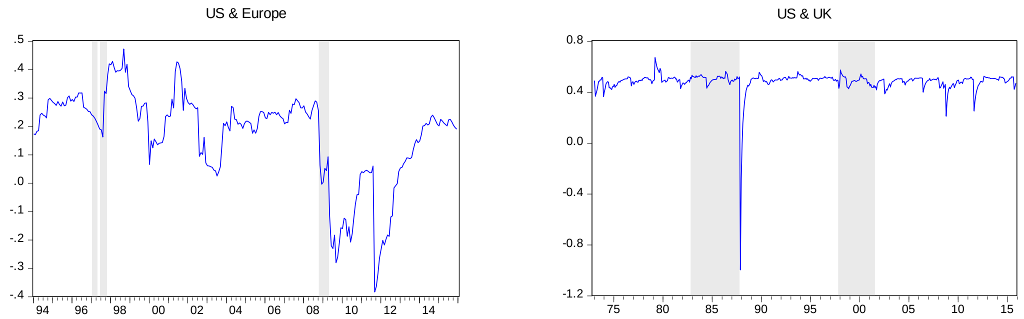


Figure 4.2: Plots of the conditional correlation of stock returns for China, Japan, European Area, and the UK with the US. The shaded area represents the bubble periods in China, Japan, European Area, and the UK.

Similarly, Figure 4.2 shows the same graphs with the Figure 4.1 but with the stamp of corresponding exuberance periods in China, Japan, Europe and the UK, separately. The correlation between the US and China suggests a negative co-movement between these two stock markets during the period of 2008 financial crisis. However, the correlation between Japan and the US shows the opposite relationship, especially when looking at the Japanese exuberant period starting from 1986 to 1988, since their correlation has an obvious rise from 0.35 to 0.50, clearly represents the first type of transmission where the contagion appears when the bubble is growing; alternatively, when we turning to the point of 2008 financial crisis, we observe a negative small spike which in turn standing for the second type of transmission that appears after the bubble burst. All these correlation movements are stamped as significant by our previous VAR results. The conclusions reached for the Europe and UK are similar with the ones in Figure 4.1. However, comparing with the Figure 4.1, we can see that in Figure 4.2, the bubble periods of Europe in the late of 90s are much shorter than those in the US, and the correlation movement within those periods again fluctuates dramatically. Furthermore, both figures illustrate that during the financial crisis in 2008, the US and Europe become negatively correlated. Again, the movement of correlation still does not recognize as contagion occurred between the European region and US since their VAR results do not show significant movement. For the UK, similar correlation graph has been obtained whilst the negative correlation spike happened in the late of 80s, directly corresponding to our second type of bubble transmission, now standing for contagion according to our VAR results (now the shaded area represents the bubble happened in the UK).

We also report some empirical results within the regions of Europe and Asia. Figure 4.3 illustrates the correlation dynamics between the Germany and entire European market. The increased correlation has been identified when the Germany and Europe experience bubbles (from 0.6 to 0.8, especially for the bubble episodes in Germany, which has eben confirmed as contagion by VAR results), while their high average correlation (around 0.5 to 0.6) shows that the exuberance in the German market possibly influences the price movement in the European market, and vice versa.

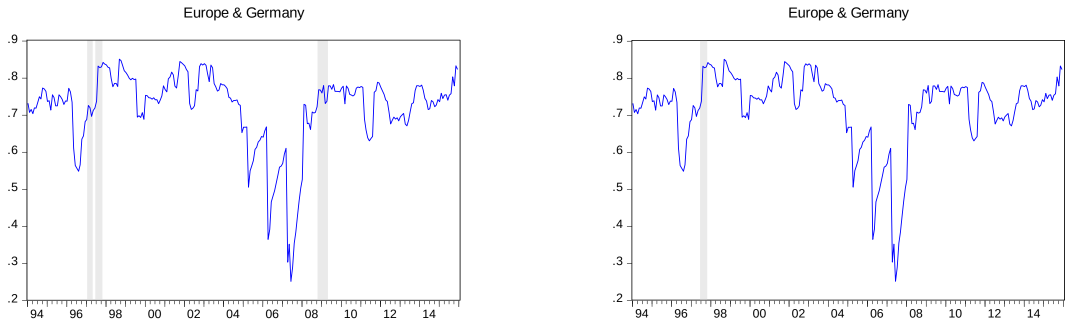


Figure 4.3: Plots the conditional correlation of stock returns between European Area and Germany. The shaded area in left graph represents the bubble periods in European Area, while the shaded area in right graph represents the exuberance in Germany.

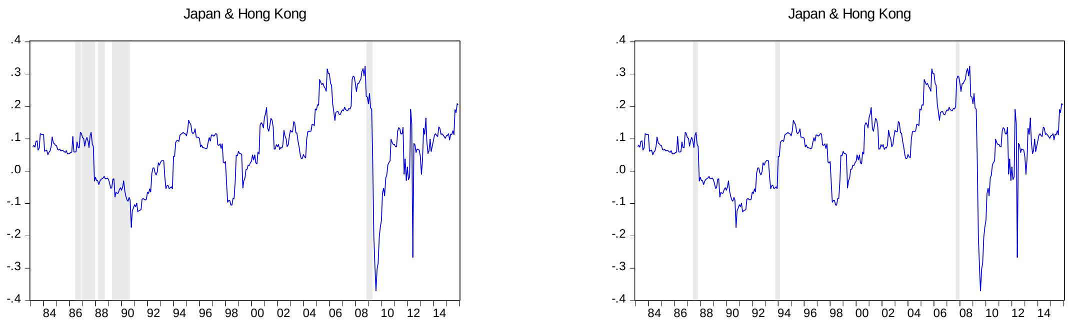


Figure 4.4: Plots the conditional correlation of stock returns between Japan and Hong Kong. The shaded area in left graph represents the bubble periods in Japan, while the shaded area in right graph represents the exuberance in Hong Kong.

To obtain a better understanding in correlation movement among Asian markets, we also study the dynamic relationship of two major Asian stock markets in Figure 4.4. We find that the financial bubbles in Japan normally lead to the correlation increase to a negative level, and the most surprising negative increase happens in the 2008 (from 0.3 to nearly –0.4) when the sub-prime crisis appears. In contrast, bubbles in Hong Kong cause their correlation rise positively, particularly during the periods of 1993 to 1994 (approximately –0.1 to 0.1) and 2007 to 2008 (approximately 0.18 to 0.3), as illustrated in the right-hand side of Figure 4.4, and those rises have been proved to be significant and correspond to contagion by our VAR results. Similar to Figures 4.1 and 4.2, Figures 4.3 and 4.4 demonstrate that different stock markets experience some identical exuberance periods in the past three decades, exhibiting the possibility of financial bubble expansion in the global markets.

Overall, the results lead us to posit the following: (i) correlations among different stock markets are time-varying, either in turmoil or normal periods; (ii) the exuberance, in most of the cases, induces the correlation to fluctuate (positively or negatively); and (iii) interdependence are suggested among few markets, since we can clearly observe some relatively high average correlations from our figures. All correlation graphs are presented in Figures 4.5.

<Figures 4.5>

4.10 Robustness Analysis

To analyze the spillover of bubbles in levels, we consider a VAR framework in this chapter where bubbles' periods are included via an index variable (the dummy variable) modifying the transmission parameters. The estimation might be inconsistent, since under some circumstances, the standard assumptions of regression analysis would be violated, especially for regression applied to time series data. Although we have attempted to lower the risk, robustness check is still required to ensure the validation of our results. Therefore, we establish respective testing models to examine results. Since VAR testing is the major framework adopted in the current chapter, we believe applying the forecasting method as a robustness check is relatively reasonable based on the work of Sims (1986).

The robustness testing model applied is based on the idea of one-step ahead forecasting.

Step 1: We establish several VAR models with the assumption that the true model may follow one of them.

Step 2: We estimate these models though one-step forecast over the forecast period.

Step 3: We apply the forecast evaluation mechanism to assess the forecast accuracy to select the best forecast VAR model. If the best forecast model fits the model proposed in section 4.9.3, then we reach the conclusion that our empirical findings are robust.

Basically, we set up three VAR forecast models: (i) Model 1, or the benchmark model, that forecasts with the variable of itself, where the returns of one country are explained by its own lags (equation 4.19); (ii) Model 2 that forecasts with itself and another explanatory variable, where the returns of one country are explained by its own lags and lags from another country (equation 4.20); and (iii) Model 3 that forecasts with itself, another explanatory variable, and a dummy, where the returns of one country are explained by the above both lags and a dummy variable of bubble periods of another country (equation 4.21). The mathematical expressions of the three VAR forecasting models are as follows:

$$\text{Model 1: } Y_{i,t} = \alpha + \sum_{k=0}^{4} \delta_{i,t-k} Y_{i,t-k} + \varepsilon_{i,t} \tag{4.19}$$

$$\text{Model 2: } Y_{i,t} = \alpha + \sum_{k=0}^{4} \delta_{i,t-k} Y_{i,t-k} + \sum_{k=0}^{4} \beta_{j,t-k} Y_{j,t-k} + \varepsilon_{i,t} \tag{4.20}$$

$$\text{Model 3: } Y_{i,t} = \alpha + \sum_{k=0}^{4} \delta_{i,t-k} Y_{i,t-k} + \sum_{k=0}^{4} \beta_{j,t-k} Y_{j,t-k} + \sum_{k=0}^{4} \gamma_{j,t-k} D_{j,t-k} Y_{j,t-k} + \varepsilon_{i,t} \tag{4.21}$$

where $Y_{i,t}$ and $Y_{j,t}$ are the returns of price-dividend ratio for major stock market indices. $D_{j,t-k}$ is set according to the date-stamping results in Section 4.9.1 and equals to 1 when bubbles are present and 0, otherwise. The lag interval sets 1 to 4, the same with that applied in Section 4.8.1. Specifically, we focus on 9 major equity markets: Australia, China, Germany, Hong Kong, Japan, Netherlands, Thailand, the UK, and the US, as well as a regional equity market of Europe. We examine these markets, separately, and all datasets used in the robustness test are the same with those employed in this chapter.

To evaluate the forecasting accuracy, we report both Root Mean Squared Errors (RMSE) and Mean Absolute Errors (MAE) of Models (1–3) as the primary indicators for each stock market in Table 4.7. Panel A of Table 4.7 shows that there is no significant difference among the three VAR forecasting models for Australia. Similar conclusions can be drawn from Panels B, C, and E for China, Hong Kong, and Thailand, respectively. However, the remaining panels of Table 7 provide some distinct results, showing that the forecasting errors of Models (2) and (3) are relatively smaller than the benchmark Model (1). For example, in Panel G for Netherlands, if Germany experiences market bubbles, RMSEs are 0.0534 and 0.0539 for Models (2) and (3), respectively, both of them are smaller than RMSE of 0.0657 from the benchmark Model (1). Similarly, in Panel H for the UK, once the bubble is present in Europe, RMSEs of Models (2) and (3) are 0.0417 and 0.0432, respectively, which are much smaller than 0.0607, the RMSE of its benchmark Model (1). For MAE, similar conclusions can be reached in terms of forecasting accuracy. We can see from the last three columns of Table 4.7 that the majority of MAEs in Model (3) have the smallest numbers as shaded by green. Again, taking Netherlands in Panel G as an example, if bubbles are present in Germany, MAE is 0.0385 for Model (3), which is smaller than 0.0388 of Model (2) and 0.0483 of Model (1). Overall, our robustness testing results suggest that the VAR forecasting Model (3) has smaller RMSE than Models (1) and (2), that is, the model with dummy variables has higher forecasting power than other models, consistent with the conclusion in Section 4.9.3, which recognizes that the bubble transmission is due to increased correlation between stock markets.

<Table 4.7>

4.11 Further Discussions

Taken together, PSY testing and date-stamping results prove that the exuberance is a widespread phenomenon which exists in a majority of global equity markets during the past four decades. To shed additional light on the bubble transmission mechanism, we apply the VAR and AG–DCC models and their test results have revealed several interesting findings. The combining results provide strong supports to our hypothesis of contagion–effect, that cross-market linkages become much stronger and significant when financial bubbles are present. Specially, the significant lags for causality confirms our consideration of a delay in the transmission, in line with Kleimeier, Lehert, and Verschoor (2008). Recall that the literature on contagion identifies at least three possible channels by which contagion in financial markets might be propagated: the correlated-information channel, the liquidity channel, and the risk-premium channel. The strong evidence that ratio returns in one market are able to forecast changes in ratio returns several months ahead from another market during its bubble period argues against the correlated-information channel as the contagion mechanism. Intuitively, the reason for this is simply that we would expect any relevant information found in one market to be very rapidly incorporated into the other actively traded markets. Therefore, we expect that there would be a nearly contemporaneous relation between shocks in one market, such as the US market and the other markets like Europe and UK if contagion is spread via the correlated-information channel. On the other hand, we suggest that the causality of the contagion contains a vector that bubbles in some markets are more likely to have significant impact on others. The test results for the UK and Netherlands provide substantial evidence of this phenomenon, i.e., bubbles that emerge in the UK will lead to the increased correlation between and the UK and Netherlands, whilst bubbles that emerge in the Netherlands do not give rise to a similar significant increase in that correlation.

Another striking finding is the impact of bubbles in the US and China. In contrast to the popular view that significant financial events in the US affect all global markets, our results demonstrate that bubbles originated in the US do not always have an impact on other stock markets. In fact, bubbles that emerge in few stock markets, such as the UK, Japan, Germany, and Australia, can have a significant impact on the US stock market. This finding is useful for investors to predict the financial stability of the US when market bubble appears elsewhere. In contrast, China seems to be a relatively ‘safe’ zone because bubbles in other markets do not seem to have any significant impact on the Chinese stock market. The possibility of a bubble transmitting from other markets to the Chinese stock market is relatively low, which is reflected in its overall better performance during the global financial crisis.

The AG–DCC results support the evidence from our VAR results and further exhibit the correlation dynamics within the turmoil periods. Importantly, we find correlations among some stock markets experience significant change at the early stage of market bubbles, which extends previous studies that only examine the financial contagion and transmission within the bubble collapsing periods (see, Longstaff, 2010; Bekaert, Ehrmann, Fratzscher and Mehl, 2014). For instance, during the period of the Dotcom bubble, the correlation between the US and the European indices has a slightly decrease at the beginning stage, but a subsequent shooting up appears when bubble continues to grow, before dropping back prior to the sudden collapse of the bubble, and finally, climbing up again after the bubble bursts. In general, our results show strong evidence that correlation experiences a dramatic fluctuation through the entire phase of the bubble period.

Perhaps the most promising explanations for significant correlation dynamics during market bubbles relate to the strategic interactions between market participants. These interactions are strongest at the time point when investors realize the potential risk in relation to bubble explosion, either before or after, leaving them to search for alternative stores of value and resulting in a significant wealth transfer in global markets. Then, the financial asset crisis and wealth transfer have precipitated a severe growth slowdown, and the excess investment in financial asset is destroyed, leading to a decrease in stock price that would trigger the negative feedback loop which causes the collapse of bubbles. Note that differing from the work of Caballero et al. (2008), we let bubble bursts at $t = 1$, allowing market participants (both local and foreign) to transfer their investment before or after $t = 1$. Such assumption is supported by our evidence that correlation changes either positively or negatively within the entire bubble evolutionary pross, and it well extends previous findings which recognize only positive or negative increase in correlation among crisis periods (see King and Wadhwani, 1990; Hon, Strauss and Yong, 2007).

In conclusion, the combination of findings from our return and volatility analyses confirm the relationship between bubbles and financial contagion, highlight the relevance of bubble transmission and provide knowledge for market participants and policymakers to establish effective surveillance mechanism on the movement of bubbles among stock markets. Our results suggest that it would be wise for policymakers to implement policies against bubble-migration if they have observed a significant change in correlation, especially for markets which are particularly sensitive to spills over, e.g., Netherlands, the US, and Europe. Moreover, investors can benefit from studying the contagion in relation to bubble episodes to guide them in attaining the optimal trade-off between risk of a portfolio and the return expected from it. For example, market participants who own portfolios mainly consisted of securities listed on the US stock market should be alerted when bubbles appeared outside of the US (e.g., Japan, Germany and the UK) since those bubbles could easily affect the market of US and take a significant impact on invested portfolios. Therefore, if investors tend to avoid magnificent fluctuation in stock price in the exuberant period, they can consider to re-allocate part of their investment from the market of US to ‘safer zones’, where based on our results, stock markets in Thailand and China.

4.12 Conclusion

Recent events, such as the Dotcom bubble and 2007–2008 global financial crisis, have highlighted that stock market bubbles can be a threat to global financial stability and to economic growth. Whilst it has been suggested that stock market bubbles can migrate between countries, there has been very little academic research on the transmission of stock market bubbles. This chapter has undertaken a large-scale empirical analysis of this issue using data on 47 stock market indices for over 40 countries. To detect and date-stamp bubbles, we have used recently developed procedures proposed by Phillips, et al. (2015a, b). Our empirical estimates of the bubble origination and collapse dates suggest a transmission mechanism from stock markets where a bubble that emerges in one stock market migrates selectively to stock markets in other countries before or after that bubble bursts.

To shed further light on this issue, we use VAR models and multivariate GARCH models, specifically AG–DCC models. The VAR results provide strong evidence of an increase in cross-market linkages during bubble periods for several countries. In contrast to previous studies, which find that only negative large shocks tend to trigger contagion, we find that contagion can increase in bubble growth periods. It is important to stress that the relationship between bubbles and contagion is not found for all stock markets considered. For some stock markets we find that bubbles strongly enhance contagion, but we do not observe the same causality for some other stock markets. The AG–DCC results support the empirical findings obtained from the VAR models as we document strong co-movements in volatilities between equity markets when one or both have bubbles within the relevant testing period. Overall, our results suggest that for many stock markets, bubble transmission is due to increased linkages between equity markets after the first bubble emerges. Thus, we reckon that in the global markets, the contagion–effect plays an important role for bubble expansion, while the length of the forecast horizon, in many cases as long as several months, argues against the view that such contagion is spread via the correlated-information channel. We envisage that our findings will be of interest to investors operating globally with investment horizons that span periods over which stock market bubbles might exist, and to central banks and financial regulators to help them build up strategies against great risk raised by exuberance in the global markets.

A key aspect of the study is that the results allow us to understand the bubble transmission mechanism; however, the discussion also raises significant issues for academics and practitioners such as what factors will influence the bubble inflation. In addition, by essentially ruling out the correlated-information channel, we left with the questions that financial contagion might have been propagated primarily via either the liquidity channel or the risk-premium channel when bubbles are present. To address these issues more definitively, however, we need to explore in more depth with accurate formulation and model selection techniques.

Table 4.1: Timeline of the exuberance during the past four decades based on the date-stamping results.

Timeline	Market conditions
Oct 1971	Booming discovered in United Kingdom
Oct 1972	Bubble collapsed in United Kingdom (UK joined EEC. Source: FTSE)
Nov 1982	Booming started again in United Kingdom (Charles & Diana marry and Falklands War begins. Source: FTSE)
Apr 1983	Exuberance discovered in United States (Followed by the exuberance in United Kingdom)
Jun 1984	Booming stopped in United States
Nov 1985	Exuberance began again in United States
Jun 1986	Bubble discovered in Japan (Beginning of the real estate bubble)
Nov 1986	Booming slowed down in Japan
Dec 1986	Booming accelerated again in Japan (Stock market encountered a huge increase, Nikkei 225 strengthened from 13.024 to 18,821 in 1986. Source: Yahoo Finance. The average land prices in Tokyo residential areas recorded an increase of 45% compared to 1985, while average land prices in Tokyo commercial districts jumped approximately 122%. Source: Ministry of Land, Infrastructure, Transport and Tourism)
Oct 1987	Exuberance stopped, and a sudden drop came up in United Kingdom and United States (The collapse in Biotechnology bubbles in the 1980s, known as the Black Monday. Source: FTSE)
Dec 1987	Booming slowed down in Japan
Feb 1989	Bubble stopped growing in Japan (The peak of the exuberance in real estate)
Jun 1989	Real Estate Bubble collapsed in Japan (Well-known as the collapse in real estate and stock market bubble in Japan. Land Prices crashed in Tokyo metropolis as residential land on average 1sq. meter declined by 4.2%. Source: Ministry of Land, Infrastructure, Transport and Tourism)
May 1995	Booming emerged in United States (Beginning of the Dotcom Bubble. Source: BBC)
Nov 1997	Exuberance appeared in United Kingdom followed by United States
Mar 2000	Bubble collapsed in United States (Known as the collapse of Dotcom Bubble. On 10 March 2000, the NASDAQ index of leading technology shares spiked, followed by a substantial price crash. Source: BBC)
Jul 2001	Bubble collapsed as well in United Kingdom (After the burst of Dotcom bubble in the United States. Source: FTSE)
Oct 2007 - Mar 2009	Substantial drop occurred in United States and Japanese stock market (The start of the Global Financial Crisis in 2008. The eye of the storm. Source: BBC)
Apr 2009	Market stabilized in United States and Japan (The end of Global financial crisis. Fighting against the recession. Source: BBC)

This table contains three major countries: United States, United Kingdom and Japan. Various sources are used to verify the event dates. Note: Starting and ending dates of bubbles are based on the PSY date-stamping results.

Table 4.2: PSY testing results.

Markets	Sources	Starting dates	No. of observations	Statistics
Asia				
Australia (AU)	FTSE Australia	1986M02	355	4.265[a]
China (CN)	China A-DS Market	1994M05	259	4.098[a]
Hong Kong (HK)	Hang Seng Index	1980M10	421	3.522[a]
India (IN)	NIFTY 500	1996M01	238	3.425[a]
Indonesia (ID)	FTSE Indonesia	1996M07	233	1.040
Israel (IL)	FTSE Israel	1993M12	264	0.076
Japan (JP)	FTSE Japan	1986M02	357	1.226
Japan Tokmacap (JP)	TOPIX	1983M02	394	2.510[b]
Malaysia (MY)	FTSE Malaysia	1993M12	263	0.273
Malaysia *KLCI* (MY)	FTSE Bursa Malaysia	1986M01	359	2.636[b]
New Zealand (NZ)	FTSE New Zealand	1986M02	355	1.565
Philippine (PH)	Philippine SE I (PSEi)	1988M01	335	1.120
Singapore (SG)	FTSE Singapore	1986M02	357	1.063
South Korea (KR)	Korea SE KOSPI 200 (KOSPI2)	1990M01	311	2.226[b]
Taiwan (TW)	Taiwan SE Weighted TAIEX	1989M07	316	0.462
Thailand (TH)	Bangkok S.E.T.	1976M01	479	7.789[a]
Europe				
Belgium (BE)	BEL 20	1990M02	310	2.160[c]
Czech Republic (CZ)	Prague SE PX	1994M04	260	1.254
Denmark (DK)	FTSE Denmark	1986M02	357	2.119[c]
Finland (FI)	FTSE Finland	1988M01	335	5.009[a]
France (FR)	France CAC 40	1988M01	334	0.898
Germany (DE)	DAX 30	1973M01	514	5.314[a]
Greece (GR)	FTSE Greece	1998M05	211	11.610[a]
Hungary (HU)	FTSE Hungary	1997M10	212	0.501
Ireland (IE)	FTSE Ireland	1986M02	358	5.263[a]
Italy (IT)	FTSE Italy	1986M02	359	2.037[c]
Netherlands (NL)	AEX Netherlands	1983M01	394	3.996[a]
Norway (NO)	FTSE Norway	1986M02	358	–0.095
Poland (PL)	FTSE Poland	1994M04	260	0.754
Portugal (PT)	FTSE Portugal	1998M05	211	1.547
Russia (RU)	FTSE Russia	2003M09	147	1.086
Russia Dollar (RU)	FTSE Dollar	2000M06	186	0.878
Spain (ES)	IBEX 35	1987M03	345	3.725[a]
Sweden (SE)	OMX Stockholm 30	1986M01	358	3.796[a]
Switzerland (CH)	Swiss Market (SMI)	1988M07	328	1.574
Turkey (TR)	BIST National 100	1988M02	333	7.199[a]
United Kingdom (UK)	FTSE All Share	1965M01	610	3.610[a]
European Area (EU)	FTSE Euro First 80 E	1993M12	264	2.613[b]
USA				
Dow Jones	Dow Jones Index	1978M02	456	3.848[a]
NASDAQ	NASDAQ Index	1973M01	516	12.48[a]
S&P 500	S&P Index	1871M01	1737	4.207[a]
America excluding USA				
Brazil (BR)	FTSE Brazil	1994M11	253	1.619
Canada (CA)	S&P/TSX Composite Index	1973M06	509	3.936[a]
Chile (CL)	FTSE Chile	1993M12	264	1.226
Colombia (CO)	FTSE Colombia	1993M12	264	4.076[a]
Mexico (MX)	Mexico IPC	1989M03	320	5.643[a]
Africa				
South Africa (ZA)	FTSE South Africa	1986M02	358	1.618

This table reports the details of our data selection including markets, sources, testing periods, and number of observations contained in each sample with the illustration of PSY testing results. [a], [b], [c] represent the 99%, 95%, 90% level of significance. All ending dates is set to 2015M12. Japan Tokmacap represents the TOPIX medium capitalization index from Japanese stock exchange. FTSE Bursa Malaysia *KLCI* consists 30 largest companies in FBMEMAS (FTSE Bursa Malaysia Emas Index) by full market capitalization. The European Area uses the FTSEEUROFIRST 80 E Index as the dataset to testing whether speculative bubbles exist in the European region.

Table 4.3: PSY date-stamping results.

Asia	
Australia (AU)	1990M01-1990M04, 1993M10-1994M05, 2003M08-2004M06
China (CN)	2007M01-2007M06, 2008M01-2008M12, 2015M04-2015M06
Hong Kong (HK)	1987M06-1987M10, 1993M10-1994M02, 2007M09-2007M12
Japan Tokmacap (JP)	1986M06-1986M11, 1986M12-1987M12, 1989M02-1989M06, 2008M11-2009M04
India (IN)	1999M12-2000M04, 2007M10-2008M02
Malaysia *KLCI* (MY)	1993M11-1994M03
South Korea (KR)	1994M01-1995M01, 1999M05-1999M10, 1999M11-2000M03
Thailand (TH)	1983M04-1984M02, 1986M09-1987M11, 1988M03-1988M09, 1989M04-1990M08, 1999M02-2000M02
Europe	
Belgium (BE)	2008M10-2009M06
Denmark (DK)	1989M03-1990M04, 1993M08-1994M04, 2000M10-2001M01
Finland (FI)	1993M03-1994M03, 1999M11-2000M03, 2008M09-2009M04
Germany (DE)	1982M12-1984M05, 1985M05-1986M07, 1997M06-1997M10
Greece (GR)	2013M04-2013M07, 2014M03-2015M12
Ireland (IE)	1997M12-1998M08, 1998M12-1999M05, 2008M06-2009M03, 2013M03-2013M12
Italy (IT)	1993M06-1993M10, 1994M03-1994M10, 2008M12-2009M04
Netherlands (NL)	1993M11-1994M04, 1997M02-1998M09, 2008M11-2009M04
Spain (ES)	1993M11-1994M04, 1996M12-1997M11, 1997M12-1998M09, 2000M02-2000M05
Sweden (SE)	1993M04-1994M07, 1999M12-2000M04
Turkey (TR)	1993M05-1994M03, 1994M11-1996M04, 1996M12-1997M05, 1997M10-1998M08, 1999M11-2000M12, 2003M10-2004M05
United Kingdom (UK)	1971M10-1972M10, 1982M11-1987M11, 1997M11-2001M07
European Area (EU)	1997M01-1997M04, 1997M06-1997M10, 2008M10-2009M04
USA	
Dow Jones	1983M02-1984M03, 1986M01-1986M10,1986M11-1987M11, 1995M12-1998M09, 1998M11-2000M07
NASDAQ	1983M04-1984M06, 1985M11-1987M11, 1995M05-2001M03, 2008M11-2009M04
S&P 500	1879M07-1880M05, 1917M09-1918M05, 1928M09-1929M11, 1955M04-1956M08, 1958M11-1959M09, 1987M01-1987M10, 1995M12-1996M07, 1996M09-2001M09
America excluding USA	
Canada (CA)	1983M04-1984M02, 1985M11-1987M10, 1993M04-1994M06, 1996M03-1998M08, 1999M03-2001M02
Colombia (CO)	2004M11-2005M03, 2005M06-2006M05
Mexico (MX)	1992M02-1992M06, 1993M05-1995M01, 2006M01-2006M05

This table provides date-stamping results for PSY dating mechanism used for our subsequent tests. The origination date of a bubble is the first observation whose backward sup-ADF statistic exceeds the critical value of the backward sup-ADF statistic and the collapsing date of a bubble is first observation after $\lfloor T\hat{r}_e \rfloor + \delta \log(T)$ whose backward sup ADF statistic falls below the critical value of the backward sup-ADF statistic. The current paper adopts the 5% significant level in PSY dating mechanism, and the bubble period should be longer than two months

Table 4.4: VAR estimation results for the whole testing samples.

Panel A: Australia

	CN	HK	JP	MY	KR	TH	BE	DK	FI	DE	IE	IT	NL	ES	SE	UK	EU	US	CA
β_1	1.170	1.494	–0.264	0.278	3.744[a]	0.574	–0.671	3.950[a]	1.360	2.761[a]	2.707[a]	2.968[a]	1.035	–0.727	–0.038	–0.725	3.608[a]	1.492	0.796
β_2	0.687	0.107	0.929	2.029	–2.172[b]	2.692[a]	–0.619	2.123[b]	0.622	0.911	1.066	1.042	0.116	–1.862	0.779	–1.415	–0.286	–1.013	2.128[b]
β_3	1.619	0.335	0.239	0.156	3.663[a]	1.608	–1.266	0.856	1.162	0.913	–0.269	0.966	0.314	0.725	0.152	1.286	0.578	1.440	2.450[b]
β_4	0.019	0.552	0.449	–0.208	–2.153[b]	–2.242[b]	–0.849	1.049	0.071	1.541	0.469	0.073	–0.653	–1.478	–0.242	0.265	0.585	–0.009	–0.048
γ_1	0.499	–2.084[b]	0.627	0.711	–0.502	–0.234	–0.954	1.549	1.547	–3.612[a]	2.011[b]	1.461	–0.010	–0.126	1.600	1.184	–0.101	–2.492[b]	0.176
γ_2	–0.032	0.561	–2.640[a]	–1.144	–0.859	–0.838	1.897[c]	2.071[b]	–0.540	0.714	2.791[a]	–0.625	1.294	0.973	0.657	1.392	–0.377	0.940	–2.626[a]
γ_3	0.965	–1.049	2.549[b]	–2.602[a]	–1.028	–1.431	0.433	0.496	1.108	–0.133	2.530[b]	0.678	–0.130	–0.950	1.276	–1.260	0.167	–0.201	–1.607
γ_4	2.001[b]	–2.550[b]	–1.726[c]	–4.747[a]	0.229	–0.707	–2.165[b]	0.018	0.471	–2.049[b]	4.145[a]	1.225	–0.999	–0.664	–0.077	–1.350	–0.007	–0.845	–0.484

Panel B: China

	AU	HK	JP	MY	KR	TH	BE	DK	FI	DE	IE	IT	NL	ES	SE	UK	EU	US	CA
β_1	0.733	1.057	–0.876	n/a	0.447	–0.147	–1.384	0.787	0.182	–0.351	1.360	0.181	–0.126	–0.123	0.074	0.456	1.655[c]	–1.339	–0.622
β_2	–1.057	0.799	0.731	n/a	0.740	0.401	1.339	1.387	0.205	–0.599	0.307	0.299	1.509	0.840	1.635	–0.004	–0.411	0.426	–0.238
β_3	1.906[c]	2.155[b]	0.488	n/a	0.764	1.260	2.329[b]	2.372[b]	0.668	3.828[a]	0.270	1.107	0.728	0.070	1.808[c]	1.531	1.903[c]	–0.211	1.923[c]
β_4	–1.404	–0.478	–0.826	n/a	0.512	–0.551	0.894	–0.958	0.958	0.687	1.569	0.547	0.874	0.165	–0.396	–0.251	0.540	0.883	–1.927
γ_1	0.440	1.427	1.262	n/a	–0.980	1.624	0.321	–3.121[a]	–0.410	–1.085	–0.738	–0.720	–0.013	1.837[c]	6.272[a]	–0.028	–1.348	1.101	0.974
γ_2	1.709[c]	–7.829[c]	–1.932[b]	n/a	0.017	–1.312	–1.302	3.689[a]	0.191	–3.286[a]	1.730[c]	0.554	–1.120	–0.543	1.493	0.776	–0.287	0.822	0.595
γ_3	–0.561	7.493[c]	–0.077	n/a	–1.160	0.826	–5.064[a]	0.397	1.167	–3.340[a]	0.898	–0.474	–0.895	0.132	1.382	–2.310[b]	–0.608	–0.540	–1.338
γ_4	0.065	–1.527	–2.700[a]	n/a	–1.082	1.351	–1.706[c]	–2.119[b]	–0.941	–3.756[a]	–0.186	–1.660[c]	–2.845[a]	–0.397	3.010[a]	1.454	–0.919	0.745	1.301

Panel C: Hong Kong

	AU	CN	JP	MY	KR	TH	BE	DK	FI	DE	IE	IT	NL	ES	SE	UK	EU	US	CA
β_1	–0.415	1.177	–0.208	0.432	2.364[b]	0.188	0.354	0.914	0.245	0.645	0.920	0.813	2.787[a]	–1.155	1.232	–0.256	0.220	0.998	–0.206
β_2	–0.387	–0.556	–0.490	0.323	–0.685	0.164	1.141	1.768[c]	0.976	1.368	–0.739	–2.088[b]	1.239	1.161	0.858	–0.395	0.382	0.108	1.528
β_3	–0.292	0.122	0.513	0.506	1.107	–0.076	–0.007	1.729[c]	1.443	1.191	–2.555[b]	0.959	1.997[b]	1.936[c]	–0.108	2.104[b]	0.946	1.756[c]	1.165
β_4	1.404	0.210	2.043[b]	–0.276	–1.567	–0.476	0.836	0.354	0.326	1.931	1.261	1.193	–0.259	–0.563	0.591	0.545	1.663[c]	–1.007	0.860
γ_1	0.285	–0.220	1.365	0.991	–1.584	1.509	1.125	–1.411	4.503[a]	–1.693[c]	1.677[c]	1.316	–0.241	–4.807[a]	–0.636	–0.474	–0.486	–0.230	0.737
γ_2	–0.723	0.595	–0.558	–5.691[a]	–2.723[a]	–0.094	0.282	0.013	–1.675[c]	1.420	2.678[a]	0.291	–1.251	0.172	0.766	1.209	0.521	–0.352	–1.429
γ_3	–0.565	1.111	1.482	–0.693	0.147	–0.039	1.340	–0.941	1.970[b]	–1.555	3.447[a]	–0.276	–1.266	–2.532[b]	0.516	–0.833	–0.369	–0.336	–1.688[c]
γ_4	1.319	0.588	–1.220	–0.165	–0.846	–0.487	–3.371[a]	0.669	–2.070[b]	–0.701	2.001[b]	0.532	–2.120[b]	–0.286	–0.300	–1.129	–2.444[b]	0.647	–0.085

Panel D: Japan

	AU	CN	HK	MY	KR	TH	BE	DK	FI	DE	IE	IT	NL	ES	SE	UK	EU	US	CA
β_1	3.843[a]	1.332	4.347a	1.345	2.138[b]	2.512[b]	1.319	3.058[a]	2.858[a]	4.326a	1.494	4.228[a]	2.267[b]	1.046	2.747[a]	4.544[a]	6.543[a]	2.543[b]	3.373[a]
β_2	1.053	–0.589	0.864	1.245	1.810[c]	–1.187	–1.223	0.641	–0.364	1.129	1.900[c]	0.206	1.739[c]	–0.103	0.564	0.041	0.979	1.092	3.053[a]
β_3	0.523	0.746	1.467	0.982	1.690[c]	1.999[b]	2.020[b]	1.928[c]	–0.445	1.131	1.839[c]	–0.951	–0.228	0.359	0.784	0.309	0.474	–0.311	2.042[b]
β_4	–0.995	–0.449	–0.955	0.864	1.894[c]	1.727[c]	0.188	–1.148	–0.076	–0.200	–0.610	0.506	0.046	0.538	1.013	0.671	0.286	1.977[b]	–0.511
γ_1	–3.368[a]	0.254	–3.322[a]	1.463	–0.203	–0.051	–0.407	–0.929	1.796[c]	–2.207[b]	0.159	–1.648	–1.403	–0.092	–0.582	–1.839	–0.144	–1.071	–0.589
γ_2	–0.669	1.462	0.491	0.210	1.860[c]	1.685[c]	0.884	–0.096	1.670[c]	–0.844	1.764[c]	1.220	–0.795	–0.097	–0.240	1.762[c]	–0.841	0.277	–1.513
γ_3	–0.377	0.355	0.096	–0.468	0.635	–0.661	–0.688	0.810	0.256	1.226	1.861[c]	–1.283	–0.386	–1.508	–1.449	–0.131	–0.615	0.361	–0.561
γ_4	1.673[c]	1.253	–0.954	–0.220	–0.994	–0.617	–2.026[b]	0.177	–0.488	0.989	1.116	–1.095	0.322	1.084	0.520	–1.233	–1.471	–1.316	–0.170

Panel E: Malaysia

	AU	CN	HK	JP	KR	TH	BE	DK	FI	DE	IE	IT	NL	ES	SE	UK	EU	US	CA
β_1	4.483[a]	1.639	5.457[a]	1.678[c]	2.944[a]	4.578[a]	1.919[b]	3.875[a]	1.656[c]	5.731[a]	1.763[b]	4.638[a]	1.262	1.789[c]	0.288	3.376[a]	6.375[a]	0.360	5.265[a]

Continued

	AU	CN	HK	JP	KR	TH	BE	DK	FI	DE	IE	IT	NL	ES	SE	UK	EU	US	CA
β_2	0.353	–1.250	1.312	–1.112	2.241[b]	–0.107	–1.184	2.145[b]	0.598	0.061	0.551	–0.012	0.545	–0.464	0.039	0.662	–0.159	2.656[a]	0.564
β_3	–0.520	1.069	1.710[c]	0.205	–0.110	0.626	–0.192	–1.078	–0.086	0.070	0.421	0.708	–0.214	–0.475	–0.650	–0.126	0.018	0.072	1.064
β_4	–0.596	–1.107	0.599	–0.196	–0.203	–0.163	–0.695	–0.409	1.424	–0.939	–0.125	–0.206	–0.107	0.571	–0.256	0.185	1.328	–0.470	–0.710
γ_1	0.716	1.052	1.100	1.026	–1.410	1.358	–0.424	3.687[a]	2.128[b]	–0.088	–0.707	0.074	–0.934	–0.055	0.488	–0.439	0.279	1.077	1.471
γ_2	–0.341	0.772	–2.232[b]	0.300	–0.012	0.932	0.185	–3.984[a]	0.769	–0.866	3.058[a]	0.132	–2.592[a]	–3.574[a]	0.675	–0.337	0.232	–1.254	–0.258
γ_3	0.449	2.668[a]	0.229	0.110	–1.883[c]	0.135	–0.851	2.101[b]	–0.017	–1.050	1.233	–0.640	–0.801	0.325	2.566[a]	0.744	–2.501[b]	0.201	–1.885
γ_4	–1.004	0.258	–1.143	1.274	–0.061	–1.196	2.910[a]	–1.176	0.939	0.866	–0.762	1.485	–1.415	–3.166[a]	–1.305	–1.241	0.767	–0.249	–0.723

Panel F: South Korea

	AU	CN	HK	JP	MY	TH	BE	DK	FI	DE	IE	IT	NL	ES	SE	UK	EU	US	CA
β_1	3.551[a]	–0.215	3.987[a]	–0.079	0.948	3.942[a]	–0.490	2.190[b]	3.465[a]	5.463[a]	–0.111	4.049[a]	–1.590	–2.615[a]	0.431	0.135	6.427[a]	0.604	2.986[a]
β_2	–1.073	0.781	1.137	–1.105	–0.593	0.497	0.360	–1.779[c]	0.416	–0.572	0.645	–0.790	0.665	–1.923[c]	–0.127	–0.913	–0.445	–1.624	–0.585
β_3	–0.453	–0.593	–1.601	0.071	0.704	0.469	–0.342	1.694[c]	–0.041	–0.715	–0.948	–0.575	0.425	–0.018	–0.760	0.908	–0.051	–0.615	0.422
β_4	0.249	–1.227	–1.189	1.053	–1.890[c]	1.974[b]	0.419	0.729	0.216	–0.037	0.823	0.072	0.391	1.353	1.793[c]	1.241	–0.692	–0.462	0.751
γ_1	–1.066	1.311	–0.491	1.245	3.827[a]	–0.289	0.575	1.757[c]	2.083[b]	0.463	5.981[a]	–2.200[b]	1.024	0.913	–0.423	0.086	–1.442	–1.551	–0.997
γ_2	0.890	–1.696[c]	0.810	–1.327	0.486	0.892	–3.293[a]	–0.019	–0.718	0.325	0.515	–1.509	–2.520[b]	–2.549[b]	–1.017	–0.470	–0.648	–2.294[b]	–0.145
γ_3	0.850	2.072[b]	1.125	–0.269	–0.113	1.283	4.086[a]	–0.481	0.727	–1.812[c]	0.514	–0.326	–0.001	0.674	–0.166	0.371	–1.922[c]	0.219	–3.178[a]
γ_4	–0.813	0.963	1.622	0.636	3.773[a]	–2.908[a]	–3.421[a]	3.955[a]	–0.433	–1.560	0.367	1.380	–1.935[c]	0.380	–0.464	–0.541	0.862	0.522	–0.951

Panel G: Thailand

	AU	CN	HK	JP	MY	KR	BE	DK	FI	DE	IE	IT	NL	ES	SE	UK	EU	US	CA
β_1	0.596	–1.050	1.178	0.646	–0.793	2.879[a]	–0.302	0.275	0.196	0.477	1.551	0.443	0.117	–0.581	0.791	1.373	1.272	2.073[b]	0.888
β_2	–0.573	0.307	–1.249	–1.090	–0.101	0.080	–0.314	–0.208	0.352	0.919	–1.868	–0.220	–1.464	–1.802	–3.912[a]	–1.642	0.045	–1.350	0.836
β_3	–0.771	–1.281	–2.030[b]	0.347	–0.283	1.006	0.688	–1.197	–1.459	–1.892[c]	–0.360	–1.009	1.556	–0.082	0.477	0.446	–1.217	–0.293	0.171
β_4	1.778[c]	–0.662	–0.192	0.582	–0.428	–1.873[b]	0.759	1.055	1.054	0.945	1.037	1.344	–0.417	0.743	0.935	1.741[c]	1.354	–0.879	–0.580
γ_1	0.348	1.952[c]	0.061	–0.705	–0.573	–1.217	–0.315	–0.783	1.284	–1.261	1.886[c]	2.374[b]	–0.139	0.207	–1.002	–0.414	–0.877	–2.126[b]	0.465
γ_2	–0.945	0.552	0.652	1.166	–0.195	–1.255	–1.223	0.389	–1.544	0.238	2.828[a]	–0.388	–0.841	–0.653	1.486	1.059	0.293	0.058	–1.630
γ_3	2.110[b]	2.501[b]	0.339	1.224	–0.615	–0.067	1.435	0.470	1.118	–0.461	0.967	–0.230	–1.365	0.930	1.537	0.013	–1.235	0.380	–2.260[b]
γ_4	–0.328	1.285	–1.116	2.067[b]	1.345	0.184	–2.038[b]	0.158	–0.116	–0.540	0.894	1.218	–1.136	–2.302[b]	–0.101	–1.205	–0.613	1.093	0.234

Panel H: Belgium

	AU	CN	HK	JP	MY	KR	TH	DK	FI	DE	IE	IT	NL	ES	SE	UK	EU	US	CA
β_1	4.973[a]	0.953	4.040[a]	–1.323	0.800	2.510[b]	3.381[a]	3.011[a]	5.580[a]	6.225[a]	1.744[c]	5.283[a]	–0.184	1.493	0.671	4.421[a]	8.164[a]	2.092[b]	4.410[a]
β_2	2.278[b]	0.517	1.513	0.028	0.592	1.535	0.823	2.382[b]	–0.646	2.560[b]	0.632	2.877[a]	2.052[b]	0.352	0.279	0.987	1.760[c]	1.434	0.944
β_3	0.280	1.651	1.604	0.193	1.113	0.758	1.568	2.585[b]	1.086	0.320	–1.238	2.639[a]	0.104	1.140	–1.591	0.532	2.426[b]	1.043	1.750[c]
β_4	0.489	1.127	0.413	0.174	0.703	0.125	1.502	0.532	–0.854	0.284	–0.204	–0.191	0.956	0.109	0.619	0.859	–0.939	–0.080	0.702
γ_1	–2.360[b]	–0.056	–1.498	2.945[a]	2.551[b]	–2.130[b]	–0.768	0.296	0.221	0.862	0.723	–0.752	0.454	3.203[a]	–0.289	–1.281	0.970	–0.919	–1.320
γ_2	1.265	1.265	–0.256	–0.707	1.001	–0.237	–2.241[b]	–0.838	0.657	–2.116[b]	1.264	–1.331	–1.983[b]	–1.034	0.085	–0.322	–0.072	–0.705	–0.245
γ_3	0.781	–0.208	–1.723[c]	3.813[a]	–4.034[a]	–1.202	–0.825	0.096	–0.263	–1.978[b]	2.285[b]	–2.328[b]	0.643	0.066	1.844[c]	–0.860	–2.273[b]	–0.405	–1.489
γ_4	–2.567[b]	1.717[c]	–0.939	1.074	–0.672	–0.630	–0.938	–0.226	1.542	–1.072	0.139	1.741[c]	1.305	–3.117[a]	–0.107	–1.602	1.839[c]	0.115	–0.385

Panel I: Denmark

	AU	CN	HK	JP	MY	KR	TH	BE	FI	DE	IE	IT	NL	ES	SE	UK	EU	US	CA
β_1	0.808	1.185	1.392	–1.314	–1.689[c]	–0.195	–0.512	–0.607	1.398	1.313	0.044	1.633	0.012	–1.870[c]	0.904	–1.047	1.619	–0.185	0.832
β_2	–0.612	0.611	–0.904	0.717	1.359	–0.827	0.443	0.474	0.778	–0.475	1.925[c]	–1.127	–0.703	–1.464	–0.357	–1.192	–0.916	–0.824	–0.195
β_3	–0.006	1.940[c]	–0.407	–1.429	0.630	0.509	0.096	–1.439	–0.187	–1.185	–4.850[a]	–0.391	–0.194	0.857	0.048	0.101	–1.491	0.193	2.083[b]
β_4	–0.165	0.384	1.093	2.148[b]	–0.355	0.086	–0.250	0.136	0.519	0.563	0.722	0.517	0.879	–0.254	0.836	1.555	0.110	0.724	–1.074
γ_1	–1.709[c]	0.047	–0.378	1.143	0.791	0.526	–0.374	–2.468[b]	1.142	–4.270[a]	8.125[a]	–0.044	–0.968	0.623	–0.086	0.877	0.669	–1.194	0.307

Continued

	AU	CN	HK	JP	MY	KR	TH	BE	FI	DE	IE	IT	NL	ES	SE	UK	EU	US	CA
γ_2	0.259	–0.202	1.325	–1.874	4.766[a]	0.660	0.047	–1.485	–0.874	1.050	0.304	–0.988	1.030	1.152	1.394	0.835	–0.887	0.321	–0.337
γ_3	–0.366	0.315	–0.653	1.822[c]	0.329	–0.826	–1.188	4.997[a]	0.797	2.496[b]	2.761[a]	–1.452	0.433	–1.123	–1.137	–1.414	–1.602	0.846	–1.063
γ_4	1.285	1.617	–0.887	0.260	–9.603[a]	–0.443	–1.025	–4.091[a]	–0.846	–0.252	–0.921	0.250	–1.307	–0.728	0.065	–1.939[c]	2.135[b]	0.096	0.967

Panel J: Finland

	AU	CN	HK	JP	MY	KR	TH	BE	DK	DE	IE	IT	NL	ES	SE	UK	EU	US	CA
β_1	1.379	0.470	1.266	–1.018	–0.746	–1.254	0.215	1.599	–0.230	–0.155	1.709[c]	0.416	–0.367	–0.823	2.191[b]	–1.883[c]	–0.354	–0.975	0.410
β_2	–0.791	0.970	0.531	1.215	0.832	2.453[b]	0.778	–1.273	–0.163	–0.192	–0.227	–0.651	0.091	0.545	–0.425	–1.240	–0.419	–0.987	–0.181
β_3	–0.397	0.349	1.071	0.301	2.176[b]	1.958[c]	1.137	–1.005	1.036	–1.625	0.173	–0.653	–0.323	–0.018	–0.003	0.416	–0.661	–0.209	2.008[b]
β_4	2.318[b]	–0.932	2.528[b]	2.183[b]	–0.506	0.550	1.191	1.496	1.156	1.524	–3.208[a]	1.523	1.872[c]	1.001	1.041	2.091[b]	0.942	2.229[b]	0.891
γ_1	0.353	0.192	0.979	–0.053	–1.141	0.293	1.090	–2.316[b]	–1.084	–2.096[b]	4.444[a]	0.896	–0.082	–0.687	–0.626	0.669	0.105	0.383	–0.923
γ_2	0.047	–0.991	–1.698[c]	–0.844	–1.856	0.381	–0.771	2.611[a]	–0.599	3.509[a]	0.289	–0.871	0.954	0.143	1.306	0.469	0.332	1.579	0.446
γ_3	–1.615	1.800[c]	–1.748[c]	1.208	–2.189[b]	–0.264	–1.447	3.245[a]	–0.803	–1.118	0.061	0.143	0.299	0.220	1.327	–0.441	–1.227	0.564	–0.039
γ_4	0.453	1.178	–0.612	–1.579	–2.451[b]	–0.703	–0.522	–3.221[a]	–0.979	–0.044	2.158[b]	1.463	–2.429[b]	–2.290[b]	–1.646	–1.384	1.765[c]	–1.518	0.610

Panel K: Germany

	AU	CN	HK	JP	MY	KR	TH	BE	DK	FI	IE	IT	NL	ES	SE	UK	EU	US	CA
β_1	1.476	0.510	–0.513	–1.285	0.194	2.527[b]	–0.610	0.405	1.858[c]	1.161	1.785[c]	1.549	0.592	–0.963	1.586	–0.865	2.652[a]	1.466	0.719
β_2	–0.561	0.643	0.472	1.289	1.245	–0.307	2.464[b]	–0.119	1.747[c]	1.650[c]	–0.203	1.334	1.314	1.848[c]	–1.081	0.976	1.230	0.967	1.090
β_3	0.032	1.057	–0.412	0.031	–0.833	0.649	1.803[c]	–1.813[c]	1.018	0.904	1.357	1.130	0.087	0.378	–0.432	–0.634	1.933[c]	–0.036	2.911[a]
β_4	1.116	–1.126	–0.740	0.553	–0.003	0.204	–1.235	1.504	–0.230	–0.868	0.051	1.217	0.045	0.395	0.581	0.568	1.068	0.486	0.281
γ_1	0.154	0.612	–0.404	–0.927	–0.375	1.182	0.040	1.652[c]	–0.831	1.501	2.046[b]	0.169	0.123	–0.078	0.409	1.910	–0.704	0.192	0.854
γ_2	0.975	–1.103	1.190	0.286	–0.618	–1.209	–0.296	0.825	0.961	–1.260	1.461	–1.055	–0.069	–0.228	2.781[a]	0.073	–1.359	0.353	–0.258
γ_3	–0.592	1.482	–1.027	1.293	2.051[b]	1.419	–1.811[c]	1.853[c]	–0.100	2.565[b]	–0.721	0.016	–0.495	–0.910	–0.719	–3.831[a]	–0.609	–0.754	–1.698
γ_4	0.713	0.803	–1.472	–1.961[c]	–0.272	–0.429	–1.409	–6.266[a]	0.338	–0.530	2.970[a]	0.428	–1.280	–0.939	–0.053	–1.032	–2.453[b]	–0.170	–0.510

Panel L: Ireland

	AU	CN	HK	JP	MY	KR	TH	BE	DK	FI	DE	IT	NL	ES	SE	UK	EU	US	CA
β_1	–0.763	–0.186	–0.162	–0.565	0.828	1.581	0.784	–0.742	0.244	–0.489	0.872	0.048	0.406	–1.752	–1.552	–0.581	0.011	–0.007	–0.265
β_2	–0.139	1.857[c]	0.328	1.365	0.635	–0.124	0.428	0.027	0.586	0.946	–0.083	0.777	0.195	0.416	0.080	0.336	0.607	–1.602	0.818
β_3	–0.921	–1.042	–0.465	–0.606	–1.402	0.786	–0.184	–0.030	0.728	–0.723	0.026	0.875	–0.775	–1.108	–2.770[a]	2.453[b]	–0.063	–0.181	–0.628
β_4	–0.533	–1.168	–0.089	0.386	–1.376	–1.256	–0.570	–0.983	–1.005	–0.937	–1.185	–0.923	–0.115	–1.104	–0.276	–0.363	–0.782	–0.756	–1.224
γ_1	0.069	2.204[b]	–0.275	–0.615	–1.763	–1.587	–0.297	–2.341[b]	0.324	–0.676	–2.350[b]	–1.148	0.816	1.406	1.528	0.336	–1.268	–0.256	1.796[c]
γ_2	–0.541	–1.308	–0.558	–2.021[b]	–0.495	1.928[c]	–1.063	5.448[a]	–0.479	–1.133	1.026	–1.311	0.955	–0.076	2.394[b]	–0.343	–1.480	1.163	–1.014
γ_3	–0.027	1.515	–0.643	2.630[a]	0.595	0.742	1.462	–4.610[a]	0.485	2.261[b]	0.035	–0.919	–1.212	–0.670	0.852	–2.649[a]	0.115	–0.379	0.235
γ_4	0.650	2.488[b]	–0.998	–1.604	–0.940	0.513	–0.636	–2.919[a]	0.561	–0.627	0.446	0.512	–1.208	0.162	–1.621	0.372	–0.573	–0.655	0.815

Panel M: Italy

	AU	CN	HK	JP	MY	KR	TH	BE	DK	FI	DE	IE	NL	ES	SE	UK	EU	US	CA
β_1	1.104	–0.863	–0.627	0.405	–0.074	1.012	–1.409	–0.067	1.463	1.258	0.456	0.812	–0.470	–1.927[c]	1.264	–2.345[b]	1.162	–0.434	0.119
β_2	0.884	0.042	0.319	0.267	–0.031	0.478	2.935[a]	0.141	1.257	–0.673	0.385	2.013[b]	0.694	–0.645	0.857	–1.023	0.177	–0.692	1.383
β_3	–0.490	1.823[c]	0.058	1.738[c]	–1.328	1.412	–0.740	–2.260	1.128	2.083[b]	–0.320	–0.333	–0.537	–1.105	–0.220	1.437	–0.632	1.496	1.836[c]
β_4	2.497[b]	–0.039	0.508	0.689	–0.771	0.333	0.806	2.504[b]	0.440	–1.223	1.106	–0.594	0.129	–0.586	0.894	1.107	–0.113	–0.409	1.300
γ_1	–0.298	–0.117	–1.244	1.118	0.120	–0.024	0.912	0.738	–1.139	2.280[b]	–2.878[a]	6.531	1.183	–0.708	–0.208	2.925[a]	0.821	0.917	–0.411
γ_2	–0.810	0.130	1.097	–0.638	1.956[c]	–0.313	–1.043	0.325	0.904	0.359	–0.634	4.478[a]	0.691	0.109	2.882[a]	0.856	1.644	0.246	–0.056
γ_3	1.414	0.250	–0.731	–0.497	3.638[a]	–1.040	–0.819	1.360	–0.099	1.616	–1.913	4.958[a]	0.077	0.075	–1.549	–3.877[a]	–0.658	–2.012[b]	–1.960
γ_4	–1.101	1.634	–0.700	–1.510	1.488	–0.732	–0.722	–2.228[b]	0.368	–0.390	0.009	1.886[c]	–0.371	–1.221	–1.000	–1.398	0.083	–0.251	–2.474[b]

Panel N: Netherlands

Continued

	AU	CN	HK	JP	MY	KR	TH	BE	DK	FI	DE	IE	IT	ES	SE	UK	EU	US	CA
β_1	6.346[a]	0.969	6.738[a]	1.389	1.777[c]	2.041[b]	4.793[a]	1.678[c]	5.097[a]	5.719[a]	9.042[a]	2.014[b]	8.434[a]	0.892	1.572	5.007[a]	14.295[a]	2.614[a]	5.545[a]
β_2	0.727	1.084	0.869	–1.334	0.837	2.768[a]	–0.551	0.593	1.187	–0.020	0.877	0.588	0.045	–0.701	–0.004	0.933	1.182	0.463	0.624
β_3	0.155	1.113	1.099	0.749	0.874	0.547	1.356	–0.035	0.971	–0.178	0.202	–2.397[b]	0.803	–0.315	–0.038	0.476	1.379	–0.167	1.037
β_4	–1.779[c]	1.502	0.256	0.711	2.153[b]	0.785	1.916	–0.535	–0.555	1.367	1.295	–1.228	1.508	–0.325	–0.179	2.300[b]	1.153	1.055	0.632
γ_1	–1.862[c]	0.130	–0.424	2.277[b]	1.290	–0.714	–0.478	1.206	0.942	1.145	–1.358	0.887	0.490	3.990[a]	–1.074	–1.728[c]	1.537	0.411	–0.773
γ_2	–0.226	1.228	–1.151	–0.440	–1.088	–0.436	0.102	–2.027	–0.554	0.535	–1.155	3.411[a]	–1.549	–2.067[b]	–0.393	1.075	0.340	–0.051	0.219
γ_3	–0.798	0.230	–0.874	–1.012	–3.163[a]	–0.742	0.083	1.178	0.654	0.689	2.700[a]	6.323[a]	–1.491	3.131[a]	2.101[b]	0.588	–2.983[a]	0.056	0.896
γ_4	0.496	1.420	–1.247	1.776[c]	2.532[b]	0.831	–3.466[a]	–1.547	–0.608	–0.021	0.390	–0.287	–0.348	–2.452[b]	–0.931	–3.102[a]	–1.150	–0.841	–0.760

Panel O: Spain

	AU	CN	HK	JP	MY	KR	TH	BE	DK	FI	DE	IE	IT	NL	SE	UK	EU	US	CA
β_1	4.558[a]	1.420	5.396[a]	0.912	1.672[c]	1.616	4.001[a]	0.971	4.026[a]	2.346[b]	5.828[a]	0.818	8.287[a]	0.493	1.804[c]	4.465[a]	10.062[a]	2.003[b]	4.617[a]
β_2	1.474	0.266	1.236	–1.574	–0.158	1.739[c]	–0.412	2.369[b]	0.815	1.698[c]	1.140	1.261	1.222	0.626	–0.388	1.580	2.095[b]	–0.940	1.486
β_3	0.350	1.005	0.775	–0.600	1.547	2.198[b]	1.412	–0.326	1.155	0.149	–2.041[b]	–2.342[b]	0.584	–0.151	–0.425	0.113	0.424	0.050	0.365
β_4	0.650	–0.330	1.174	0.908	–0.789	0.302	1.621	–0.009	1.387	0.024	1.329	–0.554	1.513	0.147	–0.089	0.296	0.171	0.638	1.247
γ_1	–1.748[c]	–0.191	0.606	3.956[a]	2.430[b]	–0.518	–0.731	0.157	0.363	1.866[c]	–4.594[a]	1.279	0.459	0.460	0.497	–1.664[c]	–0.029	–0.049	–0.416
γ_2	–0.145	0.480	–0.094	–1.215	0.549	0.060	1.233	–1.649	0.677	1.524	–4.152[a]	0.861	–1.031	0.021	2.339[b]	–0.569	–0.030	–0.203	1.917[c]
γ_3	–2.079[b]	1.452	0.325	0.964	0.290	–1.023	–0.307	4.507[a]	–0.706	1.205	1.866[c]	3.128[a]	–0.881	1.136	1.780[c]	0.861	–0.583	0.765	–0.480
γ_4	2.607[a]	0.606	–0.932	5.179[a]	1.297	–1.052	–2.000[b]	1.251	–0.004	2.820[a]	–3.326[a]	0.548	1.919[b]	1.185	–1.336	–2.177[b]	1.770[c]	0.202	–3.177[a]

Panel P: Sweden

	AU	CN	HK	JP	MY	KR	TH	BE	DK	FI	DE	IE	IT	NL	ES	UK	EU	US	CA
β_1	4.551[a]	0.731	5.604[a]	0.920	1.509	1.373	2.497[b]	1.193	3.145[a]	5.030[a]	7.882[a]	1.431	6.341[a]	0.346	0.291	2.685[a]	9.734[a]	2.284[b]	3.778[a]
β_2	1.262	0.817	0.734	–1.940	0.041	1.134	–0.584	–0.053	2.260[b]	2.365[b]	1.195	2.844[a]	1.387	0.640	–1.178	0.240	0.405	–0.357	1.327
β_3	–0.292	0.448	0.460	1.849[c]	–0.556	0.817	0.967	–0.547	–0.366	1.217	–0.458	–3.364[a]	–0.016	–0.861	0.170	0.993	–0.010	0.155	–0.132
β_4	0.482	0.957	0.564	–0.776	0.670	1.690[c]	1.545	–0.279	0.221	0.920	–1.191	0.791	0.624	0.447	0.733	1.274	0.924	0.184	0.468
γ_1	–1.637	0.974	0.213	0.848	1.980[b]	–0.192	1.009	–2.381[b]	0.426	1.011	–1.226	0.011	–1.195	0.143	0.403	–1.127	–1.934[c]	0.323	0.225
γ_2	–1.228	–1.289	–0.006	–1.418	–1.469	0.808	1.674[c]	1.903[c]	–0.824	–2.036[b]	0.064	0.062	–0.680	–0.531	–1.095	0.311	–1.894	–0.614	0.738
γ_3	–0.996	–0.897	–0.109	–0.027	–1.931[c]	0.968	–1.252	–3.062[a]	0.420	0.395	0.476	2.320[b]	–1.201	–0.200	1.623	–1.658	–0.136	0.181	0.040
γ_4	1.378	1.705[c]	–1.345	–0.014	2.471[b]	0.349	–1.692[c]	–0.887	–0.136	0.201	–0.530	–1.158	1.144	–0.549	–1.945	–0.056	–1.645	0.001	–1.540

Panel Q: United Kingdom

	AU	CN	HK	JP	MY	KR	TH	BE	DK	FI	DE	IE	IT	NL	ES	SE	EU	US	CA
β_1	5.019[a]	1.016	4.827[a]	0.623	–0.293	1.100	3.766[a]	1.154	3.707[a]	4.125[a]	4.966[a]	1.445	5.426[a]	0.402	–0.910	–0.564	8.323[a]	–0.503	4.703[a]
β_2	–1.097	1.388	–1.320	–1.916[c]	1.077	0.007	–1.917[c]	2.021[b]	0.814	0.468	0.538	1.407	0.262	1.448	0.219	0.406	2.005[b]	0.791	–0.330
β_3	0.324	1.861[c]	–0.086	0.329	1.082	0.149	1.884[c]	–0.678	0.316	0.128	1.042	–1.229	1.341	0.490	0.110	–0.887	1.958[c]	1.390	1.589
β_4	0.200	1.029	1.704[c]	0.692	–0.405	1.053	1.170	–0.912	1.532	–0.612	0.332	–0.724	1.679[c]	–0.018	1.731[c]	–0.226	1.062	–0.678	1.251
γ_1	–2.513[b]	0.131	0.644	0.199	3.422[a]	–2.331[b]	0.505	–2.621[a]	1.342	0.348	–1.496	–0.196	–0.087	–0.177	5.104[a]	0.526	–1.692[c]	–0.209	0.599
γ_2	0.606	–0.467	–0.810	–0.478	0.271	0.541	–0.776	–2.060[b]	0.165	0.593	–0.598	0.917	0.368	–0.728	–2.480[b]	0.110	–1.136	–0.960	–0.550
γ_3	–1.454	–0.620	1.539	–0.542	–1.530	–2.020[b]	–0.100	2.379[b]	0.163	–1.143	0.057	2.925[a]	–2.964[a]	0.079	1.778[c]	2.242[b]	–2.350[b]	0.168	–0.682
γ_4	0.370	0.908	–1.689[c]	2.305[b]	0.203	–0.327	–2.081[b]	2.313[b]	–1.089	2.158[b]	–0.431	–0.210	2.682[a]	0.497	–2.941[a]	0.349	1.032	1.199	–0.758

Panel R: European Region

	AU	CN	HK	JP	MY	KR	TH	BE	DK	FI	DE	IE	IT	NL	ES	SE	UK	US	CA
β_1	0.358	0.742	–0.141	–1.113	n/a	1.417	–1.694	0.675	2.028[b]	1.313	–1.669[c]	0.048	0.272	0.440	–1.777[c]	0.842	–0.997	0.311	0.069
β_2	–0.163	1.282	1.379	1.924[c]	n/a	0.057	2.619[a]	–0.179	1.849[c]	0.179	0.503	0.855	1.023	–0.111	0.230	0.546	–0.117	–0.383	2.584[b]
β_3	0.131	1.450	0.556	–0.146	n/a	2.120[b]	1.623	–1.356	1.462	0.043	–1.286	0.107	1.407	0.633	0.492	0.852	1.890[c]	0.473	1.886[c]
β_4	0.877	–1.235	0.208	0.146	n/a	–0.295	–0.607	1.276	1.316	0.169	0.373	–0.935	0.646	–0.425	–1.252	0.775	1.036	0.768	–0.035

Continued

	AU	CN	HK	JP	MY	KR	TH	BE	DK	FI	DE	IE	IT	NL	ES	SE	UK	US	CA
γ_1	1.293	–0.644	–0.295	0.667	n/a	0.014	0.678	0.573	–7.429[a]	2.871[a]	–4.880[a]	7.693[a]	1.362	0.698	–0.179	–0.609	1.338	0.395	0.649
γ_2	–0.962	–0.073	0.361	0.135	n/a	–0.620	–1.047	0.831	–0.835	–0.647	0.022	4.234[a]	–2.150[b]	0.768	0.468	1.080	0.057	1.073	–1.141
γ_3	1.081	1.242	–1.418	3.301[a]	n/a	–0.759	–1.799[c]	2.486[b]	2.820[a]	2.549[b]	–6.111[a]	2.356[b]	–0.013	–0.057	–1.582	–2.573[b]	–2.316[b]	–0.153	–1.952[c]
γ_4	–2.465[b]	0.832	–0.964	–1.080	n/a	–0.874	1.090	–4.112[a]	–1.656[c]	–0.432	–6.031[a]	3.330[a]	–1.204	–1.361	–0.669	–2.426[b]	–1.651[c]	–1.049	1.082

Panel S: United States

	AU	CN	HK	JP	MY	KR	TH	BE	DK	FI	DE	IE	IT	NL	ES	SE	UK	EU	CA
β_1	4.658[a]	1.445	5.185[a]	1.220	0.761	–0.120	4.712[a]	–1.147	3.873[a]	3.928[a]	6.059[a]	1.283	6.761[a]	–0.619	–1.181	0.690	1.381	7.040[a]	7.256[a]
β_2	0.208	1.796[c]	–0.088	–0.758	–1.015	1.219	–1.554	1.376	–0.252	1.253	–0.809	–0.025	0.020	1.076	–0.227	0.304	–0.611	–0.260	1.155
β_3	–0.777	0.214	0.154	0.843	1.909[c]	1.129	1.178	–1.717[c]	0.311	–0.879	–0.012	–0.961	–0.652	–0.469	0.378	–1.359	–1.525	1.125	0.924
β_4	–0.974	0.606	0.356	–0.125	0.162	1.088	1.573	–0.753	0.401	–1.024	–2.355[b]	–0.708	1.280	–0.245	0.809	–0.563	2.213[b]	–1.542	0.729
γ_1	–3.913[a]	–0.310	–2.444[b]	2.548	0.523	0.720	–1.298	0.659	0.345	0.270	–1.133	0.607	–0.125	0.566	2.464[b]	1.410	–0.219	–1.420	–0.200
γ_2	0.986	–0.753	–1.165	–1.576	2.287[b]	1.124	0.519	–2.109	–0.988	1.358	3.736[a]	1.970[b]	–0.785	–0.318	–1.386	0.287	0.635	0.542	1.347
γ_3	–0.043	1.051	0.914	0.288	–3.194[a]	–2.414[b]	0.169	2.670[a]	–0.854	–0.018	2.011[b]	2.539[b]	–0.239	0.131	0.451	2.589[b]	2.043[b]	–1.295	–0.318
γ_4	0.028	1.108	–1.270	1.341	0.683	0.267	–1.872[c]	0.077	1.075	1.310	1.761[c]	0.053	2.481[b]	0.990	–1.449	–0.965	–3.096[a]	2.080[b]	–0.816

Panel T: Canada

	AU	CN	HK	JP	MY	KR	TH	BE	DK	FI	DE	IE	IT	NL	ES	SE	UK	EU	US
β_1	0.909	1.343	0.555	–2.200[b]	0.048	1.955[c]	–0.058	–0.350	1.992[b]	0.433	0.995	0.032	0.975	–0.030	–1.293	0.782	0.208	1.493	0.913
β_2	–0.033	–0.008	–2.183[b]	–1.375	1.358	–1.006	0.475	–0.041	–0.069	–0.710	–0.508	–1.044	1.284	–0.291	–0.617	–0.338	–0.212	–0.351	–1.152
β_3	–1.522	–0.426	–0.227	–0.320	–0.616	0.728	–0.053	–0.330	0.383	0.373	–1.116	–1.983[b]	–0.462	–0.720	0.513	–0.916	1.757[c]	–0.630	0.561
β_4	0.632	0.288	–0.372	0.049	–1.332	–1.601	–0.784	0.057	0.046	0.554	1.185	0.460	1.802[c]	0.362	0.209	1.931[c]	1.126	1.597	0.301
γ_1	0.119	1.466	–0.855	0.641	0.204	–1.361	–0.959	–1.498	–1.203	3.259[a]	0.577	2.410[b]	0.855	0.188	–1.099	–0.118	–0.030	0.347	0.148
γ_2	–0.347	–0.225	1.038	–1.334	–0.483	–0.596	0.854	0.385	0.411	–0.673	5.470[a]	4.893[a]	–0.980	0.270	–0.292	0.750	1.798[c]	–1.066	0.089
γ_3	–0.117	1.953[c]	–0.871	1.660[c]	–0.119	0.382	0.330	–1.186	–0.691	0.872	–0.169	1.040	–1.600	–1.075	–0.470	0.235	–1.844[c]	0.067	0.547
γ_4	0.491	1.272	–1.660[c]	–2.167[b]	0.634	–0.744	–1.470	–0.335	0.509	–1.344	–2.155[b]	0.992	0.349	–2.415[b]	–1.030	–0.801	–2.327[b]	–2.110[b]	–0.442

The table (Panels A to T) reports the Newey–West *t*–statistics for the indicated coefficients (β_ks and γ_ks) from the estimation of the VAR specification show below. The table primarily reports the *t*–statistics of the null hypothesis that whether one of β_ks or γ_ks is zero. In this specification, *Y* denotes the growth of price–dividend ratio for each country, while *D* represents the dummy variable that whether in the exuberance period or not (bubble indicator). The dummy is set to 1 when there is an exuberance according to the previous date–stamping results and 0 otherwise. The lag number is set to 4 considering the transmission may take time to appear. [a], [b], [c] represents the 99%, 95%, 90% level of significance, respectively. Missing values (N/A) in the table are due to the perfectly collinear problem.

$$Y_{i,t} = \alpha + \sum_{k=1}^{4} \delta_{i,t-k} Y_{i,t-k} + \sum_{k=1}^{4} \beta_{j,t-k} Y_{j,t-k} + \sum_{k=1}^{4} \gamma_{j,t-k} D_{j,t-k} Y_{j,t-k} + \varepsilon_{i,t}$$

Table 4.5: VAR estimation results for ten stock markets.

	γ_1	γ_2	γ_3	γ_4	p_1	p_2
Panel A: Australia						
China	0.499	–0.032	0.965	2.001b	0.4063	0.3803
	(0.114)	(0.083)	(0.139)	(0.151)		
Hong Kong	–2.084^{b}	0.561	–1.049	–2.550^{b}	0.066^{c}	0.075^{c}
	(0.106)	(0.090)	(0.102)	(0.132)		
Japan	0.627	–2.640^{a}	2.549b	–1.726^{c}	0.006^{a}	0.002^{a}
	(0.172)	(0.150)	(0.193)	(0.254)		
Thailand	–0.234	–0.838	–1.431	–0.707	0.002^{a}	0.906
	(0.107)	(0.087)	(0.082)	(0.081)		
Germany	–3.612^{a}	0.714	–0.133	–2.049^{b}	0.001^{a}	0.001^{a}
	(0.111)	(0.116)	(0.171)	(0.215)		
Netherlands	–0.010	1.294	–0.130	–0.999	0.234	0.519
	(0.133)	(0.128)	(0.206)	(0.214)		
United Kingdom	1.184	1.392	–1.260	–1.350	0.088^{c}	0.076^{c}
	(0.139)	(0.133)	(0.150)	(0.160)		
European Area	–0.101	–0.377	0.167	–0.007	0.242	0.978
	(0.299)	(0.229)	(0.260)	(0.252)		
United States	–2.492^{b}	0.940	–0.201	–0.845	0.161	0.131
	(0.088)	(0.086)	(0.095)	(0.117)		

	γ_1	γ_2	γ_3	γ_4	p_1	p_2
Panel B: China						
Australia	0.440	1.709	–0.561	0.065	0.114	0.164
	(0.250)	(0.180)	(0.266)	(0.276)		
Hong Kong	1.427	–7.829^{a}	7.493^{a}	–1.527	0.000^{a}	0.000^{a}
	(0.163)	(0.119)	(0.147)	(0.129)		
Japan	1.262	–1.932^{c}	–0.077	–2.700^{a}	0.037^{b}	0.036^{b}
	(0.391)	(0.219)	(0.332)	(0.292)		
Thailand	1.624	–1.312	0.826	1.351	0.179	0.242
	(0.090)	(0.201)	(0.127)	(0.114)		
Germany	–1.085	–3.286^{a}	–3.340^{a}	3.756^{a}	0.000^{a}	0.000^{a}
	(0.118)	(0.141)	(0.132)	(0.135)		
Netherlands	–0.013	–1.120	–0.895	–2.843^{a}	0.028^{b}	0.195
	(0.176)	(0.171)	(0.209)	(0.172)		
United Kingdom	–0.028	0.776	–2.310^{b}	1.454	0.265	0.045^{b}
	(0.249)	(0.282)	(0.265)	(0.299)		
European Area	–1.348	–0.287	–0.608	–0.919	0.462	0.754
	(0.194)	(0.183)	(0.272)	(0.325)		
United States	1.101	0.822	–0.540	0.745	0.363	0.454
	0.440	1.709	–0.561	0.065		

	γ_1	γ_2	γ_3	γ_4	p_1	p_2
Panel C: Hong Kong						
Australia	0.285	–0.723	–0.565	1.319	0.041^{b}	0.081^{c}
	(0.204)	(0.211)	(0.165)	(0.147)		
China	–0.220	0.595	1.111	0.588	0.924	0.759
	(0.087)	(0.103)	(0.104)	(0.150)		
Japan	1.365	–0.558	1.482	–1.220	0.357	0.280
	(0.313)	(0.476)	(0.272)	(0.246)		
Thailand	1.509	–0.094	–0.039	–0.487	0.313	0.277
	(0.147)	(0.136)	(0.099)	(0.097)		
Germany	–1.693^{c}	1.420	–1.555	–0.701	0.142	0.100^{c}
	(0.153)	(0.227)	(0.231)	(0.302)		
Netherlands	–0.241	–1.251	–1.266	–2.120^{b}	0.003^{a}	0.782
	(0.244)	(0.194)	(0.236)	(0.162)		
United Kingdom	–0.474	1.209	–0.833	–1.129	0.159	0.248
	(0.175)	(0.132)	(0.160)	(0.181)		
European Area	–0.486	0.521	–0.369	–2.444^{b}	0.120	0.160
	(0.381)	(0.290)	(0.323)	(0.197)		
United States	–0.230	–0.352	–0.336	0.647	0.520	0.803
	(0.129)	(0.137)	(0.120)	(0.140)		

	γ_1	γ_2	γ_3	γ_4	p_1	p_2
Panel D: Japan						
Australia	–3.368^{a}	–0.669	–0.377	1.673^{c}	0.000^{a}	0.001^{a}
	(0.125)	(0.211)	(0.098)	(0.132)		
China	0.254	1.462	0.355	1.253	0.867	0.870
	(0.055)	(0.037)	(0.049)	(0.048)		
Hong Kong	–3.322^{a}	0.491	0.096	–0.954	0.000^{a}	0.056^{b}
	(0.068)	(0.096)	(0.096)	(0.143)		
Thailand	–0.051	1.685^{c}	–0.661	–0.617	0.426	0.417
	(0.080)	(0.083)	(0.093)	(0.082)		
Germany	–2.207^{b}	–0.844	1.226	0.989	0.000^{a}	0.153
	(0.108)	(0.115)	(0.117)	(0.111)		
Netherlands	–1.403	–0.795	–0.386	0.322	0.199	0.560
	(0.109)	(0.083)	(0.114)	(0.095)		
United Kingdom	–1.839^{c}	1.762^{c}	–0.131	–1.233	0.000^{a}	0.051^{c}
	(0.104)	(0.071)	(0.105)	(0.120)		
European Area	–0.144	–0.841	–0.615	–1.471	0.000^{a}	0.922
	(0.195)	(0.151)	(0.098)	(0.107)		
United States	–1.071	0.277	0.361	–1.316	0.235	0.424
	(0.078)	(0.065)	(0.082)	(0.077)		

Continued

Table 4.5 (Continued)

Panel E: Thailand	γ_1	γ_2	γ_3	γ_4	p_1	p_2
Australia	0.348	–0.945	2.110^{b}	–0.328	0.200	0.206
	(0.173)	(0.284)	(0.208)	(0.288)		
China	1.952^{c}	0.552	2.501^{b}	1.285	0.266	0.718
	(0.076)	(0.088)	(0.064)	(0.177)		
Hong Kong	0.061	0.652	0.339	–1.116	0.447	0.582
	(0.243)	(0.239)	(0.165)	(0.216)		
Japan	–0.705	1.166	1.224	2.067^{b}	0.139	0.247
	(0.215)	(0.194)	(0.207)	(0.209)		
Germany	–1.261	0.238	–0.461	–0.540	0.273	0.738
	(0.213)	(0.174)	(0.252)	(0.156)		
Netherlands	–0.139	–0.841	–1.365	–1.136	0.286	0.851
	(0.235)	(0.197)	(0.233)	(0.293)		
United Kingdom	–0.414	1.059	0.013	–1.205	0.369	0.460
	(0.195)	(0.266)	(0.179)	(0.203)		
European Area	–0.877	0.293	–1.235	–0.613	0.385	0.711
	(0.273)	(0.212)	(0.291)	(0.213)		
United States	–2.126^{b}	0.058	0.380	1.093	0.163	0.215
	(0.137)	(0.181)	(0.137)	(0.154)		

Panel F: Germany	γ_1	γ_2	γ_3	γ_4	p_1	p_2
Australia	0.154	0.975	–0.592	0.713	0.731	0.828
	(0.112)	(0.101)	(0.098)	(0.128)		
China	0.612	–1.103	1.482	0.803	0.431	0.417
	(0.073)	(0.077)	(0.061)	(0.095)		
Hong Kong	–0.404	1.190	–1.027	–1.472	0.420	0.450
	(0.064)	(0.079)	(0.114)	(0.223)		
Japan	–0.927	0.286	1.293	–1.961^{c}	0.036^{b}	0.042^{b}
	(0.131)	(0.179)	(0.184)	(0.118)		
Thailand	0.040	–0.296	–1.811^{c}	–1.409	0.015^{b}	0.323
	(0.098)	(0.078)	(0.119)	(0.089)		
Netherlands	0.123	–0.069	–0.495	–1.280	0.409	0.707
	(0.125)	(0.147)	(0.128)	(0.165)		
United Kingdom	1.910^{b}	0.073	–3.831^{a}	–1.032	0.000^{a}	0.000^{a}
	(0.110)	(0.097)	(0.084)	(0.121)		
European Area	–0.704	–1.359	–0.609	–2.453^{b}	0.010^{a}	0.979
	(0.251)	(0.194)	(0.222)	(0.095)		
United States	0.192	0.353	–0.754	–0.170	0.590	0.856
	(0.085)	(0.088)	(0.103)	(0.095)		

Panel G: Netherlands	γ_1	γ_2	γ_3	γ_4	p_1	p_2
Australia	–1.862^{c}	–0.226	–0.798	0.496	0.000^{a}	0.356
	(0.135)	(0.098)	(0.078)	(0.066)		
China	0.130	1.228	0.230	1.420	0.953	0.700
	(0.065)	(0.062)	(0.095)	(0.087)		
Hong Kong	–0.424	–1.151	–0.874	–1.247	0.000^{a}	0.760
	(0.106)	(0.155)	(0.070)	(0.152)		
Japan	2.277^{b}	–0.440	–1.012	1.776^{c}	0.014^{b}	0.020^{b}
	(0.183)	(0.204)	(0.134)	(0.164)		
Thailand	–0.478	–0.102	0.083	–3.466^{a}	0.000^{a}	0.024^{b}
	(0.146)	(0.060)	(0.054)	(0.054)		
Germany	–1.358	–1.155	2.700^{a}	0.390	0.000^{a}	0.048^{b}
	(0.184)	(0.093)	(0.086)	(0.099)		
United Kingdom	–1.728^{c}	1.075	0.588	–3.102^{a}	0.000^{a}	0.039^{b}
	(0.106)	(0.131)	(0.121)	(0.088)		
European Area	1.537	0.340	–2.983^{a}	–1.150	0.000^{a}	0.017^{b}
	(0.094)	(0.104)	(0.098)	(0.148)		
United States	0.411	–0.051	0.056	–0.841	0.127	0.848
	(0.083)	(0.090)	(0.090)	(0.079)		

Panel H: United Kingdom	γ_1	γ_2	γ_3	γ_4	p_1	p_2
Australia	–2.513^{b}	0.606	–1.454	0.370	0.000^{a}	0.043^{b}
	(0.090)	(0.110)	(0.053)	(0.082)		
China	0.131	–0.467	–0.620	0.908	0.949	0.746
	(0.052)	(0.071)	(0.055)	(0.147)		
Hong Kong	0.644	–0.810	1.539	–1.690	0.000^{a}	0.305
	(0.102)	(0.149)	(0.113)	(0.167)		
Japan	0.199	–0.478	–0.542	2.305	0.034^{b}	0.357
	(0.229)	(0.261)	(0.187)	(0.211)		
Thailand	0.505	–0.776	–0.100	–2.081^{b}	0.003^{a}	0.079^{c}
	(0.173)	(0.074)	(0.059)	(0.056)		
Germany	–1.496	–0.598	0.057	–0.431	0.000^{a}	0.795
	(0.097)	(0.074)	(0.109)	(0.079)		
Netherlands	–0.177	–0.728	0.079	0.497	0.964	0.849
	(0.146)	(0.090)	(0.134)	(0.218)		
European Area	–1.692^{c}	–1.136	–2.350^{b}	1.032	0.000^{a}	0.054^{c}
	(0.146)	(0.163)	(0.144)	(0.129)		
United States	–0.209	–0.960	0.168	1.199	0.471	0.509
	(0.067)	(0.082)	(0.082)	(0.097)		

Continued

Table 4.5 (Continued)

	γ_1	γ_2	γ_3	γ_4	p_1	p_2
Panel I: European Area						
Australia	1.293	–0.962	1.081	–2.465[b]	0.343	0.103
	(0.137)	(0.098)	(0.088)	(0.087)		
China	–0.644	–0.073	1.242	0.832	0.373	0.656
	(0.057)	(0.051)	(0.832)	(0.098)		
Hong Kong	0.767	–0.489	–1.349	–0.172	0.003[a]	0.005[a]
	(0.075)	(0.105)	(0.079)	(0.181)		
Japan	0.667	0.135	3.301	–1.080	0.000[a]	0.000[a]
	(0.327)	(0.300)	(0.139)	(0.204)		
Thailand	0.678	–1.047	–1.799	1.090	0.049[b]	0.143
	(0.096)	(0.054)	(0.086)	(0.051)		
Germany	–4.880[a]	0.022	–6.111[a]	–6.031[a]	0.000[a]	0.000[a]
	(0.123)	(0.088)	(0.079)	(0.071)		
Netherlands	0.698	0.768	–0.057	–1.361	0.390	0.206
	(0.135)	(0.147)	(0.111)	(0.173)		
United Kingdom	1.338	0.057	–2.316[b]	–1.651[c]	0.042[b]	0.019[b]
	(0.155)	(0.155)	(0.128)	(0.178)		
United States	0.395	1.073	–0.153	–1.049	0.838	0.379
	(0.105)	(0.099)	(0.104)	(0.104)		

	γ_1	γ_2	γ_3	γ_4	p_1	p_2
Panel J: United States						
Australia	–3.912[a]	0.986	–0.043	0.028	0.000[a]	0.000[a]
	(0.106)	(0.283)	(0.101)	(0.005)		
China	–0.310	–0.753	1.051	1.108	0.749	0.295
	(0.083)	(0.084)	(0.061)	(0.098)		
Hong Kong	–2.444[b]	–1.165	0.914	–1.270	0.000[a]	0.219
	(0.104)	(0.099)	(0.094)	(0.153)		
Japan	2.548[b]	–1.576	0.288	1.341	0.000[a]	0.004[a]
	(0.145)	(0.238)	(0.164)	(0.223)		
Thailand	–1.298	0.519	0.169	–1.872	0.000[a]	0.643
	(0.129)	(0.112)	(0.082)	(0.076)		
Germany	–1.133	3.736[a]	2.011[b]	1.761	0.000[a]	0.062[c]
	(0.160)	(0.010)	(0.157)	(0.102)		
Netherlands	0.676	–0.230	–0.173	0.787	0.904	0.818
	(0.135)	(0.153)	(0.136)	(0.188)		
United Kingdom	–0.219	–0.635	2.043[b]	–3.096[a]	0.010[a]	0.024[b]
	(0.119)	(0.179)	(0.150)	(0.131)		
European Area	–1.420	0.542	–1.295	2.080b	0.000[a]	0.146
	(0.172)	(0.158)	(0.219)	(0.170)		

The table (Panels A to J) reports the Newey-West *t*-statistics for the indicated coefficients from the estimation of the VAR specification show below. Also reported is the *p*-values for the F-tests of the hypothesis that $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \boldsymbol{\gamma_1} = \boldsymbol{\gamma_2} = \boldsymbol{\gamma_3} = \boldsymbol{\gamma_4}$ $(\boldsymbol{p_1})$ and $\boldsymbol{\gamma_1} = \boldsymbol{\gamma_2} = \boldsymbol{\gamma_3} = \boldsymbol{\gamma_4}$ $(\boldsymbol{p_2})$**.** In this specification, Y denotes the return of price-dividend ratio for each country while D represents the dummy variable that whether in the exuberance period or not. The dummy is set to 1 when there is an exuberance according to the previous date-stamping results whereas 0 when bubble is not present. The lag number is set to 4 considering the transmission may take time to appear. [a], [b], [c] represents the 99%, 95%, 90% level of significance.

$Y_{i,t} = \alpha + \sum_{k=1}^{4} \delta_{i,t-k} Y_{i,t-k} + \sum_{k=1}^{4} \beta_{j,t-k} Y_{j,t-k} + \sum_{k=1}^{4} \gamma_{j,t-k} D_{j,t-k} Y_{j,t-k} + \varepsilon_{i,t}$.

Table 4.6: Univariate GARCH models.

Country	Model selected	ω	α	γ	β
Australia	GARCH	0.0003**	0.0222**		0.9417***
China	EGARCH	–0.1978***	0.0520	0.1767***	0.9646***
Hong Kong	TGARCH	0.0004**	0.1760***	–0.1456***	0.8638***
Japan	TGARCH	0.0008***	0.0232	0.2184***	0.6042***
Thailand	EGARCH	–0.3552***	0.2898***	0.0513**	0.9716***
Germany	GARCH	0.00004*	0.0585***		0.9353***
Netherlands	GARCH	0.0004**	0.1158***		0.7959***
United Kingdom	EGARCH	–0.4253***	0.2189***	–0.0653***	0.9532***
European Area	GARCH	0.0006*	0.1619**		0.6716***
United States	EGARCH	–0.5098***	0.2070***	–0.0959***	0.9327***

This table reports the selected specifications and parameter estimates for the univariate GARCH models used to standardize each return series. Six of ten models selected for the stock returns include a significant asymmetric term: China, Hong Kong, Japan, Thailand, United Kingdom and United States. Four stock return series are fitted in EGARCH form (China, Thailand, United Kingdom and United States) and the remaining two where the TGARCH parameterization is adopted ((Hong Kong and Japan). We currently employ the Bayesian information criterion (BIC) to select the univariate volatility specifications. Although other criteria are available, the use of BIC is appropriate as it leads to the correct model specification. ***, **, * represent the 99%, 95%, 90% level of significance.

GARCH: $h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$;

AVGARCH: $h_t^{1/2} = \omega + \alpha|\varepsilon_{t-1}| + \beta h_{t-1}^{1/2}$;

EGARCH: $\ln(h_t) = \omega + \alpha\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} + \gamma\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta\ln(h_{t-1})$;

TGARCH: $h_t^{1/2} = \omega + \alpha|\varepsilon_{t-1}| + \gamma I[\varepsilon_{t-1} < 0]|\varepsilon_{t-1}| + \beta h_{t-1}^{1/2}$;

GJR-GARCH: $h_t = \omega + \alpha\varepsilon_{t-1}^2 + \gamma I[\varepsilon_{t-1} < 0]\varepsilon_{t-1}^2 + \beta h_{t-1}$.

The simplest of the models are GARCH and AVGARCH without the consideration of threshold effects. EGARCH, TGARCH and GJR-GARCH allow for threshold effects but use different powers of the variance in the evolution equation. Although some of the GARCH models above have different expressions with their original representations, their qualitative features remain unchanged. The modifications are intended to improve their comparability according to the Cappiello et al. (2006).

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Table 4.7: Robustness testing results.

	Root Mean Squared Error			Mean Absolute Error		
	Model 1	**Model 2**	**Model 3**	**Model 1**	**Model 2**	**Model 3**
Panel A: Australia						
Australia	0.0895			0.0633		
Japan		0.0894	0.0885		0.0635	0.0632
China		0.0906	0.0885		0.0641	0.0628
Thailand		0.0881	0.0878		0.0627	0.0632
Hong Kong		0.0893	0.0886		0.0631	0.0626
Germany		0.0887	0.0882		0.0627	0.0625
Netherlands		0.0892	0.0889		0.0626	0.0623
United Kingdom		0.0893	0.0887		0.0633	0.0630
European Area		0.0902	0.0901		0.0628	0.0627
United States		0.0892	0.0887		0.0634	0.0632
Panel B: China						
China	0.1182			0.0817		
Australia		0.1171	0.1168		0.0804	0.0800
Japan		0.1176	0.1169		0.0815	0.0807
Thailand		0.1172	0.1164		0.0805	0.0806
Hong Kong		0.1155	0.1144		0.0806	0.0789
Germany		0.1138	0.1131		0.0806	0.0795
Netherlands		0.1180	0.1170		0.0814	0.0802
United Kingdom		0.1178	0.1167		0.0814	0.0811
European Area		0.1173	0.1169		0.0811	0.0807
United States		0.1176	0.1171		0.0811	0.0816
Panel C: Hong Kong						
Hong Kong	0.0911			0.0674		
Australia		0.0881	0.0878		0.0641	0.0638
Japan		0.0884	0.0878		0.0649	0.0644
China		0.0823	0.0818		0.0613	0.0606
Thailand		0.0908	0.0902		0.0672	0.0667
Germany		0.0905	0.0894		0.0670	0.0666
Netherlands		0.0881	0.0873		0.0643	0.0637
United Kingdom		0.0907	0.0903		0.0671	0.0667
European Area		0.0822	0.0811		0.0605	0.0601
United States		0.0905	0.0905		0.0677	0.0678
Panel D: Japan						
Japan	0.0563			0.0425		
Australia		0.0551	0.0539		0.0425	0.0422
China		0.0508	0.0505		0.0402	0.0401
Thailand		0.0545	0.0541		0.0418	0.0418
Hong Kong		0.0540	0.0535		0.0415	0.0410
Germany		0.0532	0.0529		0.0400	0.0398

Continued

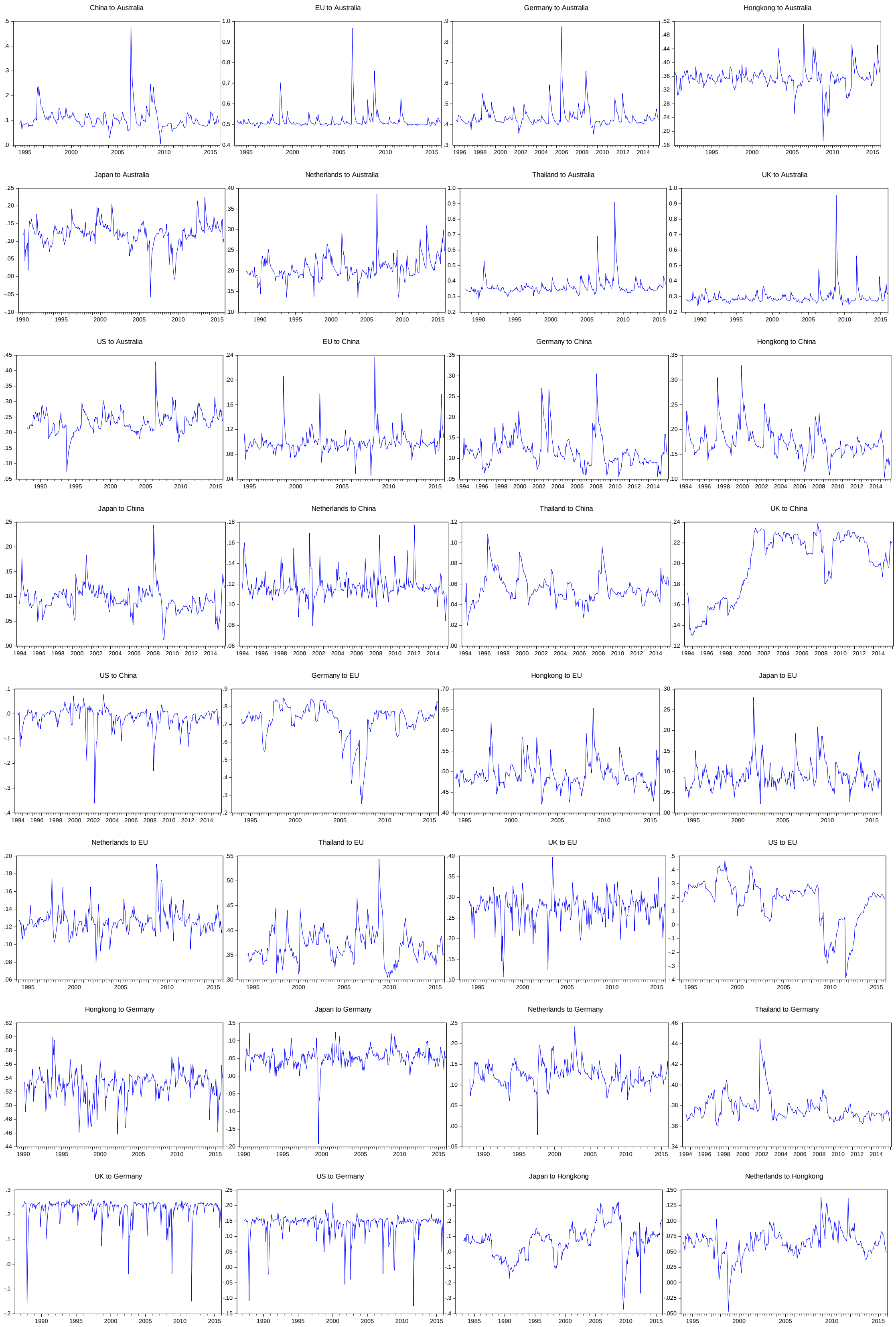
Table 4.7 continued	Root Mean Squared Error Model 1	Model 2	Model 3	Mean Absolute Error Model 1	Model 2	Model 3
Netherlands		0.0558	0.0557		0.0421	0.0418
United Kingdom		0.0541	0.0536		0.0409	0.0409
European Area		0.0455	0.0452		0.0359	0.0357
United States		0.0540	0.0553		0.0415	0.0422
Panel E: Thailand						
Thailand	0.0936			0.0649		
Australia		0.1028	0.1022		0.0745	0.0745
Japan		0.0990	0.0985		0.0701	0.0692
China		0.1044	0.1026		0.0728	0.0719
Hong Kong		0.0954	0.0951		0.0679	0.0676
Germany		0.0929	0.0926		0.0649	0.0651
Netherlands		0.0986	0.0979		0.0695	0.0691
United Kingdom		0.0934	0.0929		0.0651	0.0652
European Area		0.1030	0.1024		0.0742	0.0738
United States		0.0934	0.0927		0.0648	0.0646
Panel F: Germany						
Germany	0.0654			0.0471		
Australia		0.0711	0.0710		0.0517	0.0517
Japan		0.0703	0.0700		0.0511	0.0512
China		0.0732	0.0727		0.0529	0.0527
Thailand		0.0653	0.0644		0.0469	0.0466
Hong Kong		0.0691	0.0685		0.0505	0.0500
Netherlands		0.0703	0.0701		0.0512	0.0511
United Kingdom		0.0650	0.0642		0.0468	0.0461
European Area		0.0724	0.0717		0.0524	0.0522
United States		0.0650	0.0649		0.0469	0.0469
Panel G: Netherlands						
Netherlands	0.0657			0.0483		
Australia		0.0590	0.0587		0.0433	0.0433
Japan		0.0651	0.0643		0.0482	0.0478
China		0.0687	0.0681		0.0509	0.0510
Thailand		0.0626	0.0621		0.0463	0.0461
Hong Kong		0.0598	0.0594		0.0439	0.0441
Germany		0.0539	0.0534		0.0388	0.0385
United Kingdom		0.0629	0.0621		0.0460	0.0451
European Area		0.0492	0.0483		0.0344	0.0344
United States		0.0646	0.0645		0.0479	0.0479
Panel H: United Kingdom						
United Kingdom	0.0607			0.0412		
Australia		0.0524	0.0522		0.0370	0.0368
Japan		0.0536	0.0528		0.0373	0.0368

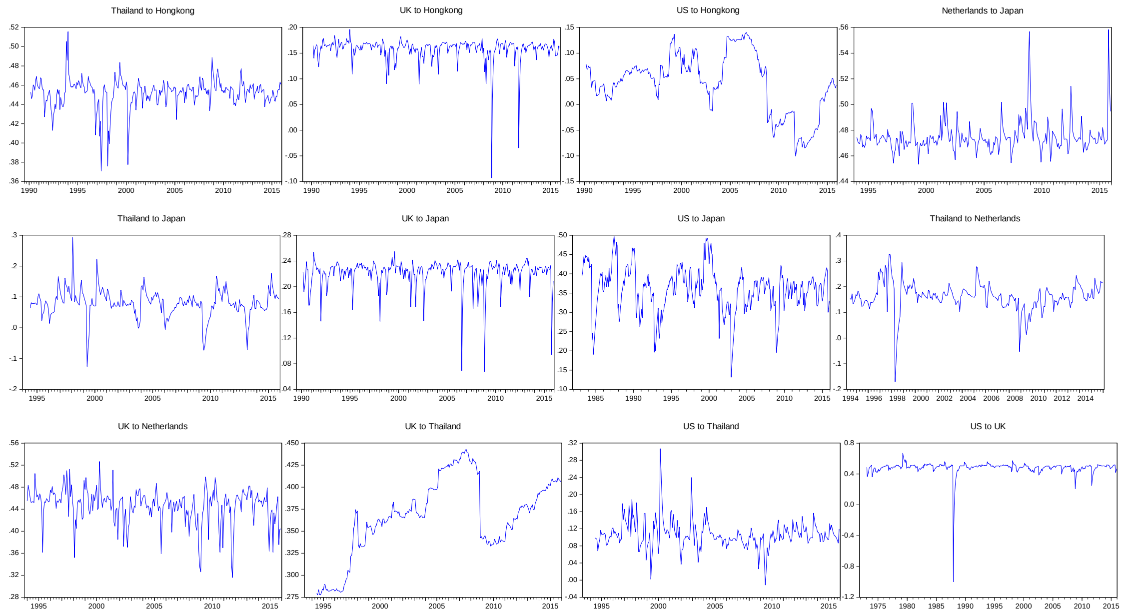
Continued

Table 4.7 continued	Root Mean Squared Error Model 1	Model 2	Model 3	Mean Absolute Error Model 1	Model 2	Model 3
China		0.0511	0.0506		0.0377	0.0375
Thailand		0.0529	0.0525		0.0369	0.0368
Hong Kong		0.0508	0.0496		0.0350	0.0355
Germany		0.0595	0.0594		0.0399	0.0398
Netherlands		0.0539	0.0539		0.0373	0.0374
European Area		0.0432	0.0417		0.0309	0.0311
United States		0.0625	0.0623		0.0415	0.0415
Panel I: European Area						
European Area	0.0604			0.0465		
Australia		0.0603	0.0601		0.0464	0.0463
Japan		0.0599	0.0594		0.0460	0.0456
China		0.0595	0.0592		0.0458	0.0456
Thailand		0.0589	0.0584		0.0450	0.0447
Hong Kong		0.0602	0.0599		0.0461	0.0462
Germany		0.0597	0.0583		0.0459	0.0445
Netherlands		0.0600	0.0596		0.0464	0.0460
United Kingdom		0.0602	0.0593		0.0462	0.0450
United States		0.0604	0.0601		0.0465	0.0463
Panel J: United States						
United States	0.0797			0.0543		
Australia		0.0790	0.0783		0.0538	0.0536
Japan		0.0803	0.0795		0.0544	0.0534
China		0.0858	0.0855		0.0586	0.0587
Thailand		0.0757	0.0752		0.0523	0.0648
Hong Kong		0.0769	0.0763		0.0526	0.0523
Germany		0.0717	0.0709		0.0497	0.0489
Netherlands		0.0806	0.0642		0.0544	0.0542
United Kingdom		0.0794	0.0621		0.0542	0.0534
European Area		0.0684	0.0674		0.0487	0.0482

This table reports the forecasting results for Australia, China, Hong Kong, Japan, Thailand, Germany, Netherlands, United Kingdom, European Region, and Untied States separately in order to examine the robustness of VAR results. The sub-columns of Model 1 in both Root Mean Squared Error and Mean Absolute Error represent the benchmark model $(Y_{i,t} = \alpha + \sum_{k=0}^{4} \delta_{i,t-k} Y_{i,t-k} + \varepsilon_{i,t})$ which the returns of one market are explained by its own lags. The sub-columns of Model 2 is the testing results obtained from the forecasting model $(Y_{i,t} = \alpha + \sum_{k=0}^{4} \delta_{i,t-k} Y_{i,t-k} + \sum_{k=0}^{4} \beta_{j,t-k} Y_{j,t-k} + \varepsilon_{i,j,t})$ that returns of one market are explained by its own lags and lags from another market. Finally, the sub-columns of Model 3 show the forecasting errors estimated through the model $(Y_{i,t} = \alpha + \sum_{k=0}^{4} \delta_{i,t-k} Y_{i,t-k} + \sum_{k=0}^{4} \beta_{j,t-k} Y_{j,t-k} + \sum_{k=0}^{4} \gamma_{j,t-k} D_{j,t-k} Y_{j,t-k} + \varepsilon_{i,j,t})$ which contains both lags and bubble periods of another market. $Y_{i,t}$ and $Y_{j,t}$ are the returns of price-dividend ratio for major stock market indices from different markets. $D_{j,t-k}$ is set according to the date-stamping results in Section 4.9.1 and equals to 1 when bubbles are present and 0, otherwise. The lag interval sets 0 to 4, the same with that in Section 4.8.1. The numbers highlighted by green color represent the lowest Root Mean Square Errors and Absolute Mean Errors.

Figure 4.5: Correlation Graphs.




Thailand to Hongkong
UK to Hongkong
US to Hongkong
Netherlands to Japan
Thailand to Japan
UK to Japan
US to Japan
Thailand to Netherlands
UK to Netherlands
UK to Thailand
US to Thailand
US to UK

Chapter 5 Stock market bubbles and stock market predictability

5.1 Introduction

The dividend yield, by definition, is the aggregation of discounted future expected dividend growth; according to the theory, its variation must reflect similar variations in expected returns and/or expected dividend growth. The critical question, however, is which variable dominates the variation. This question helps financial economists to have a better understanding in how the stock market works, and has profound implications for the major blocks of asset valuation – portfolio allocation, sources of systematic risk, risk management, and so on. Campbell and Shiller (1987, 1988a, b) introduce a dividend-price model that allows both expected dividends and discount rates to vary over time, and such an approach has become extremely popular in empirical research. An important feature of the model is that with the assumption of no price bubbles, it is consistent with the presence of stock market predictability and/or dividend-growth predictability. In particular, the log dividend-price ratio for a stock will gain forecasting power to either the stock returns and/or the dividend-growth; or by implication – stock returns will only be unpredictable if the dividend growth is predictable. There has been a large amount of empirical discussions focusing on whether stock market returns and dividend growth are predictable using the dividend yield and other macroeconomic variables; see, for example, Fama (1981), Keim and Stambaugh (1986), Campbell and Shiller (1988a, b), Fama and French (1988,1989), Nelson and Kim (1993), Stambaugh (1999), Goyal and Welch (2003), Welch and Goyal (2008), and Cochrane (2008).

Although it has become a stylized fact that stock return predictability can be consistent with orthodox financial theory, several authors have argued that there are statistical reasons to believe the strong support for predictability obtained in earlier studies could be spurious. Nelson and Kim (1993) and Stambaugh (1999) show that high persistence predictors lead to biased coefficients in predictive regressions if the innovations driving the predictors are correlated with returns, as is known to be the case for many of the popular macroeconomic and financial variables used as predictors. Goyal and Welch (2003) exhibit that the persistence of dividend-based valuation ratios critically increased over the typical sample periods used in empirical studies of predictability and they argue that as a consequence, there is no convincing connection between in-sample and out-of-sample forecasting performance borrowed in the literature to explain the usefulness of dividend ratios in predicting for investment purposes. When estimation and inference techniques are applied that take account of the high degree of persistence of the typical financial and macroeconomic variables used as predictors, the statistical evidence of short-horizon and long-horizon predictability is considerably weaker, and in some cases disappears completely; see, for example, Ang and Bekaert (2007), Boudoukh, Richardson and Whitelaw (2007), Welch and Goyal (2008) and Breitung and Demetrescu (2015).

Cochrane (2008) provides an important remark on stock market predictability since it is one of the few recent studies that is supportive of the argument that stock returns are predictable using the dividend yield. To avoid statistical issues raised in the literature, Cochrane (2008) examines the return predictability by setting up a joint null in which returns are not forecastable must also specify that dividend growth is forecastable. He finds evidence on stock return predictability is much stronger than previously thought, that stock returns *are* predictable by the dividend yield and that dividend growth is not predictable by the dividend-price ratio.

One crucial assumption in the empirical literature on the Campbell-Shiller's model and stock market predictability (including Cochrane, 2008) is that stock price bubbles are not present. However, as discussed in Chapter 3 of this thesis and demonstrated in Chapter 4, empirical research suggests that price bubbles are present in historical data on the US stock market and for stock markets in other countries. The first part of this chapter empirically investigates the predictive power of the log dividend-price ratio for S&P Composite index returns and the dividend growth. The analysis differs from previous research on this issue because we allow for the presence of a bubble. More specifically, we use the PSY date-stamping methodology to detect when a bubble exists. We then use this information to investigate the in-sample predictability of returns and dividend growth in the bubble and non-bubble periods and we compare with the results obtained if a bubble is ignored. We focus on a long sample of monthly data but divided into two sub-samples: 1981-1949 and 1950-2017. Furthermore, Campbell-Shiller's model provides a perfect guideline to study the predictability of other variables to dividend-price ratios, such as the monetary variables, by using the VAR framework. To add monetary variables, we are able to investigate the role of monetary policy in driving stock market data within both bubble and non-bubble periods. Note that in the first part, we only analyze the predictive power of selected two monetary variables on the monthly basis from 1950 to 2017 for simple illustration. Then, in the second part, we exploit their relationship deeper by using more and higher frequency (weekly) data through rolling regime. However, we are not the first to study the role of monetary policy. Patelis (1997) examines whether shifts in the stance of monetary policy can account for the observed predictability in excess stock returns. By adopting the idea of conventional dividend-price model and applying vector autoregressions on both monetary and financial variables, he concludes that, in the non-bubble period, an increase in the Federal funds rate has a significant negative impact on predicted stock returns in the short-run, but a positive one at longer horizons. That predictability works largely through the effect of Federal funds rate changes on anticipated excess returns down the road, rather than dividends or expected returns.

Alternatively, Bernanke and Kuttner (2005) use an event-study approach, based on daily changes observed on monetary policy decision dates, to uncover the effects on stock prices of unanticipated changes in the federal funds rate. They find a surprise 25-basis-point reduce in the Federal funds rate linked with approximately 1 percent increase in stock prices. Their analysis largely attributes that response to a persistent decline in the equity premium, and to a lesser extent of the relevant cash flows. However, they do not analyze the dynamic response of stock prices to the monetary policy shifts. Rigobon and Sack (2004) obtain similar findings for the response of stock prices to the changes in interest rates using a heteroskedasticity based estimator that explores the increase in the volatility of interest rates on FOMC (The Federal Open Market Committee) meeting and Humphrey-Hawkins testimony dates. Also, Gurkaynak, Brian and Eric (2005) use intraday data to estimate the response for asset prices to two factors associated with FOMC decisions. The first factor corresponds, similar with Bernanke and Kuttner (2005), to the unanticipated movements in the Federal funds rate target. The estimated impact on stock price movement is also very similar to that uncovered by Bernanke and Kuttner (2005). The second factor is associated with revisions in expectations about future rates, given the funds rate target, and appears to be correlated to the statement accompanying the FOMC decisions. Furthermore, its effect on stock prices is significant, whereas more muted than the first, possibly because revision in expectations on output and inflation which may partly offset the impact of anticipated changes in interest rates.

Overall, the current chapter contains two parts focusing on distinct research questions. For the first part of this chapter, we are particularly interested in whether empirical results on the predictability of stock returns by the dividend-price ratio (and the absence of dividend-growth predictability by the dividend-price ratio) is affected by the presence of a bubble. Is the predictability observed in previous research because a bubble is present but it is being ignored? Are stock returns (and the dividend growth) found to be more or less predictable when we allow for the possibility that a bubble may be present for part of the sample period? Is the predictive power of monetary variables affected by the presence of a bubble? To answer these questions, we mainly fill the gap by relaxing the fundamental assumption of no bubbles in the literature when carrying out similar tests to examine the predictability of dividend-price ratio. While in the second part, we contribute to the literature by studying the explanatory power of monetary variables to price-dividend ratios for both bubble and non-bubble periods. The application of weekly datasets, rather than monthly, provides us more detailed dates when bubbles appeared and crashed. Our results also contribute to the empirical literature on exploring the causality dynamics of monetary variables within the bubble period in order to disclose the implications of monetary policy in relation to the bubble evolutionary process.

The next section of this chapter outlines the Campbell-Shiller log-linear approximation. Section 5.3 describes the data used and sets out the methodology. Section 5.4 discusses the results from orthodox predictive regressions using the monthly data which act as a benchmark for comparison. Section 5.5 tests for the presence of a bubble and dates the bubble regimes using the monthly data. Section 5.6 discusses the predictive regression results allowing for the presence of a bubble using monthly data. Sections 5.7-5.9 run the analysis by using weekly data. Section 5.10 discusses results, and Section 5.11 concludes.

5.2 The Campbell-Shiller approximation and return predictability

5.2.1 The Campbell-Shiller Approximation

In the rational valuation function (RVF hereafter), the ex-post one-period log real holding-period return on a stock is

$$h_{1,t+1} \equiv \log(P_{t+1} + D_{t+1}) - p_t, \quad (5.1)$$

where P_{t+1} is the real stock price at the end of period t+1, D_{t+1} is the real dividend paid during period t+1 and p_t is the log real stock price at time t. A first-order Taylor expansion of (5.1) gives the approximate one-period log real return:

$$h_{1,t+1} \equiv \delta_t - \rho\delta_{t+1} + \Delta d_{t+1} + k, \quad (5.2)$$

where k is a constant, ρ is a number a little smaller than unity, δ_t is the log dividend price ratio $d_t - p_t$ and Δd_{t+1} is the real dividend growth. Now define h_{it} as the discounted i-period log real return:

$$h_{it} \equiv \sum_{j=1}^{i-1} \rho^j \, h_{1,t+j}. \quad (5.3)$$

h_{it} is the discounted sum of approximate one-period log real returns from t to $t + i - 1$. Combining equations (5.2) and (5.3) we can write the discounted i-period return as a linear function of δ_t, δ_{t+1} and Δd_{t+1+j}:

$$h_{it+1} = \delta_t - \rho^i \delta_{t+1} + \sum_{j=0}^{t-1} \rho^j \Delta d_{t+1+j} + \frac{k(1-\rho^i)}{1-\rho}. \quad (5.4)$$

This equation shows the implications for the behavior of the dividend-price ratio of a particular model of equilibrium returns. Rearranging (5.4), using (5.3) and taking expectations at the end of time t, we have a log-linear version of RVF

$$\delta_t = \sum_{j=0}^{t-1} \rho^j E(h_{1,t+1-j} - \Delta d_{t+1+j}) + \rho^i E\delta_{t+1} - \frac{k(1-\rho^i)}{1-\rho}. \quad (5.5)$$

Equation (5.5) states that the log dividend-price ratio is equal to the discounted present value of expected one-period returns in excess of real dividend growth, and the terminal dividend-price ratio (plus a constant). Note that the condition of $\lim_{i \to \infty} \rho^i \delta_{t+i} = 0$ rules out the presence of an asset price bubble. Imposing this condition, it can be seen from (5.5) that the Campbell-Shiller's model implies that the log dividend-price ratio must have predictive ability for returns and/or dividend growth when bubbles are not present in the market.

Earlier empirical research on the empirical implications of the Campbell-Shiller's model focuses on the relationship of the dividend price ratio with the discount rate and dividend growth, rather than on the relationship of the dividend-price ratio with stock returns and dividend growth – see for example Campbell and Shiller (1988a, b) and Cuthbertson, Hayes and Nitzsche (1997). This is because the expected return is unobservable, but it can be replaced in (5.5) with the discount rate and an assumed risk premium. For example, assuming constant expected excess returns (i.e. a constant risk premium rp) and a time-varying discount rate it follows that $E_t h_{1,t+1} = E_t r_{t+1} + rp$, where r_{t+1} denotes the discount rate (the safe rate). Equation (5.5) then becomes

$$\delta_t = \sum_{j=0}^{t-1} \rho^j E(r_{t+1-j} - \Delta d_{t+1+j}) + \rho^i E\delta_{t+1} - \frac{(rp-k)(1-\rho^i)}{1-\rho}, \tag{5.6}$$

And with the no-bubbles condition of $\lim_{i\to\infty} \rho^i \delta_{t+i} = 0$,

$$\delta_t = \sum_{j=0}^{\infty} \rho^j E(r_{t+1-j} - \Delta d_{t+1+j}) + \frac{(rp-k)}{1-\rho}. \tag{5.7}$$

Equation (5.7) can be interpreted as a dynamic version of the Gordon dividend growth model.

In the first part of this chapter, we follow the more recent literature and focus on the empirical predictability of *stock returns* and *dividend growth*. The regression models used in this literature are simple bivariate regressions with the return and dividend growth as a dependent variable, and the lagged dividend-price ratio or lag of some other variable (monetary variables here) thought to be relevant as the explanatory variable. The predictive power of these models is typically assessed using simple *t*-tests and *R*-squared. The regression models can be written:

$$y_t = \alpha + \beta x_{t-1} + \varepsilon_t$$

where ε_t is a zero mean random error term, y_t is either the observed stock return r_t or the dividend growth g_t, and x_{t-1} is either the lagged dividend-price ratio or another relevant variable (selected monetary variables: government bonds spread and Baa-Aaa spread here) . We use OLS for parameter estimation and when t-statistics are calculated we use Newey-West standard errors (Newey and West, 1987) to allow for possible heteroskedasticity and autocorrelation in the fitted residuals. The empirical literature on predictability using this approach is discussed in more detail in the next section.

5.2.2 The Campbell-Shiller Approximation, Stock Return Predictability and Dividend Growth Predictability

The literature on stock return predictability and dividend growth predictability is far too extensive to review fully here. For example, Campbell and Shiller (1988a, b), Cochrane (1992, 2001 2008), Pesaran and Timmermann (1995), Goyal and Welch (2003, 2008), Ang and Bekaert (2007), Campbell and Thompson (2008), Chen and Zhao (2008), and Chen (2009) provide excellent works. Generally, these studies have focused on discussing the ability of the dividend yield to predict returns and dividend growth. Most of them focus on return predictability; fewer on dividend growth predictability. Overall, in the US, it has become a stylized fact that stock returns are predictable by the dividend-price ratio while dividend growth is not. This predictability pattern is especially pronounced when returns and dividend growth are measured over long (multi-year) horizons, and it has been interpreted as implying that almost all variation in dividend yields is due to changing expectations of future long-term returns with changing expectations of future long-term dividend growth playing essentially no role (see e.g., Cochrane 2001, 2008). However, this fact has been challenged by Chen (2009) , who shows that for the period up to the end of the Second World War, the opposite predictability pattern characterizes the US stock market: Long-horizon returns are unpredictable while long-horizon dividend growth is predicable by the dividend yield. Alternatively, for the post war period, Chen obtains results consistent with the 'fact' view, which is predictable stock returns and unpredictable dividend growth.

The finding that changing expectations of future dividend growth have no role to play in explaining movements in the dividend yield is against the standard textbook model for stock price determination. One possible explanation is provided by Lettau and Ludvigson (2005), who argue that movements in expected dividend growth are positively correlated with movements in expected returns and this co-movement has offsetting effects on the dividend yield which make it unable to uncover the time-varying nature of expected dividend growth. In addition, Menzly, Santos, and Veronesi (2004) provide a general equilibrium habit persistence interpretation for a common component in expected returns and expected dividend growth, and they show that changes in risk preferences eliminate the dividend-price ratio's ability to predict future dividend growth. From their model, what should forecast dividend growth is the dividend yield scaled by a particular price-consumption ratio, and this implication has been proved in the post war US data. Chen, Da and Priestley (2009) argues that due to smoothing, manipulation, or structural shifts in firms' corporate financial policy, measured dividend may not be a good measure of true value-related cashflows and this may explain the lack of dividend growth predictability by the dividend yield.

To extend findings from the US to global markets, Engsted and Pedersen (2010) run tests by using annual US data that many previous authors have used, and then do similar steps on long annual time series for aggregate stock prices and dividends in the three European countries: Denmark, Sweden and the UK. Surprisingly, they find that predictability patterns for returns and dividend growth are very sensitive to whether these variables are measured in real or nominal terms. They confirm Cochrane's (2008) results for real returns and dividend growth using annual CRSP data in which monthly dividends are reinvested in the stock market, and they also confirm most of Chen's (2009) findings for nominal returns and dividend growth using S&P/Cowles data with no reinvestment of dividends. However, their results show that many of the conclusions for nominal returns and dividend growth are turned upside down when these variables are measured in real terms. To understand the differences between nominal and real predictability, they believe the key is inflation predictability. According to Campbell and Shiller's (1988a, b) dividend yield decomposition, the log dividend-price ratio reflects expected future long-term returns and dividend growth, and this decomposition holds for both nominal and real variables. The difference between the nominal and real versions of the decomposition is inflation. Thus, if the dividend-price ratio predicts nominal and real variables differently, it must be because the ratio predicts inflation.

5.3 Data and Methodology Description

5.3.1 Data

The empirical analysis in this chapter focuses on the US stock market. We use two datasets: a monthly dataset and a weekly dataset. The monthly US stock market data has been downloaded from Robert Shiller's website.[6] We compute results for the full sample of data, 1871:1-2017:12, and also for two sub-samples. Sub-sample 1 is 1871:1-1949:12; sub-sample 2 is 1950:1-2017:12. To confirm the starting and ending dates of bubble episodes, we apply the PSY procedures on the monthly price-dividend ratios among both sub-samples. The predictive power of two monetary variables is also analyzed: the long-short interest rate

[6] The website is http://www.econ.yale.edu/~shiller/data.htm.

spread for US government bonds, and the Baa-Aaa yield spread for US corporate bonds (details of these two will be shown later in this section). Monthly data on these variables (long-short interest rate spread and Baa-Aaa yield spread) is from the Federal Reserve Bank of St Louis (FRED) database and it covers the period of 1950:1-2017:12 (sub-sample 2). Price and dividend series are computed in real values using the monthly Consumer Price Index (CPI) as a deflator. Dividend-price ratio and dividend growth are expressed in logarithm form while other variables use raw values in our estimations.

The weekly US stock market data (S&P 500 index price and dividend series) is downloaded from the DataStream, and the rest of monetary weekly data is collected from the FRED database. Similar to our monthly testing, the PSY strategy is applied to identify bubble periods and then we distinguish our full sample into four sub-samples: 1980:1-1996:11 (Pre-bubble period), 1996:11-2001:2 (In-Dotcom bubble period), 2001:2-2008:9 (Post-Dotcom bubble period), and 2008:9-2015:9 (Post-2008 crisis period). To ensure stationarity, we detrend all weekly datasets by using Hodrick-Prescott Filter in non-bubble periods, while in the bubble period, we apply the first difference in all weekly datasets except for dividend growth and variance. Below we have a short list of introductions for selected weekly financial and monetary variables.

A. Financial Variables

We borrow Campbell-Shiller's model but consider different determinants of equilibrium expected returns: the constant expected real return, constant expected excess returns, and allowing the safe rate to vary in the CAPM specifications (will be discussed further in the Methodology Section). Therefore, we select three financial variables: the 3-month treasury bills rate (safe rate), dividend growth, and return variance (squared ex-post real one-week stock return) to build up the basic model.

B. Monetary Policy Indicators

The effective federal funds rate: The federal funds rate is the interest rate at which depository institutions trade federal funds (balances held at Federal Reserve Banks) with each other overnight and the rate that the borrowing institution pays to the lending institution is determined between the two banks. The weighted average rate for all of these types of negotiations is called the effective federal funds rate. The effective federal funds rate is essentially determined by the market but influenced by the Federal Reserve through open market operations to reach the Federal funds rate target. It influences other interest rates such as the prime rate, which is the rate banks charge their customers with higher credit ratings, and indirectly influences longer-term interest rates such as mortgages, loans, and savings, all of which are very important to consumer wealth and confidence.

Long-short interest rate spread for US government bonds: is the difference between 10-year treasury bond yield and 3-month treasury bond yield. This spread has been largely borrowed as a predictor of future economic growth, inflation and recessions, and it is included in the Financial Stress Index published by the FRED.

Baa-Aaa yield spread for US corporate bonds: the difference in yield between Baa and Aaa corporate bonds. This spread is also one widely-used default-risk indicator and many works use this spread to predict future economic activity.

Small-time deposits in Commercial Banks and Thrift Institutions: here in our work, we try to include small-time deposits at Commercial Banks and Thrift Institutions in our VAR framework to find evidence to support theories which attribute the bubble burst to a coordinated behavioral change from market investors.

We use logarithm form in price-dividend ratio, dividend growth and small-time deposits at commercial banks and thrift institutions while for the others, we use their raw values. All weekly variables are computed for real values by using weekly CPIs. Although weekly CPIs are not available, we follow the Linear-Match Last method to translate monthly CPIs collected through Shiller's online database into weekly, that is, we place the monthly observation into the last weekly observation in the corresponding month, and in-between weekly observations are filled by performing a linear interpolation between the last week of the previous month and the last week of the current one. A statistical summary of the monthly and weekly data is given in Tables 5.1 and 5.2 separately.

<Tables 5.1 and 5.2>

5.3.2 Methodology

The whole chapter has been divided into two parts, with different objectives and datasets. The first part aims to examine the predictability of dividend yield to return and dividend growth by using VAR framework on monthly basis. The main tests include three steps:

Step 1: As a benchmark, using the monthly data we compute separate orthodox predictive regressions for stock returns and the dividend growth using the dividend-price ratio as a predictor, assuming no bubble. We compute results for the full sample, 1871:1-2017:12, and also for two sub-samples: Sub-sample 1 is 1871:1-1949:12 and sub-sample 2 is 1950:1-2017:12. We also compute results using two monetary variables as predictors: the long-short government bond spread, and the Baa-Aaa corporate bond spread. The sample period in this case is 1950:1-2017:12. The regression model can be expressed as:

$$y_t = \alpha + \beta x_{t-1} + \varepsilon_t. \tag{5.8}$$

where y_t can be either return or dividend growth, and x_t is either the lagged dividend-price ratio or monetary variables.

Step 2: We test for a bubble in the full sample of data on the monthly price-dividend ratio and find statistically significant evidence that a bubble is present. We then generate a monthly dummy variable using the Phillips et al. (2015a, b) (PSY) date-stamping approach employed in the previous chapters. The dummy variable is defined as follows: $BI_t = 1$ if the PSY date-stamping approach says that a bubble exists and $BI_t = 0$ if the PSY date-stamping approach says there is no bubble.

Step 3: We repeat all of the regressions in step 1 but we use the dummy variable from step 2 to allow for a bubble. The regression model can be written:

$$y_t = (\alpha_1 + \beta_1 x_{t-1})(1 - BI_t) + (\alpha_2 + \beta_2 x_{t-1})BI_t + \varepsilon_t. \tag{5.9}$$

The second part of this chapter aims to answer different research questions but still borrowing the idea while extending the Campbell-Shiller's model by adding monetary variables in the interest of studying their predictability to price-dividend ratio to uncover the role of monetary policy in both bubble and non-bubble periods.[7]

Step 4: Similar to Step 2, we apply the PSY strategy on our weekly price-dividend ratios to

[7] Unlike the first part, here in the second part we use price-dividend ratio rather than dividend-price ratio in our tests as price-dividend ratios will provide a better way to understand our results.

identify bubbles in our sample period starting from 1980 to 2015. Then we divide our sample into four sub-samples: 1980:1-1996:11 (Pre-Dotcom bubble), 1996:11-2001:2 (In-Dotcom bubble), 2001:2-2008:9 (Post-Dotcom bubble), and 2008:9-2015:9 (Post-2008 crisis). Our model lays on the foundation of Campbell-Shiller's model, and we have different assumptions regarding the determinants of equilibrium expected returns: the constant expected real return (5.10), constant expected excess return (5.11), and allowing the safe rate to vary in the CAPM specification (5.12):

$$E_t h_{1,t+1} = r, \tag{5.10}$$

$$E_t h_{1,t+1} = E_t r_{t+1} + rp, \tag{5.11}$$

$$E_t h_{1,t+1} = E_t r_{t+1} + \alpha E_t V_{t+1}. \tag{5.12}$$

where r is a constant, rp represents the constant risk premium, and V_{t+1} is the expected market variances. For each non-bubble sub-sample, we stack all variables that help measure or forecast price-dividend ratios into a vector z_t and run the following VAR framework (lag length k =3):

$$y_t = \sum_{k=0}^{3} A_{t-k} z_{t-k} + \varepsilon_t. \tag{5.13}$$

where y_t is the price-dividend ratio, *A* is a companion matrix of VAR and ε_t is the error vector. By assessing the Wald statistics for each vector, we are able to see which variables have significant predictability to the movement of price-dividend ratio. Furthermore, we undertake the generalized Impulse Response Functions for each significant predictor to obtain a clear view in terms of the exact response of price-dividend ratio to monetary and financial shocks.

Step 5: To answer the question of whether movements in the stance of monetary variables can account for the observed predictability in the growth rate of price-dividend ratio within the bubble period, we repeat step 4 first and then apply bivariate rolling regime by running equation (5.13) repeatedly forward, using subsets of the sample data incremented by one observation at each pass with the initial sample size of 10. Lag length 3 is selected and to ensure the data stationarity, we take first difference for all data before putting into estimation regressions.[8]

5.4 Orthodox Predictive Regression Results: Monthly Data

This section discusses the benchmark predictive regressions for stock return and dividend growth employing the monthly data. The results from estimating the predictive regression model given in equation (5.8) using the full sample of monthly data are provided in Table 5.3 for the stock return and dividend growth respectively, and where one-month returns and dividend growth are measured in real terms. In each case we present the fitted parameters, the *t*-statistics for testing statistical significance (using robust Newey-West standard errors) and the orthodox R-squared (in %).

<Table 5.3>

It can be seen from Table 5.3 that for the monthly data with the dividend-price ratio as an explanatory variable, the market return is unpredictable, with the corresponding estimated coefficient of 0.261 and it is not significant at 10% level; while the dividend growth is predictable, and its estimated coefficient is –0.445 and highly significant at 1% level. The *R*-squared statistics also obtain similar conclusion, that the dividend-price ratio enjoys better forecasting relationship to dividend growth than return, as its *R*-squired is 96% bigger than the number of return estimation (1.803>0.078).

Then we take step 2 to run estimation on our two sub-samples. Table 5.4 reports respective estimated parameters, the *t*-statistics for testing statistical significance (again using robust Newey-West standard errors) and the orthodox *R*-squared (in %) for sub-samples 1 and 2, where sub-sample 1 covers 1871:1 to 1949:12 and sub-sample 2 starts from 1950:1 to 2017:12. From Table 5.4, we can observe that in sub-sample 1, the dividend-price ratio has no predictive power to market return, since its estimated coefficient is 0.466 and it is not reach our tolerant level to reject null hypothesis. However, dividend growth shows a completely different result, with highly significant negative parameter of 1.897, strongly against the null hypothesis that dividend-price ratio has no predictability to dividend growth. Its *R*-squared also gains similar results, as the number of dividend growth estimation is much higher than

[8] Here for the In-Dotcom bubble testing, although the *t*-statistics and *p*-values are useful indicators, they do not have exactly the same interpretation as when there is no bubble. This is because the usual distributions for the *t*-statistics which are fine when there is no bubble, are not 100% accurate when there is a bubble, even if we take differences of the data. However, we can still discuss the *t*-statistics and *p*-values.

the return (5.887>0.05).

<Table 5.4>

The results in sub-sample 2 are completely opposite to sub-sample 1. The dividend-price ratio now gains predictability to return with positive coefficient of 0.56, which is significant at 10 percent level. However, when looking at the dividend growth, the ratio now loses predictability, as its coefficient is –0.197 and *t*-statistic (–1.439) is far away from 10% significant level. Its *R*-squared also reduces dramatically, from 5.887 in sub-sample 1 to 1.379 now.

To take a glance at the effect of monetary policy on return and dividend growth, we report two monetary variables' predictability: Long-short government bond spread and Baa-Aaa corporate bond spread. Tables 5.5 and 5.6 illustrate them separately. From these two tables, we can see that two spreads have opposite predictability pattern to market return and dividend growth. In sub-sample 2, government bond spread can predict the movement of return with a positive coefficient of 3.455 but it loses forecasting ability to dividend growth in the same period. In contrast, corporate bond spread enjoys highly significant predictive power to dividend growth with a negative coefficient of 4.671; however, it is unable to predict the movement of market return.

<Tables 5.5 and 5.6>

Taken above results together, we can see that without considering bubbles, our full sample evidence (1871-2017) is well against the 'stylized fact' documented in asset pricing textbooks (e.g., see Cochrane, 2001), that US stock returns are predictable by the dividend-price ratio while dividend growth is not. Alternatively, our sub-sample results are highly consistent with conclusions made by recent works: for period up to the end of the Second World War, returns are unpredictable but dividend growth is predictable by the dividend-price ratio; while for the post war period, results are in line with the 'stylized fact' view, namely predicable stock returns and unpredictable dividend growth (see Chen, 2009). Furthermore, by adding monetary variables, we find that two popular monetary policy indicators have respective predictability to returns and dividend growth in post war period: returns are predictable by using long-short government bond spread while corporate bond spread can forecast the movement of dividend growth. Over the past two decades there has been mounting evidence in the literature that points out the predictability of monetary policy indicators in relation to stock returns. In our work, we find significant result in government bond spared in predicting the movement of stock returns, which is quite consistent with the conclusion made in the literature (see Patelis, 1997), but failed to obtain similar findings for the corporate bond spread. Instead, the corporate bond spread has the ability to forecast the movement of dividend growth, and its negative coefficient sign speaks that the larger spread will induce the lower dividend growth. Such finding follows the logic that when the Baa-Aaa spread is larger, the likelihood of default in corporate bonds becomes higher, then investors tend to lower their expectations on obtaining future cash flows, for example, dividends from stocks.

5.5 PSY test and Date-stamping Results: Monthly Data

In this section we test for the presence of bubbles by applying monthly S&P Composite data (price-dividend ratio). Since we have discussed the PSY method in detail in Chapter 3, we do not discuss the theory here but just present and discuss the results. Table 5.7 contains the dates of the bubble regimes and the $GSADF(r_0)$ test statistic.

<Table 5.7>

5.6 Predictive Regression Results Allowing for a Bubble: Monthly Data

In this section we repeat the predictive regressions estimated in Section 5.4, but we allow for the presence of a bubble. We do this by setting a bubble indicator $BI_t = 1$ when bubble is present and $BI_t = 0$ otherwise. Thus, BI_t is a dummy variable and we use it in this way to fit separate parameters in the predictive regression models into bubble and no-bubble (or 'normal') periods. The regression models can be written:

$$y_t = (\alpha_1 + \beta_1 x_{t-1})(1 - BI_t) + (\alpha_2 + \beta_2 x_{t-1})BI_t + \varepsilon_t$$

where ε_t is a zero mean random error term, y_t is either the return r_t or the dividend growth g_t, and x_{t-1} is either the lagged dividend-price ratio or the interest rate spreads. OLS is used for parameter estimation and as before, Newey-West standard errors are computed to allow for possible heteroskedasticity and autocorrelation in the fitted residuals.

The full sample results are given in Table 5.8. The sub-sample results are given in Tables 5.9

and 5.10. The results with the interest rate spreads are given in Tables 5.11 and 5.12. From the Table 5.8, we can clearly observe that from 1871 to 2017, in the non-bubble periods, results are consistent with those in Table 5.3: dividend-price ratio does not have predictive power to return but correctly (negatively) predicts the movement of dividend growth. However, when looking at bubble periods, for return, we see opposite results – dividend-price ratio gains highly significant predictive power to return with positive parameter of 1.887 but having reduced forecasting power to dividend growth with a 'wrong' (positive) sign in slope parameter.

<Tables 5.8, 5.9 and 5.10>

Then we repeat our estimations and run for two sub-samples: sub-sample 1 covers 1871 to 1949 and sub-sample 2 starts from 1950 to 2017. Table 5.9 documents the results for sub-sample 1. From the table, in the non-bubble periods, we can see that results are also highly consistent with what we have seen in Table 5.4, that returns are not predictable by using dividend yield but dividend growth are predictable with a 'correct' (negative) sign. In the bubble periods, dividend yield still remains no predictive power to market return while its predictability to dividend growth has reduced dramatically and becomes insignificant. For sub-sample 2, the return results in non-bubble periods are clearly opposite to sub-sample 1: dividend-price ratio now gains significant predictive power to return, and it also has highly significant forecasting power in predicting the movement of dividend growth in the non-bubble periods. When it comes to bubble period, we clearly observe a dramatic rise in predictability of dividend yield for both return and dividend growth. Dividend yield now obtains highly significant predictive power with positive slope parameter of 2.042 to return and it also enjoys better predictability but a reversal in sign (from negative to positive) to dividend growth. Overall, R-squared for dividend growth is much bigger than the R-squared of return, with the number of 6.839 to 1.853.

By distinguishing bubble and non-bubble periods, it provides an opportunity to see the difference in predictability of monetary policy indicator for return and dividend growth. Table 5.11 reports the results for government bond spread which covers the period from 1950 to 2017. For return, we can observe that government bond spread is a good predictor, since in both bubble and non-bubble periods, it has positive forecasting power to return. However, when looking at dividend growth, it now has poor performance in both periods, as we can see that none of the slope parameter is significant at 10% level. For results of Baa-Aaa spread in Table 5.12, we conclude that its forecasting power to dividend growth is reduced in the bubble periods compared with non-bubble periods, while for market return, no significant forecasting power has been discovered in both periods. In sum, it is obvious that government bond spread is a better policy indicator than Baa-Aaa spread in predicting movement of return in either periods, whilst for Baa-Aaa spread, it has succeeded its significant forecasting power from non-bubble periods to bubble periods with negative impact on the dividend-growth.

<Tables 5.11 and 12>

Overall, in this section, we believe several interesting findings has been spotted: (1) for the period up to the end of the Second World War, bubbles may have a negative impact on the predictability of dividend yield to dividend growth, because from non-bubble to bubble periods, forecasting ability of dividend-price ratio to dividend growth has reduced dramatically, (2) for the post war period, it seems that bubbles do have a positive impact on the predictive power of dividend yield to both return and dividend growth. In particular, for dividend growth, dividend yield has predictive power with a negative slope parameter in the non-bubble period, whereas with a 'wrong' (positive) slope parameter in the bubble period. According to the theory, the slope parameter for dividend growth should always be negative, not positive, and (3) government bond spread has better performance than Baa-Aaa spread in predicting movement of returns in either bubble or non-bubble periods, while Baa-Aaa spread gains better predictability to dividend growth in both periods, but in the bubble periods, its forecasting ability reduces to a lower level.

5.7 PSY test and Date-stamping results: Weekly Data

The second part of this chapter aims to discover the role of monetary policy in the stock market for both bubble and non-bubble periods but with the application of higher frequency data. The initial step to do this is to distinguish bubble periods from our sample. We apply the same PSY strategy on weekly price-dividend ratio and then we demonstrate our testing statistics and date-stamping results in Table 5.7.

<Table 5.7>

Table 5.7 shows that the testing statistic rejects the null hypothesis of no bubble and the date-stamping strategy captures the well-known bubble episode named Dotcom bubble from the year of 1996 to 2001 and the most recent financial crisis from 2008 to 2009 in the US stock market. In our work, since the number of observations in the crisis period of 2008 is not enough to carry out subsequent tests and it only contains half of the bubble evolutionary process, we therefore treat the result of 2008 as a short-lived blip and being ignored in the following tests.

5.8 VAR Results in Non-bubble Periods: Weekly Data

To better understand the causality–shift for each of our variable across non-bubble sub-samples, we now run the VAR regressions (equation 5.13) based on the Campbell-Shiller's model. We split our test into three, and each test corresponds to Pre-Dotcom bubble, Post-Dotcom bubble and Post 2008 crisis period respectively. Generally, we use 4 financial variables (logarithm in price-dividend ratio and dividend growth, raw values of 3-month treasury bills rate, and market variances) and 5 monetary variables (first difference in logarithm form of small-time deposits at Commercial Banks and Thrift Institutions, raw values of effective federal funds rate, long-short government bond spread, and Baa-Aaa corporate bond spread) to construct our VAR model. Data stationarity are examined by applying the ADF test for three sub-periods. Table 5.13 reports the testing statistics with the null hypothesis of whether the variable contains a unit root. We confirm that all of our weekly series are I (0) at 10% level, which means they are stationary in the relevant case.

<Table 5.13>

Testing results in Table 5.14 provide evidence for causality movement across non-bubble sub-samples. In particular, Column (2) considers the period of Pre-Dotcom bubble, column (3) examines the relationship after the collapse of Dotcom bubble, and column (4) shows the causality performance in the period of Post 2008 financial crisis. We can clearly observe the poor forecasting performance of selected variables in the Post-Dotcom bubble period, since only one variable – market variance – gains the predictive power to price-dividend ratio. Surprisingly, unlike previous evidence which documents the availability of weak form dividend-price model and significant predictive power of market variance over dividend yield (see Cuthbertson, et al., 1997), neither of them has been consistently confirmed over our sub-sample results. We can see that the safe rate only gains significant forecasting power before the year of 1997, and such relationship soon disappears in the subsequent years. It is the same for market variance, since its forecasting ability over price-dividend ratio has only been spotted as significant in the post-Dotcom sub-sample, no similar results has been obtained in the other periods. These findings provide an alternative view that the stock market may not as efficient as the literature assumed, and the close relationship between the ratio and market volatility may not be stable over time.

<Table 5.14>

Furthermore, results of momentary variables also provide important findings. It is obvious that in the pre-Dotcom period, using effective federal funds rate to forecast the movement of price-dividend ratio is much better than using government bond spread, as we can see from the column (2) that the predictive power of effective federal funds rate is significant at 5% level but no significant relationship has been stamped for government bond spread. However, a dramatic reversal has occurred after the 2008 financial crisis. The effective federal funds rate is not as efficient as what it performs as a predictor in the period of before Dotcom bubble and it now loses its predictive power to price-divided ratio; however, after staying silent for a long period of time, the government bond spread has taken over the position of federal funds rate and plays an important role in forecasting the movement of price-dividend ratio. Turning to the corporate bond spread, it somehow holds ‘stable’ predictability, as we can see that the spread only loses forecasting ability to price-dividend ratio in the period of Post-Dotcom bubble; in the other two sub-samples, it gains weakest form of significance (10% significant level).

To analyse the response of variables to monetary and financial shocks, we therefore undertake the generalized IRFs. Figures 5.1 to 5.3 present orthogonalized IRFs obtained with our VAR model on the effect of financial and monetary shocks (using variables which are confirmed to be stationary and significant to ensure the validity of system) to price-dividend ratio with the asymptotic 90% error bands generated by Monte Carlo simulation (1000 repetitions). Particularly, Figure 5.1 presents the results for the period of Pre-Dotcom bubble, and Figures

5.2 and 5.3 show the respective response of shocks in Post-Dotcom bubble and Post 2008 crisis periods. From Figure 5.1, we see that before the occurrence of Dotcom bubble, shocks from the safe rate lead to a negative impact on price-dividend ratio that lasts for more than 10 weeks after the first shock occurred, and it keeps increasing. Similar movement has been spotted for effective federal funds rate, as we can observe from graph 3 that it has negative but small impact to the ratio. The graph of Baa-Aaa spread supports its VAR result in Table 5.9 because we find it has a positive but very small impact on the movement of price-dividend ratio and dies out quickly after 3 weeks.[9]

<Figures 5.1 to 5.3>

Now turning to Figures 5.2 and 5.3. Figure 5.2 shows that the impact of market variances has a completely different movement than the other variables. It is clear that its impact on the ratio becomes smaller in the first 2 weeks but quickly grows and stays large at least for 10 weeks. Thus, we notice that there is a close positive relationship between price-dividend ratio and market volatility for the period of Post-Dotcom bubble and such finding can be used to explain the well-documented ability of the ratio in predicting stock returns while this explanation is only available for this period. Looking at Figure 5.3, we notice that the impact of Baa-Aaa spread to price-dividend ratio grows larger and keeps longer, comparing with its impact within the period of Pre-Dotcom bubble; however, the direction of such impact has reversed, from positive to negative. Furthermore, shocks from government bond spread tends to have positive impact on price-dividend ratio, and such impact reaches the top after 3 weeks when the first shock has occurred, and smoothly declines afterwards.

In sum, the above results present a perfect illustration for predictability–shift across different time intervals. We now understand that there is no such a ‘perfect’ predictor for price-dividend ratio that always remains constant and sufficiently large forecasting power over time. Furthermore, by using IRFs, we see that publics normally put negative expectations on price-dividend ratio when there is a shock from the risk-free rate and effective federal funds rate in the Pre-Dotcom bubble period; however, in the Post-2008 crisis period, shocks from

[9] Although we have selected stationary and significant variables to build up our IRFs, we still observed that a few testing results in Figure 5.1 are not reduced to insignificant after 10 weeks, which may indicate the stability of our VAR system is impaired. However, after we extending our testing length from 10 weeks to 100 weeks (almost 2 years), we have seen that results return to ‘normal’, that the response effect generally dies out after 15 weeks, implying our VAR system is stable. These testing results will be demonstrated in Appendix 5.8.

two interest spreads have completely opposite impact: publics put positive expectations on price-dividend ratio when there is a monetary policy announcement in relation to government bond, whilst negative expectations on price-dividend ratio when there is a credit risk exposure from corporate bond.

5.9 VAR Results in Bubble Period: Weekly Data

To obtain a detailed view for what forces driving the performance of price-dividend ratio in the bubble period, in this section, we repeat the VAR estimation first and then apply rolling regime with the purpose of observing predictability dynamics. To ensure the data stationarity, we take the first difference in all weekly datasets except for dividend growth and market variance. Newey-west estimators are also employed to correct the covariance matrix for possible heteroscedasticity, and lag 3 is selected for each test. Table 5.15 below provides the detailed Wald statistics for the In-Dotcom bubble sub-sample.

<Table 5.15>

From Table 5.15, we clearly observe that any strong forecasting relationships existed in the non-bubble periods is disappeared in the bubble period, as none of the corresponding Wald statistics are significant at 10% level. However, are these insignificant relationships stay constant over time within bubble period? This question leads us to adopt the concept of bivariate rolling regime to obtain a full view. Figure 5.4 addresses the respective movement of *p*-values for indicated coefficients. We can see that the indicated financial and monetary coefficients fluctuates greatly through the entire bubble evolutionary process. The rolling *p*-values of dividend growth (lags 1 and 2) and 3-month treasury bills rate (lags 1 and 2) demonstrate a U-shape movement, that is, there is no predictive power at the beginning of the bubble period while their *p*-values drop below 10% during the middle and again become insignificant at the end of the period. The movement of *p*-values for small-time deposits at Thrift Institutions (lag 2) exhibit similar trend; however, unlike 3-month treasury bills rate and dividend growth, its forecasting power is highly significant at the beginning while quickly dying out after the year of 1997 but regaining predictability between 1998 to 1999 and then losing power again afterwards. Alternatively, government bond spread (lag1) shows opposite movements, since its indicated coefficient is significant at the early and end of the bubble period (1996 to 1998 and 2000 to the early of 2001) but becoming higher than 10% significance in the middle. Effective federal funds rate (lag 2) has identical moving trend but with different time points for significance shift. It only has a short period of time starting from the end of 1996 to the middle of 1997 with significant predictive power but becoming insignificant in the middle of 1999 and then regaining power through the remaining period. Furthermore, market variance shows a 'stable' forecasting power at the latter part of the bubble period, while the moving trend of small-time deposits at Commercial Banks (lag 1) is opposite to variance, given its great significant predictive power at the beginning of the exuberance, but insignificant values through the remaining period.

<Figure 5.4>

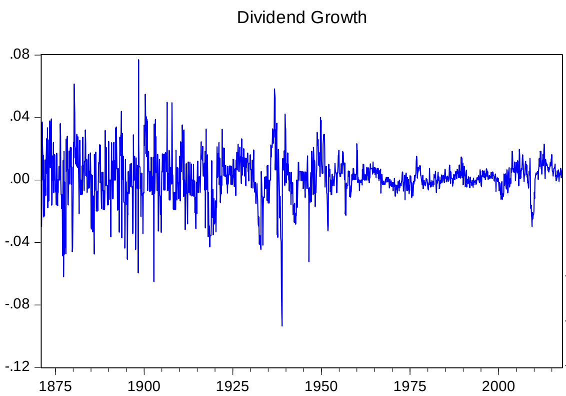
To explore the impact of financial and monetary variables on the price-dividend ratios, we report the movement of significant rolling coefficients in Figure 5.5. From the figure, we observe that the majority of variables tend to have positive impact during the time points when those variables are stamped with significant predictability. These variables contain effective federal funds rate (lag 2), dividend growth (lags 1 and 2), market variance (lag 1), small-time deposits at Commercial Banks (lag 1) and Thrift Institutions (lag 2). Remaining variables exhibit a negative sign in the VAR estimation which include the 3-month treasury bills rate (lags 1 and 2) and government bond spread (lag 1).

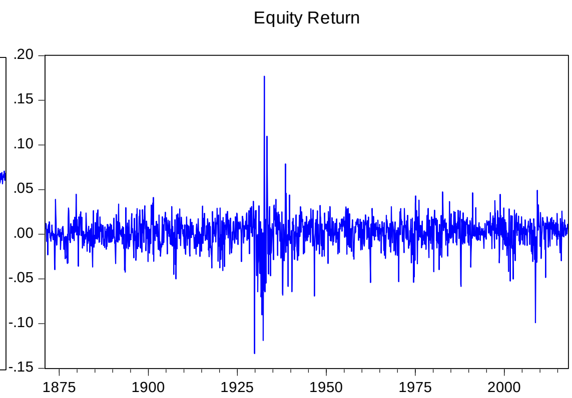
<Figure 5.5>

Taken together, we obtained significant findings for dynamic relationships between price-dividend ratio and selected variables, and that may help us figure out the actual impact of monetary policies initiated on the market when bubble is present.

5.10 Further Discussions

Our work greatly benefits from the work of Philips et al. (2015a, b). By using their date-stamping strategy, we are able to distinguish our full sample into sub-samples and further allow us to compare forecasting power of selected variables over bubble and non-bubble periods. In the first part of this chapter, we have shown a dramatic reversal of the relative predictability for dividend growth and return over the prewar and post war periods conditional on the absence of stock price bubbles. Such a result, if reliable, suggests that profound changes occurred in the stock market. The question is what has caused such a reversal. Chen (2009) offers several hypotheses: (1) a natural guess is that there are many fewer firms in the earlier years than in the later years, and thus the later period is much more representative of the market. However, he finds the conclusions still hold after controlling the size and industry factors, (2) he seeks to explain the reversal by using unstable corporate policy. Again, he rejects this hypothesis by studying earnings predictability and he concludes that changing dividend policies seems unlikely to fully explain why there is a reversal of predictability, and (3) dividend growth rate is very volatile in the prewar period but becoming much less so in the post war period, while equity return remains volatile in both pre and post war periods, as showing below. Chen believes this could be the main reason for the predictability reversal. After he running the test on dividend growth volatility (controlling for dividend volatility) with return and dividend growth rate, he concludes that dividend growth is predictable in the prewar period not because it is more volatile per se, but because it moves in the direction predicted by the dividend yield. Reduced cash flow volatility is unlikely to be the direct source of the reversal of predictability.





When considering bubbles, our results clearly show that bubbles do have positive/negative impacts on predictability. To explain those observed impacts, we raise several hypotheses. In the prewar period, we reckon that the explosive nature of bubble is the main reason to cause the dividend yield losing significant predictability in the bubble period. One important characteristic of bubble phenomenon is that during both run-up and run-down periods, the asset encounters high volume trading which will significantly increase the asset price volatility. In contrast, dividend received from asset remains stable as the bubble has no impact on the expected dividends. Therefore, the ability of dividend-price ratio to forecast the movement of dividend growth in the bubble period would be reduced dramatically. In the post war period, this mechanism still works for the predictability of dividend yield to return: the higher volatility in the bubble periods seems lead to a closer relationship between dividend yield and return; thus, we see that there is a clear rise in the forecasting power of dividend yield to market return. However, the results of dividend growth show different results from the literature. Unlike findings confirmed by Chen (2009) that real dividend growth is significantly predictable but in the 'wrong' (positive) direction during the entire post war-period, we only spotted such positive relationship in the period of post-war bubble, results from the non-bubble period still remains consistent with the statement made by the theory. We now have a reason to believe that the positive relationship of dividend yield to dividend growth from 1950 to 2005 discovered by Chen (2009) may due to the fact that its positive relationship in the post-war bubble periods surpasses its negative power in the remaining non-bubble periods. To understand the puzzle of 'wrong' predicting sign, Engsted and Pedersen (2010) may provide us an interpretation. They believe the key to understanding such reversal is inflation predictability. In fact, if inflation is sufficiently negatively predictable by the dividend yield, it may generate significant predictability of real dividend growth in the positive direction, exactly as what we observe in the post-war bubble period for the US.

In the second part of this chapter, we critically discuss the role of monetary policy indicators in forecasting the price-dividend ratio through both bubble and non-bubble periods. The separate granger-causality tests reveal significant differences in predictive power among selected variables when a bubble is not present. Particularly, the adoption of dividend growth, safe rate and market variances allows us to examine the availability of traditional dividend-price model in the US stock market, and the conclusion is different from the literature which speaks that the weakest form of CAPM can be satisfied. Our results clearly reject the model under any assumptions regarding the determinants of equilibrium expected returns. Furthermore, we only spotted a close relationship between dividend-price ratio and market volatility in the sub-sample of post Dotcom bubble (2001 to 2008). Thus, unlike the others, we cannot recognize this evidence as a possible explanation for well-documented forecasting ability of dividend yield in predicting stock returns over time (see Cuthbertson, et al., 1997). For monetary variables, one important finding is that the effective federal funds rate, which has been critically discussed in the last decade, has lost its predictability in recent years, and interest rate spread now plays a more important role in forecasting the movement of the price-dividend ratio.

To closely examine the causality dynamics within the bubble period, we implement a rolling

VAR regime. Testing results are substantial, since they disclose that some variables have significant predictive power to the growth of price-dividend ratio during part of the exuberance. We confirmed a strong forecasting relationship between the market variances and the growth of price-dividend ratio. The indicated coefficients suggest that if the market variance becomes higher, the growth rate of price-dividend ratios will be higher, and this positive relationship is highly significant during the period when the bubble is sufficiently large. This implies that during the phase of bubble inflation, the behavior of market investors has challenged the conventional view; instead, they tend to seek the risk, not to avoid it. This finding is consistent with the bubble riding assumption (see Abreu and Brunnermeier, 2003), which suggests that rational arbitrageurs understand the market will eventually collapse but meanwhile would like to ride the bubble as it continues to grow and generate high returns. Ideally, they would like to exit the market just prior to the crash, but commonly market timing is a difficult task.

When combing the findings of rolling results from 3-month treasury bills rate, we may provide a complete story. The forecasting ability of 3-month treasury bills rate is not strong at the beginning but gradually increasing to a significant level with a negative impact when the bubble growing larger (1998 to the late of 1999), while losing its predictability for a short period of time and regaining significant negative lead-lag relationship when the size of the bubble grows massively. To have a better understanding in the role of interest rate for bubble evolution, we divided the whole process into two phases: (1) the size of the bubble is small but under high growth rate (1998 to 1999), and (2) its size becomes sufficiently large (after 2000). At the first stage, we see that the higher growth rate in the interest rate still predicts the lower growth rate in the price-dividend ratio like the ‘normal’ times. According to the theory, an increase in interest rate always reduces the ‘fundamental’ price of the asset, an effect that should be dominant in non-bubble periods, or in the period that the bubble component is small (see Gali and Gambetti, 2015). However, in the second stage where the bubble becomes sufficiently large and close to burst, we observe that interest rate returns to its negative impact on price-dividend ratio, which implies that it works normally as in the first stage. This phenomenon could be interpreted by two reasons: (i) an interest rate hike may end up lowering the observed asset price due to its negative effect on either bubble or fundamental components of an asset, or (ii) its negative impact on the fundamental component more than offsetting the positive effect on the bubble term. Furthermore, interest rate regained negative impact sheds light on the change in investing preference of publics, that market participants tend to invest in interest rate products when the size of the bubble is large rather than it is small; therefore, when the bubble grows massively, the higher growth rate in interest rate creates high selling pressure in the stock market, which would lead to the collapse of a bubble. This empirical evidence supports the theoretical remarks proposed by Abreu and Brunnermeier (2003), who present that an asset bubble would not burst until a coordinated selling effort occurs. They point out the large price movement can only occur if the accumulated selling pressure exceeds some threshold; in other words, a permanent shift in price levels requires a coordinated attack. By showing the significant negative forecasting relationship between safe rate and price-dividend ratio, we now have a better understanding in the source of coordinated selling pressure.

We also notice that the growth of small-time deposits at Commercial Banks depicts an interesting causality movement, that strong causality exists at the beginning but weak linkage through the middle and the end of bubble period. Particularly, their strong linkage tends to be positive, briefly suggesting that the higher growth of small-time deposits generally predicts the higher growth rate in price-dividend ratios. However, this result is opposite to our expectation on the relationship. We expect the sign of coefficient to be negative, because based on the Shiller's feedback loop theory (see Shiller, 2015; Chapter 5), the past price increase should induce current and potential investors to continue buying and creates further upward pressure on prices. Initially, the increase in stock price raises the investment interest of market participants to buy equities rather than saving in the bank, then the increase in stock prices attracts other investors to enter the market and causing further upward movement that cannot be supported by the growth in deposits. Therefore, we would expect that there is a negative rather than positive sign at the beginning of Dotcom bubble.

The remaining variables also depict some important findings. The effective federal funds rate, which has been argued that this is a good indicator for monetary policy actions, enjoys strong forecasting power to the price-dividend ratio during the late of 1999; however, such ability only lasts for half a year and be vanished after the year of 2000. Surprisingly, the rolling coefficients have a positive sign when their relationship is significant, strongly supporting that the tighter monetary conditions (indicated by a higher growth in the federal funds rate) predict higher growth rate in the ratios. These empirical findings are well against the assumption that (i) monetary policy consistently has impact on stock price bubbles and (ii) that tighter monetary policies, in the form of higher short-term interest rates, may help dis-inflate bubbles. Empirically, our evidence supports the theoretical model suggested by Gali (2014), who briefly discusses the linkage between the monetary policy and rational bubble. Their model shows that the increase in the rate engineered by the central bank will lead to higher growth in the size of the bubble, although the objective of such a policy implementation is completely opposite. They point out that to cool down the market, the policy should strike a balance between stabilization of current aggregate demand which calls for a positive interest rate response to the bubble, and stabilization of the bubble itself which could warrant a negative interest rate. If the average size of the bubble is sufficiently large, the latter motive will be dominant, making it optimal for the central bank to lower interest rates in the face of growing bubble. However, in fact, our results find that the central bank's rate only plays the role in the first part that leads to the increase in the size of the bubble, whereas the expected part of the policy never works in the stage where the bubble becomes sufficiently large.

Alternatively, another monetary policy indicator – government bond spread – shows an opposite result, since its predictive power is significant at the growing stage of the bubble and tend to have a negative impact on the growth rate of price-dividend ratio: the higher change rate in government bond spread predicts the lower growth rate in price-dividend ratio. We can see that it perfectly matches the objective of policy implementation for dis-inflating the bubble; therefore, our results suggest that macroeconomic variables which tend to have impact on the movement of government bond spread (see e.g., Ang and Piazzesi, 2003, Smith and Taylor, 2009) would work satisfactorily against bubble inflation.[10] However, we emphasis that this negative relationship is only present for the very beginning of the exuberance. Policymakers should be aware of that dis-inflating bubble based on targeting government bond spread works only when the bubble is small and under growing, it cannot be

[10] Here we notice that monetary policy focused on manipulating federal funds rate might reduce the size of bubble, not through direct impact, but through indirect channel over the government bond spread.

an effective tool when the bubble grows large.

Overall, our findings reveal the dynamic forecasting ability of financial and monetary variables to price-dividend ratio, interpreting their rationale behind bubble evolutionary process and highlighting the importance of when and which variable should be monitored by regulators with the purpose of defending bubble inflation.

5.11 Conclusion

In this chapter, we critically assess the predictability of financial and monetary variables in the US stock market on the basis of Campbell-Shiller's model by using both monthly and weekly datasets. The evidence we have presented in this chapter is intriguing, since we show the dynamic predictability on stock market data through our bubble and non-bubble sub-periods, and further unfold the puzzle behind the bubble evolution while providing guidelines for policy implementation within the period of exuberance. In general, our monthly data results show that bubbles *do* have a significant impact on the predictability to stock market data, and our weekly results reject the traditional dividend-price model under any circumstances while they support the majority of theoretical works focused on analyzing bubble evolutionary process by showing the role of investors' behavior. In addition, our results suggest a better policy indicator – government bond spread – in a role of against bubble growth.

However, we also notice that some empirical evidence is well against the theoretical model. The negative forecasting relationship between small-time deposits at bubble growing stage is against one of the popular interpretations in bubble inflation – Shiller's feedback loop theory. Furthermore, we also point out that the price-dividend ratio is not a perfect indicator of bubbles – because it has two components – the fundamental and the bubble component. The fundamental part is always there even when there is a bubble, but the bubble component is only existed during the bubble period. Therefore, our results only give approximate information about the relationship between monetary policy and the bubble.

Although monetary variables can be used as predictors for stock market data either in the non-bubble and bubble periods, arguments based only on monetary perspective cannot conclude the movement of stock market data, nor explaining all forces behind bubble inflating mechanism. Thus, there are several alternative explanations depending on other promising perspectives, and more studies are required to shed light on those potential interpretations.

Table 5.1: Monthly Data Summary Statistics.

	Observations	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Panel A: Full sample stock market data								
S&P log Dividend-Price Ratio	1763	–3.22	–3.15	–1.98	–4.50	0.43	–0.69	3.17
Log real returns	1763	0.56	0.92	42.15	–30.36	4.06	–0.29	14.35
Log real dividend growth	1763	0.13	0.18	7.70	–9.35	1.44	–0.59	7.72
Panel B: Monetary Variables in sub-sample 2								
Baa-Aaa Corporate Bond Spread	816	0.08	0.07	0.28	0.03	0.04	1.83	7.74
Long-Short Government Bond Spread	816	0.12	0.12	0.37	–0.22	0.10	–0.14	2.91

Table 5.1 presents descriptive statistics for the monthly stock market data in full sample and two monetary variables in sub-sample 2. Panel A shows the Stock market data with real logarithm form of dividend-price ratio, real returns and dividend growth covering 1871 to 2017, while Panel B illustrates the two monthly monetary variables with Baa-Aaa Corporate Bond Spread and Long-Short Government Bond Spread starting from 1950 to 2017.

Table 5.2: Weekly Data Summary Statistics.

	Observations	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
S&P log Price-Dividend Ratio	1864	1.61	1.66	1.97	1.18	0.19	–0.31	2.32
Log real dividend growth	1864	0.02	0.02	1.65	–2.15	0.22	–1.41	22.54
Variances	1864	0.0001	0.00003	0.0068	0.0001	0.0003	14.3362	275.8865
Real 3-month Treasury Bills Rate	1864	1.05	1.05	1.17	1.00	0.04	0.72	3.43
Real Effective Federal Funds Rate	1864	1.05	1.05	1.20	1.00	0.04	0.93	4.09
Real Baa-Aaa Corporate Bond Spread	1864	0.01	0.01	0.03	0.01	0.00	1.81	7.01
Real Long-Short Government Bond Spread	1864	0.02	0.02	0.05	–0.04	0.01	–0.7	3.52
Log real Small-time Deposits at Commercial Banks	1864	5.90	5.93	6.09	5.49	0.11	–1.65	5.69
Log real Small-time Deposits at Thrift Institutions	1820	5.72	5.70	6.10	5.08	0.27	–0.44	2.65

Table 5.2 illustrates descriptive statistics for the weekly stock market and monetary variables starts from 1980:1 to 2015:9. Stock market data consists of real logarithm form of price-dividend ratio, real dividend growth and market variance, while monetary variables are real 3-month treasury bills rate, real effective federal funds rate, real Baa-Aaa corporate bond spread, real long-short government bond spread, and log small-time deposits at Commercial Banks and Thrift Institutions.

Table 5.3: Predictability by the dividend-price ratio: full sample, 1871:1-2017:12.

	Parameters	*t*-statistics
Dependent variable	**Returns**	
Constant	1.398	1.408
Slope	0.261	0.878
R-squared (%)	0.078	
Dependent variable	**Dividend Growth**	
Constant	–1.304	–2.545***
Slope	–0.445	–2.976***
R-squared (%)	1.803	

This table reposts the testing statistics for full sample period starts from 1871 to 2017 without considering bubbles. Note. *, **, ***, indicates statistical significance at the 10%, 5% and 1% levels respectively using Newey-West robust standard errors.

Table 5.4: Predictability by the dividend-price ratio: sub-sample results.

	Parameters	*t*-statistics
Panel A: Sub-sample 1: 1871:1-1949:12		
Dependent variable	**Returns**	
Constant	1.895	0.614
Slope	0.466	0.454
R-squared (%)	0.06	
Dependent variable	**Dividend Growth**	
Constant	–5.531	–4.183***
Slope	–1.897	–4.280***
R-squared (%)	5.887	
Panel B: Sub-sample 2: 1950:1- 2017:12		
Dependent variable	**Returns**	
Constant	2.570	2.156**
Slope	0.560	1.670*
R-squared (%)	0.46	
Dependent variable	**Dividend Growth**	
Constant	–0.521	–1.068
Slope	–0.197	–1.439
R-squared (%)	1.379	

This table reposts the testing statistics for sub-sample period without considering bubbles. Panel A covers the sub-sample 1 from 1871:1 to 1949:12, while Panel B covers the period starts from 1950:1 to 2017:12. Note. *, **, ***, indicates statistical significance at the 10%, 5% and 1% levels respectively using Newey-West robust standard errors.

Table 5.5: Predictability by the government bond spread: sub-sample 2, 1950:1-2017:12

	Parameters	***t*-statistics**
Dependent variable	**Returns**	
Constant	0.178	0.725
Slope	3.455	1.974*
R-squared (%)	0.893	
Dependent variable	**Dividend Growth**	
Constant	0.154	2.149***
Slope	0.145	0.275
R-squared (%)	0.038	

This table reposts the testing statistics of government bond spread for sub-sample 2 starts from 1950:1 to 2017:12 without considering bubbles. Note. *, **, ***, indicates statistical significance at the 10%, 5% and 1% levels respectively using Newey-West robust standard errors.

Table 5.6: Predictability by the Baa-Aaa bond spread: sub-sample 2, 1950:1-2017:12.

	Parameters	***t*-statistics**
Dependent variable	**Returns**	
Constant	0.343	0.780
Slope	3.256	0.559
R-squared (%)	0.116	
Dependent variable	**Dividend Growth**	
Constant	0.544	4.342***
Slope	–4.671	–3.035***
R-squared (%)	5.769	

This table reposts the testing statistics of Baa-Aaa spread for sub-sample 2 starts from 1950:1 to 2017:12 without considering bubbles. Note. *, **, ***, indicates statistical significance at the 10%, 5% and 1% levels respectively using Newey-West robust standard errors.

Table 5.7: PSY date-stamping results.

Market	Source	Testing periods	NO.	$GSADF(r_0)$	Date-stamping Result
Panel A: Monthly					
S&P 500	S&P INDEX	1871/01 to 2017/12	1763	4.160***	1879/10 to1880/04 1917/08 to 1918/04 1928/11 to 1929/10 1955/01 to 1956/04 1986/06 to 1987/09 1995/11 to 2001/08 2009/02 to 2009/04
Panel B: Weekly					
S&P 500	S&P INDEX	1980/1 to 2015/9	1864	2.263**	1996/11/12 to 2001/02/20 2008/09/26 to 2009/04/03

In Table 5.7, we report the details of our data selection for stock market index in the US, including sources, testing periods, number of observations contained for price-dividend ratio, either monthly or weekly, and we also demonstrate conclusion of PSY testing statistics as well as the date-stamping results. The monthly S&P INDEX (in Panel A) is collected from Robert Shiller's website: http://www.econ.yale.edu/~shiller/data.htm, while the weekly S&P INDEX (in Panel B) comes from the DataStream database. Note that in our testing procedures, we use the logarithmic form of price-dividend ratio. *** represents 99% level of significance, ** is the 95% level of significance and * is the 90% level of significance.

Table 5.8: Predictability by the lagged dividend-price ratio allowing for a bubble: full-sample, 1871:1-2017:12.

	Parameters	*t*-statistics
Dependent variable	**Returns**	
	No bubble	
Constant	1.760	1.552
Slope	0.398	1.152
	Bubble	
Constant	8.603	3.680***
Slope	1.887	2.953***
R-squared (%)	0.764	
Dependent variable	**Dividend Growth**	
	No bubble	
Constant	–1.834	–3.287***
Slope	–0.617	–3.733***
	Bubble	
Constant	2.539	1.725*
Slope	0.611	1.696*
R-squared (%)	2.966	

This table reposts the testing statistics for full sample period starts from 1871 to 2017 with bubble and non-bubble periods. Note. *, **, ***, indicates statistical significance at the 10%, 5% and 1% levels respectively using Newey-West robust standard errors.

Table 5.9: Predictability by the lagged dividend-price ratio allowing for a bubble: sub-sample 1, 1871:1-1949:12.

	Parameters	*t*-statistics
Dependent variable	**Returns**	
	No bubble	
Constant	2.391	0.757
Slope	0.645	0.614
	Bubble	
Constant	28.93	1.096
Slope	8.16	1.020
R-squared (%)	0.409	
Dependent variable	**Dividend Growth**	
	No bubble	
Constant	–5.515	–4.032***
Slope	–1.893	–4.118***
	Bubble	
Constant	–25.747	–1.114
Slope	–7.969	–1.161
R-squared (%)	6.16	

This table reposts the testing statistics for sub-sample period starts from 1871:1 to 1949:12 with bubble and non-bubble periods. Note. *, **, ***, indicates statistical significance at the 10%, 5% and 1% levels respectively using Newey-West robust standard errors.

Table 5.10: Predictability by the lagged dividend-price ratio allowing for a bubble: sub-sample 2, 1950:1-2017:12

	Parameters	*t*-statistics
Dependent variable	**Returns**	
	No bubble	
Constant	2.885	2.151**
Slope	0.688	1.790*
	Bubble	
Constant	9.280	3.591***
Slope	2.042	2.958***
R-squared (%)	1.853	
Dependent variable	**Dividend Growth**	
	No bubble	
Constant	–1.267	–2.247**
Slope	–0.418	–2.615**
	Bubble	
Constant	2.831	3.543***
Slope	0.687	3.427***
R-squared (%)	6.839	

This table reposts the testing statistics for sub-sample period starts from 1950:1 to 2017:12 with bubble and non-bubble periods. Note. *, **, ***, indicates statistical significance at the 10%, 5% and 1% levels respectively using Newey-West robust standard errors.

Table 5.11: Predictability by the lagged government bond spread allowing for a bubble: sub-sample 2, 1950:1-2017:12

	Parameters	***t*-statistics**
Dependent variable	**Returns**	
	No bubble	
Constant	0.062	0.242
Slope	3.503	1.968**
	Bubble	
Constant	0.269	0.339
Slope	10.949	1.656*
R-squared (%)	1.783	
Dependent variable	**Dividend Growth**	
	No bubble	
Constant	0.171	2.280**
Slope	0.051	0.094
	Bubble	
Constant	–0.023	–0.095
Slope	1.711	1.008
R-squared (%)	0.289	

This table reposts the testing statistics of government bond spread for sub-sample period starts from 1950:1 to 2017:12 with bubble and non-bubble periods. Note. *, **, ***, indicates statistical significance at the 10%, 5% and 1% levels respectively using Newey-West robust standard errors.

Table 5.12: Predictability by the lagged Baa-Aaa spread allowing for a bubble: sub-sample 2, 1950:1-2017:12

	Parameters	***t*-statistics**
Dependent variable	**Returns**	
	No bubble	
Constant	0.137	0.294
Slope	4.529	0.745
	Bubble	
Constant	1.035	0.982
Slope	3.559	0.235
R-squared (%)	0.728	
Dependent variable	**Dividend Growth**	
	No bubble	
Constant	0.568	4.175***
Slope	–0.418	–2.936***
	Bubble	
Constant	0.591	2.142**
Slope	–7.151	–1.944*
R-squared (%)	6.200	

This table reposts the testing statistics of Baa-Aaa spread for sub-sample period starts from 1950:1 to 2017:12 with bubble and non-bubble periods. Note. *, **, ***, indicates statistical significance at the 10%, 5% and 1% levels respectively using Newey-West robust standard errors.

Table 5.13:Augmented Dicky-Fuller test for non-bubble periods

Financial and Monetary Variables	Testing statistics
Panel A: Pre-Dotcom bubble period	
Log (Price-dividend Ratio)	–3.46***
Log (Dividend Growth)	–29.35***
Variances	–9.45***
3-month Treasury Bills rate	–6.25***
Long-Short Government Bond Spread	–3.62***
Effective Federal Funds Rate	–9.14***
Baa-Aaa Spread	–7.14***
Panel B: Post-Dotcom bubble period	
Log (Price-dividend Ratio)	–1.78*
Log (Dividend Growth)	–18.47***
Variances	–3.14***
3-month Treasury Bills rate	–4.42***
Long-Short Government Bond Spread	–5.27***
Effective Federal Funds rate	–5.06***
Baa-Aaa Spread	–4.81***
Panel C: Post 2008 crisis period	
Log (Price-dividend Ratio)	–4.68***
Log (Dividend Growth)	–17.97***
Variances	–10.53***
3-month Treasury Bills rate	–5.17***
Long-Short Government Bond Spread	–4.01***
Effective Federal Funds rate	–5.07***
Baa-Aaa Spread	–5.33***

Table 5.13 reports the ADF values with the null hypothesis that the variables have a unit root. Panel A covers the period of Pre-Dotcom bubble, Panel B represents the period of Post-Dotcom bubble, and Panel C shows the testing results for Post 2008 crisis period. *** represents 99% level of significance, ** is the 95% level of significance and * is the 90% level of significance.

Table 5.14: Granger-causality test for non-bubble periods

	Pre-Dotcom bubble		Post-Dotcom bubble		Post 2008 crisis	
Financial and Monetary Variables	**Obs.**	**Wald Statistics**	**Obs.**	**Wald Statistics**	**Obs.**	**Wald Statistics**
Null hypothesis: X does not Granger-cause price-dividend ratio						
3-month Treasury Bills rate (safe rate)	877	6.46***	394	0.33	333	1.61
Dividend Growth	877	0.67	394	0.35	333	1.34
Variance	875	1.05	394	4.53***	333	0.30
Long-Short Government Bond Spread	876	0.79	394	0.39	333	9.16***
Baa-Aaa Spread	876	2.30*	394	1.22	333	2.34*
Effective federal funds rate	876	2.61**	394	0.59	333	1.91
Diff (Small-time Deposits at Commercial Banks)	876	0.61	394	0.15	333	0.07
Diff (Small-time Deposits at Thrift Institutions)	832	0.60	394	0.59	333	0.29

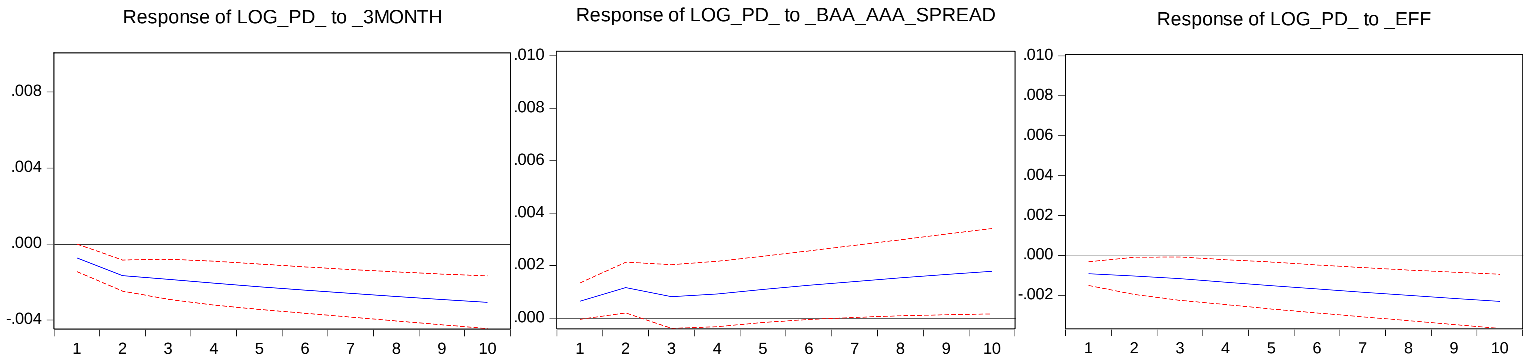
Table 5.14 generally shows the number of observations, Wald-statistics and significance for each of the corresponding Granger-causality test which are included in the Pre-Dotcom bubble, Post-Dotcom bubble and Post 2008 crisis sub-samples, respectively. X represents the following financial and monetary variables: price-dividend ratio, dividend growth, variance, 3-month treasury bills rate (safe rate), long-short Government Bond spread, Baa-Aaa spread, effective federal funds rate, and first differences in small-time deposits at Commercial Banks and Thrift Institutions. All monetary variables and financial variable are weekly based and expressed in their real values. We use logarithm form in price-dividend ratio, dividend growth and small-time deposits at commercial banks and thrift institutions while for the others, we use their raw values. The lag interval of 1 to 3 has been selected in the model to eliminate any residual serial correlation. Newey-West estimators are employed to correct the covariance matrix for possible heteroscedasticity. * represents the 90% significant level, while ** is the 95% significant level and *** shows the causality relationship is significant at 99% level.

Table 5.15: Granger-causality test for bubble period.

Financial and Monetary Variables	Obs.	Wald Statistics
Null hypothesis: X does not granger cause the growth of the growth of price-dividend ratio		
Diff(3-month)	221	1.02
Dividend Growth	221	0.67
Variance	221	1.92
Diff (Government bond Spread)	221	0.33
Diff (Baa-Aaa Spread)	221	1.63
Diff (Effective federal funds rate)	221	1.55
Diff (Small-time Deposits at Commercial Banks)	221	0.37
Diff (Small-time Deposits at Thrift Institutions)	221	0.50

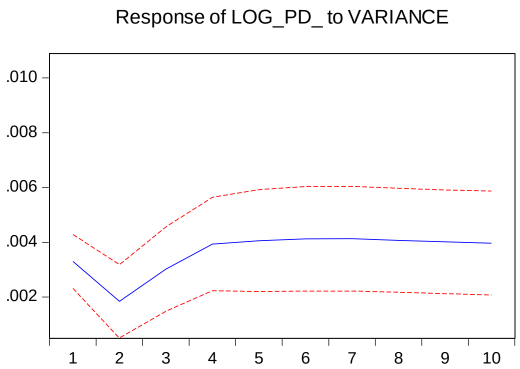
Table 5.15 generally shows the number of observations, Wald-statistics and significance for each of the corresponding VAR test which are included in the bubble period. Financial and monetary variables include 3-month Treasury Bills Rate, Baa-Aaa spread, effective federal funds rate, dividend growth, market variance, price-dividend ratio, Long-short government bond spread, and small-time deposits at Commercial Banks and Thrift Institutions. We take the first difference for all variables expect for dividend growth and variances. All financial and monetary variables are weekly based and expressed in their real values. We use logarithm form in price-dividend ratio, dividend growth and small-time deposits at commercial banks and thrift institutions while for the others, we use their raw values. The lag interval of 1 to 3 has been selected in the model to eliminate any residual serial correlation. Newey-West estimators are employed to correct the covariance matrix for possible heteroscedasticity. * represents the 90% significant level, while ** is the 95% significant level and *** shows the causality relationship is significant at 99% level.

Figure 5.1: Price-dividend ratios in response to selected variables within the Pre-Dotcom bubble period.



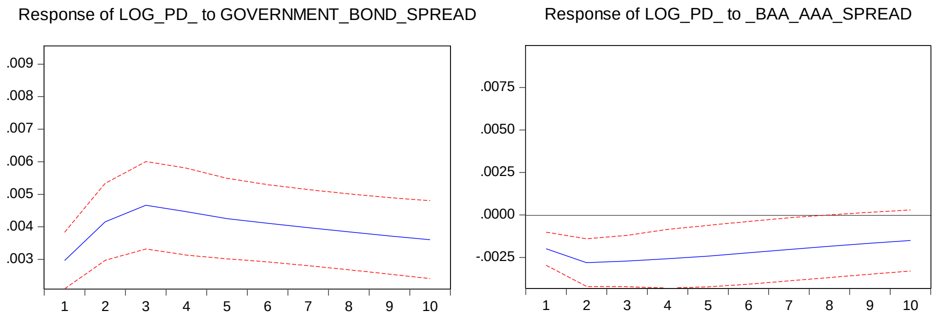
Graphs 1 to 3 represent the testing results of 3-month Treasury Bills rate (safe rate), Baa-Aaa corporate bond spread, and effective federal funds rate, respectively.

Figure 5.2: Price-dividend ratios in response to selected variables within the Post-Dotcom bubble period.



This graph represents the testing results of variance in the post-dotcom bubble period.

Figure 5.3: Price-dividend ratios in response to selected variables within the Post-2008 crisis period.



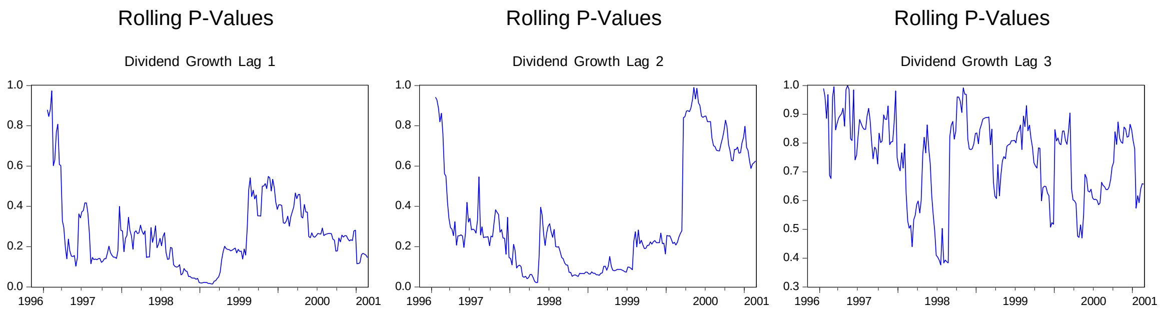
Graphs 1 to 2 show the testing results of Long-short government bond spread and Baa-Aaa corporate bond spread in the post-2008 crisis period.

Figure 5.4: Rolling VAR *p*-values of selected variables to price-dividend ratio within the bubble period.

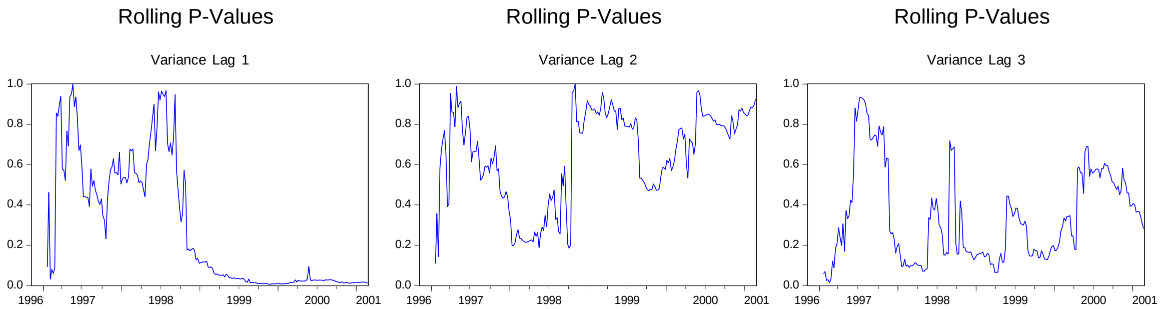
Graphs below show the movement of the *p*-values for the indicated coefficients from the estimation of the bivariate rolling VAR specification. y_1 denotes the change of price-dividend ratio for the S&P 500, while y_2 represents the financial and monetary variables of dividend growth, conditional market variances, 3-month Treasury Bills rates, effective federal funds rate, Baa-Aaa spread, government bond spread, and small-time deposits at Commercial Bank and Thrift Institutions. The sample period starts from the late of 1996 and ends in the early of 2001. The lag number is set to 3 to eliminate any residual serial correlation.

$y_{1,t} = \alpha + \sum_{k=0}^{3} \beta_{t-k} y_{1,t-k} + \sum_{k=0}^{3} \gamma_{t-k} y_{2,t-k} + \varepsilon_{i,t}.$

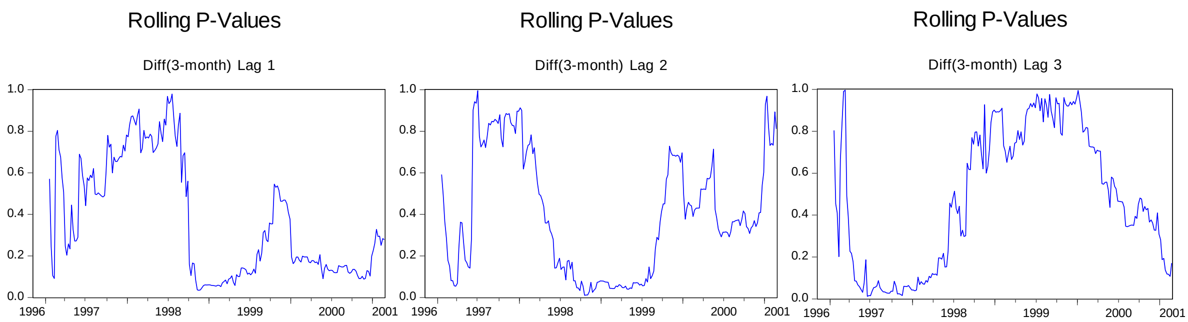
A: Plots of the rolling *p*-value movement for the dividend growth.



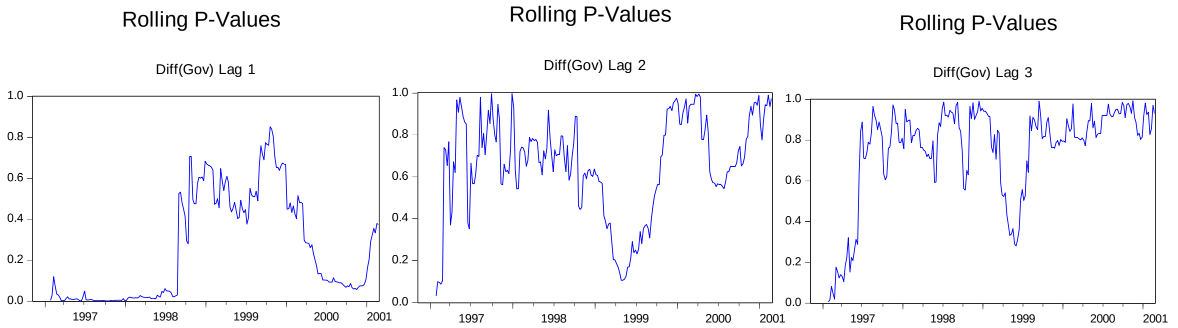
B: Plots of the rolling *p*-value movement for the conditional market variances.



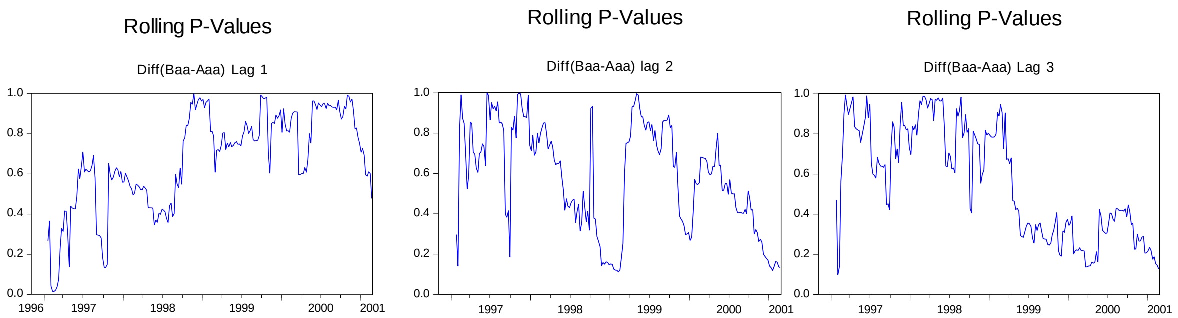
C: Plots of the rolling *p*-value movement for the 3-month Treasury Bills rate. Diff (3-month) represents the first difference in 3-month Treasury Bills rate.



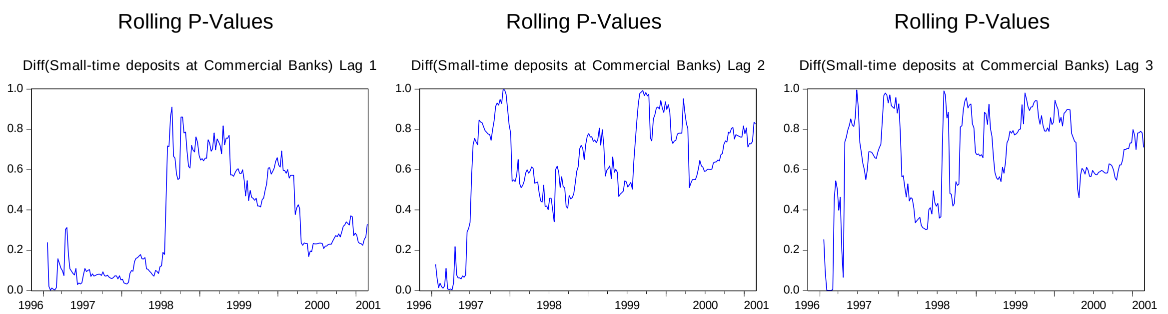
D: Plots of the rolling *p*-value movement for the long-short government bond spread. Diff (gov) is the first difference in government bond spread.



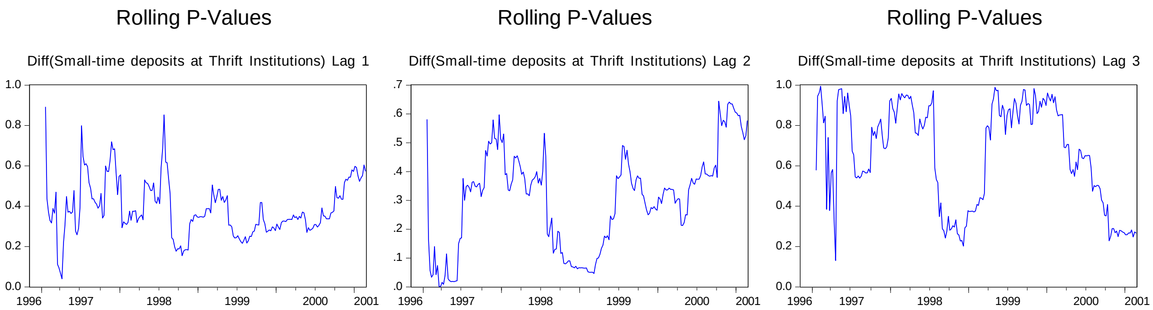
E: Plots of rolling *p*-value movement for the Baa-Aaa spread. Diff (Baa-Aaa) is the first difference in Baa-Aaa spread.



G: Plots of the rolling *p*-value movement for the Small-time deposits at Commercial Banks. Diff (small-time deposits at Commercial Banks) is the first difference in small-time deposits at Commercial Banks.



H: Plots of the rolling *p*-value movement for the Small-time deposits at Thrift Institutions. Diff (small-time deposits at Thrift Institutions) means the first difference in small-time deposits at Thrift Institutions.



J: Plots of the rolling *p*-value movement for the Effective federal funds rate. Diff (effective federal funds rate) represents the first difference in effective federal funds rate.

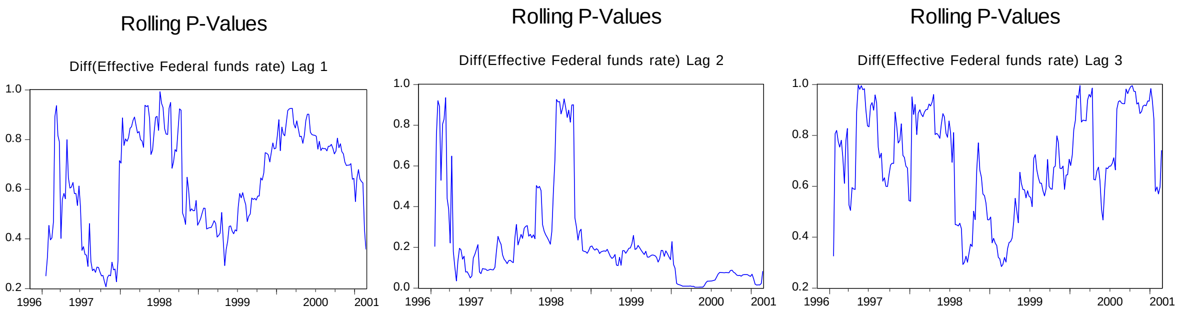
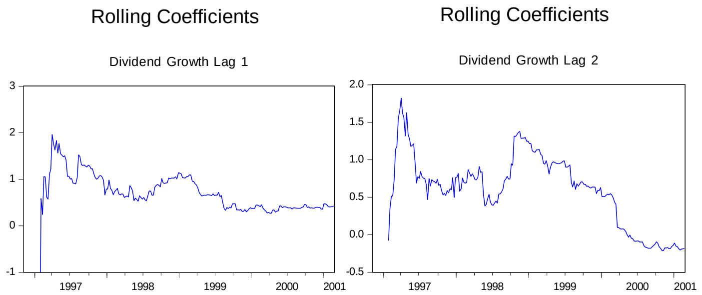


Figure 5.5: Significant rolling VAR coefficients of financial and monetary variables to price-dividend ratio within the bubble period

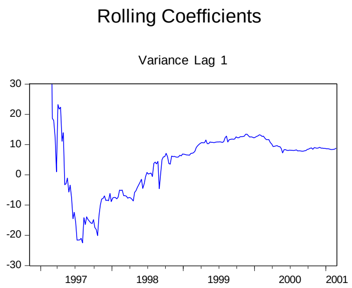
Graphs below show the movement of significant rolling coefficients from the estimation of the bivariate rolling VAR specification. y_1 denotes the growth of price-dividend ratio for the S&P 500, while y_2 represents the financial and monetary variables of dividend growth, conditional market variances, 3-month Treasury Bills rates, effective federal funds rate, Baa-Aaa spread, government bond spread, and small-time deposits at Commercial Bank and Thrift Institutions. The sample period starts from the late of 1996 and ends in the early of 2001. The lag number is set to 3 to eliminate any residual serial correlation.

$$y_{1,t} = \alpha + \sum_{k=0}^{3} \beta_{t-k} y_{1,t-k} + \sum_{k=0}^{3} \gamma_{t-k} y_{2,t-k} + \varepsilon_{i,t}.$$

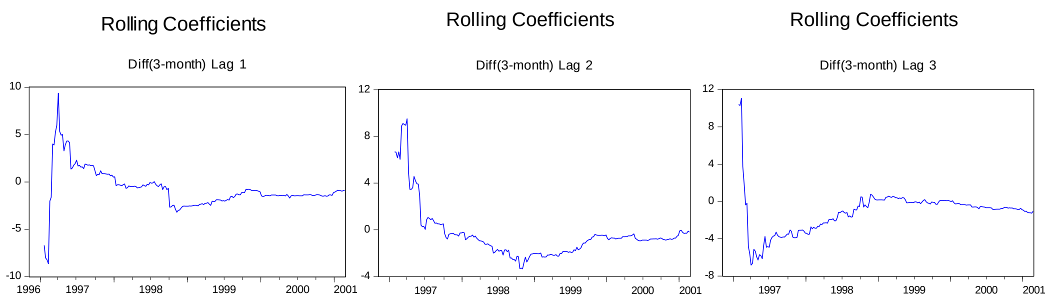
A: Plots of the significant rolling coefficients movement for the dividend growth.



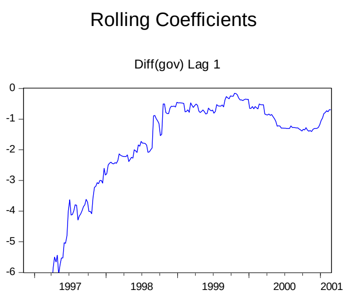
B: Plots of the significant rolling coefficients movement for conditional market variances.



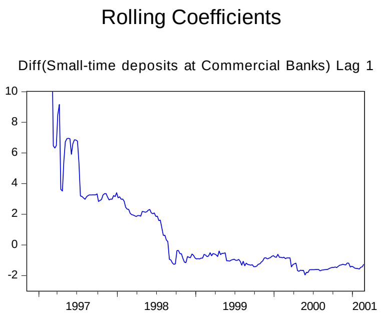
C: Plots of the significant rolling coefficients movement for the 3-month Treasury Bills rate. Diff (3-month) represents the first difference in 3-month Treasury Bills rate.



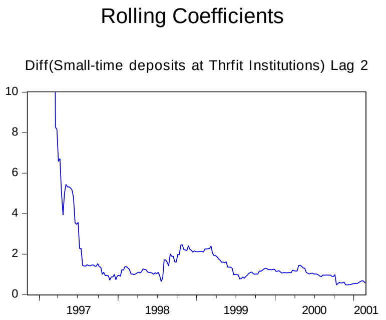
D: Plots of the significant rolling coefficients movement for the long-short government bond spread. Diff (gov) represents the first difference in government bond spread.



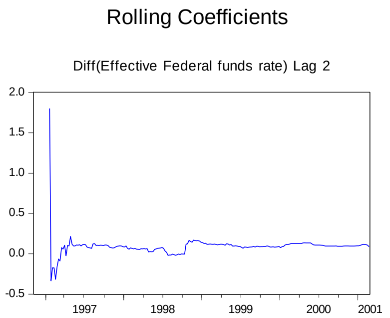
F: Plots of the significant rolling coefficients movement for the Small-time deposits at Commercial Banks. Diff (small-time deposits at Commercial Banks) is the first difference in small-time deposits at Commercial Banks.



G: Plots of the significant rolling coefficients movement for the Small-time deposits at Thrift Institutions. Diff (small-time deposits at Thrift Institutions) means the first difference in small-time deposits at Thrift Institutions.



I: Plots of the significant rolling coefficients movement for the Effective federal funds rate. Diff (effective federal funds rate) represents the first difference in effective federal funds rate.



Chapter 6 Conclusion

6.1 Introduction

This chapter summarizes the thesis and provides suggestions for future academic research. The overall thesis aims to study the nature and evolutionary process of asset price bubbles, especially for bubbles emerging in the international equity markets. Primary aspects include discovery of asset price bubbles, bubble transmission mechanism and market predictability conditional on the presence of bubbles. Our expectations are that bubble phenomena, which has a serious impact on stock markets, should widely exist in the global markets, hence by discovering and examining its nature, we intend to shed some lights on the policy implications for defending bubbles.

To answer the above research questions, we take a number of steps, which inevitably, involved making certain selections with regards to the study sample, the research design and methodology, but also the data analysis and interpretation. Being aware that during each step of any research process, the choices make possible limitations, in this chapter we evaluate the study outcomes and make critical discussions, as to whether our findings are significant and robust, but also as the limitations introduced to the findings. Furthermore, in our attempt to assess the practical relevance and the prescriptive value of our results, we explain our empirical findings to make suggestions for policymakers, regulators and market participants. Finally, we express our own views for the future prospects of policy making research and suggest some promising future directions for the professions in the field.

6.2 Main Findings and Their Implications

By clearly defining the bubble condition, Chapter 3 examined the existence of stock price bubbles globally over the past four decades. To reach our research objective, we primarily adopt three testing mechanisms: traditional ADF test, PWY (2011) and PSY (2015a, b). Testing results confirm that PWY (2011) enjoys better performance than traditional ADF test when bubbles are periodically collapsing, while PSY (2015a, b) has stronger testing power than PWY (2011) when the testing sample contains several bubbles. In addition, both PWY (2011) and PSY (2015a, b) provide date-stamping strategies for practitioners, assisting to record the bubbles' starting and collapsing dates without using subjective but econometric method. The results are substantial, recognizing not only well-known exuberance but also debatable explosiveness. For example, PSY date-stamping results for Chinese market prove the existence of exuberance in the middle of 2015, which has been questioned by many market analysts. Overall, this chapter provides strong evidence of bubbles across countries and record the origination and collapse dates of those bubbles over the past four decades.

By briefly discussing the chronology for some of the major bubble episodes recognized in chapter 3, we build up a timeline and it suggests that potential linkage may be present between stock markets when they experience bubbles. Just as the recent financial crisis of 2007-2009 is not an isolated event, most of the cross-border exuberant periods are closely related and result in severe global impact. Understanding the nature of such expansion is of fundamental importance to study the bubble's evolutionary course in order to assist market participants and policymakers gain deeper insights when dealing with a bubble. It is this latter issue that shapes the research objective of chapter 4. By applying VAR and AG-DCC (multivariate GARCH) models, we critically discuss the causality relationship between 10 major equity markets in order to test our bubble transmission hypothesis, that bubble moves from one market to another because of the *contagion–effect*. The VAR results provide strong evidence of an increase in cross-market linkages during bubble periods for several countries. In contrast to previous studies, which have found that only negative large shocks tend to trigger contagion, we confirm that the contagion can also appear in the bubble growth period. It is important to stress that the relationship between bubbles and contagion is not found for all stock markets considered. For some stock markets we find that bubbles strongly enhance contagion, but we do not observe the same phenomenon for other selected markets. The AG–DCC results support the empirical findings obtained from the VAR models as we document strong co-movements in volatility between stock markets when one or more of them have bubbles within the relevant test periods. In conclusion, we find that for some stock market bubbles, a *contagion–effect* does exist, which amplifies the potential impact of that bubble on global financial stability. We envisage that our findings will be of interest to investors operating globally with investment horizons that span periods over which stock market bubbles may exist, and to central banks and financial regulators to help them identify priority targets when they attempt to lower the potential risk raised by exuberance.

Chapter 5 provides two main concluding remarks. By using monthly data, we find evidence that: (1) for the period from 1871 to 1949, bubbles may have a negative impact on the predictability of dividend yield to dividend growth, and (2) for the post Second World War period, it seems that bubbles do have a positive impact on the predictive power of dividend-price ratio to both return and dividend growth. Therefore, our results fill the gap by relaxing the assumption of no bubbles when examining the predictive power of dividend yield to return and dividend growth, and show that bubbles have significant impact on the predictability.

Alternatively, our weekly results confirm significant differences in forecasting power of monetary policy indicators to price-dividend ratio over time. We now understand that there is no such a 'perfect' predictor that always remains constant and sufficiently large forecasting power in predicting the movement of ratios over time. Specifically, in the bubble period, our rolling results provide empirical evidence to support previous theories which focus on investors' behavior to answer the question of what forces are responsible for bubble evolution. We also highlight the importance of when and which variable should be monitored with the purpose of defending bubble inflation. Overall, we suggest to use government bond spread, rather than effective federal funds rate, as a target of monetary policy actions to defend bubble growth.

6.3 Limitations and Further studies

The empirical findings of the current thesis are based on the international equity market data and then narrow down to the US. Although these findings yield promising results, they can be more accurate and comprehensive if additional work is conducted. The future direction of each chapter is described below.

In Chapter 3, we discover the existence of bubbles in the international markets based on a variety of assumptions such as the type of explosive behavior and bubble model. Relaxing one of those assumptions could result in diminished testing power of PWY or PSY test. Therefore, we believe that the future research should consider more generalized testing and date-stamping mechanism to discover bubbles in the market.

Chapter 4 extensively reviews spillover effect when multiple countries experience market bubbles in terms of discussing the nature and evolutionary process of stock price bubbles. The VAR results confirm the information channel is not the primary transmission channel; however, we haven't discussed whether the other two channels play an important role in the bubble transmission mechanism. Therefore, further studies can examine those aspects to assist practitioners obtain knowledge about market bubble expansion.

In Chapter 5, we notice that some relationships cannot be explained by the literature. The negative forecasting relationship between small-time deposits at the growing stage of the bubble is against one of the popular interpretations in bubble inflation – Shiller's feedback loop theory. Thus, further evidence is needed to uncover the essence of such relationship. Also, the price-dividend ratio is not a perfect indicator of a bubble – because it has two components – the fundamental and the bubble component. The fundamental part is always there even when there is a bubble, but the bubble component is only existed during the bubble period. Therefore, our results only give approximate information about the relationship between monetary policy and the bubble. To obtain their true relationship, further studies are required for detailed formulations to separate the bubble component from the price. Furthermore, although monetary variables can be used as predictors for stock market data either in the non-bubble and bubble periods, arguments based only on monetary perspective cannot conclude the movement of stock market data, nor explaining all forces behind bubble inflating mechanism. Therefore, there are several alternative explanations depending on other promising perspectives, and more studies are required to shed light on those potential interpretations.

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Appendix 2.1: Asymptotic Properties of the Dating Algorithms.

The limit theory of these date-stamping strategies requires very detailed calculations which are provided in the Phillips, et al. (2015b) (for more details, please see Phillips, et al., 2015b). The main results and import of the theory for empirical practice are reviewed below. We look in turn at cases where there are no bubbles, a single bubble, and multiple bubbles in the data, and we will explain the reason that why PSY strategy has superior power than PWY when dealing with multiple bubbles case.

No bubbles: under the null hypothesis of no bubble episodes in the data the asymptotic distributions of the ADF and sup-ADF statistics follow limit distribution in (2.18). The backward ADF test with observation $\lfloor Tr_2 \rfloor$ (T represents the entire sample) is a special case of the generalized sup-ADF test with $r_1 = 0$ (r_1 is the r_1^{th} fraction of the total sample T) a fixed r_2 (r_2 is the r_2^{th} fraction of the total sample) and the backward sup-ADF test is a special case of the generalized sup-ADF test with a fixed r_2 and $r_1 = r_1 - r_w$. Therefore, from the limit theory given in (2.18), we have the following asymptotic distributions of these two statistics,

$$F_{r_2}(W) := \frac{\frac{1}{2}r_2[W(r_2)^2 - r_2] - \int_0^{r_2} W(r)drW(r_2)}{r_2^{1/2}\left\{r_2\int_0^{r_2} W(r)^2dr - \left[\int_0^{r_2} W(r)dr\right]^2\right\}^{1/2}}, \tag{2.21}$$

$$F_{r_2}^{r_0}(W) := sup_{\substack{r_1 \in [0, r_2 - r_0] \\ r_w = r_2 - r_1}} \left\{\frac{\frac{1}{2}r_w[W(r_2)^2 - W(r_1)^2 - r_w] - \int_{r_1}^{r_2} W(r)dr[W(r_2) - W(r_1)]}{r_w^{1/2}\left\{r_w\int_{r_1}^{r_2} W(r)^2dr - \left[\int_{r_1}^{r_2} W(r)dr\right]^2\right\}^{1/2}}\right\}. \tag{2.22}$$

Define cv^{β_T} as the $100(1-\beta_T)\%$ quantile of $F_{r_2}(W)$ and scv^{β_T} as the $100(1-\beta_T)\%$ quantile of $F_{r_2}^{r_0}(W)$ (r_0 is the smallest sample window width fraction). We know that $cv^{\beta_T} \to \infty$ and $scv^{\beta_T} \to \infty$ as $\beta_T \to 0$. Given $cv^{\beta_T} \to \infty$ and $scv^{\beta_T} \to \infty$ under the null hypothesis of no bubbles, the probabilities of (false) detecting the origination of bubble expansion and the termination of bubble collapse using the backward ADF statistic and the backward sup-ADF statistic tend to zero, so that both $\Pr\{\hat{r}_e \in [r_0, 1]\} \to 0$ and $\Pr\{\hat{r}_f \in [r_0, 1]\} \to 0$.

One bubble: PSY (2015b) study the consistency properties of the date estimates $\hat{r}_e$ and $\hat{r}_f$ under different alternatives. The simplest is a single bubble episode, similar to the one considered in PWY. The following generating process used in PWY is an effective reduced form mechanism that switches between a martingale mechanism, a single mildly explosive episode, collapse, and subsequent renewal of martingale behaviour,

$$X_t = X_{t-1}1\{t < \tau_e\} + \delta_T X_{t-1}1\{\tau_e \leq t \leq \tau_f\} +$$

$$\left(\sum_{k=\tau_f+1}^{t} \varepsilon_k + X_{\tau_f}^*\right) 1\{t > \tau_f\} + \varepsilon_t 1\{j \leq \tau_f\}. \tag{2.23}$$

In the equation (2.23), $\delta_T = 1 + cT^{-\alpha}$ with $c > 0$ and $\alpha \in (0,1)$, $\varepsilon_t \xrightarrow{iid} (0, \sigma^2)$, $X_{\tau_f}^* = X_{\tau_e} + X^*$ with $X^* = O_p(1)$, $\tau_e = \lfloor Tr_e \rfloor$ dates the origination of bubble expansion and $\tau_f = \lfloor Tr_f \rfloor$ dates the termination of bubble collapse ($\tau = \lfloor T\mathrm{r} \rfloor$ represents a bubble phase in the overall trajectory). The pre-bubble period $N_0 = [1, \tau_e)$ is assumed to be a pure random walk process but this is not essential to the asymptotic theory. The bubble expansion period $\mathrm{B} = [\tau_e, \tau_f]$ is a mildly explosive process with expansion rate given by the AR coefficient δ_T. As discussed in PWY, mildly explosive processes are well suited to capturing market exuberance. The process then collapses abruptly to $X_{\tau_f}^*$, which equals X_{τ_e} plus a small perturbation, and continues its random wandering martingale path over the subsequent period $N_1 = (\tau_f, \tau]$. The equation above captures the main features of interest when there is a single bubble episode and is useful in analysing test properties for a bubble alternative.

Under the above equation and certain rate conditions both ADF and Backward sup-ADF detectors provide consistent estimates of the origination and termination dates of the bubble. Consistent estimation of the bubble dates also requires that the minimum window size r_0 not exceed r_e otherwise the recursive regressions do not include r_e and the origination date is not identified. When the point estimates $\hat{r}_e$ and $\hat{r}_f$ are obtained as in PWY using the ADF test and the first crossing times (2.16) then $(\hat{r}_e, \hat{r}_f) \xrightarrow{p} (r_e, r_e)$ as $T \to \infty$ provided the following rate conditions on the critical value cv^{β_T} holds,

$$\frac{1}{cv^{\beta_T}} + \frac{cv^{\beta_T}}{T^{1/2}\delta_T^{r-r_e}} \to 0, as\ T \to \infty, \tag{2.24}$$

Consistency of $(\hat{r}_e, \hat{r}_f)$ was first proved in a working paper of Phillips and Yu (2009). When the point estimates $\hat{r}_e$ and $\hat{r}_f$ are obtained from the Backward sup-ADF detector using the crossing time criteria (2.20), they again have consistency $(\hat{r}_e, \hat{r}_f) \xrightarrow{p} (r_e, r_f)$ as $T \to \infty$ under the corresponding rate condition on the critical value scv^{β_T}, viz.,

$$\frac{1}{scv^{\beta_T}} + \frac{scv^{\beta_T}}{T^{1/2}\delta_T^{r-r_e}} \to 0, as\ T \to \infty \tag{2.25}$$

Thus, both strategies consistently estimate the origination and termination points when there is only a single bubble episode in the sample period. The rate conditions (2.24) and (2.25) require for consistency of $(\hat{r}_e, \hat{r}_f)$ that $(cv^{\beta_T}, scv^{\beta_T})$ pass to infinity and that their orders of magnitude be smaller than $T^{1/2}\delta_T^{r-r_e}$. It is sufficient for consistency of $(\hat{r}_e, \hat{r}_f)$ that the critical values cv^{β_T} and scv^{β_T} applied in the recursions expand slowly as $T \to \infty$. The probability of false rejection of normal behaviour then goes to zero. The upper rate condition that delimits the rate at which $(cv^{\beta_T}, scv^{\beta_T})$ pass to infinity ensures the successful detection of mildly explosive behaviour under the alternative. In effect, the critical values used in the crossing times (2.20) must not pass to infinity too fast relative to the strength of exuberance in the data which is governed by the value of the localizing parameter $\alpha < 1$ in the AR coefficient $\delta_T = 1 + cT^{-\alpha}$.

Multiple bubbles: Multiple bubble episodes maybe analysed in a similar way using more complex alternative models and more detailed calculations, which are reported in PSY (2015b). The key results are showed in the case of two bubble cases, which are generated in the following system extending the model proposed in single bubble episode.

$$X_t = X_{t-1}1\{t < N_0\} + \delta_T X_{t-1}1\{t \in B_1 \cup B_2\} + \left(\sum_{k=\tau_{1f}+1}^{t} \varepsilon_k + X^*_{\tau_{1f}}\right)1\{t \in N_1\} +$$

$$\left(\sum_{k=\tau_{2f}+1}^{t} \varepsilon_k + X^*_{\tau_{2f}}\right)1\{t \in N_2\} + \varepsilon_t 1\{j \in N_0 \cup B_1 \cup B_2\}. \tag{2.26}$$

In the new system (2.26), different notation has been used: $N_0 = [1, \tau_{1e})$, $B_1 = [\tau_{1e}, \tau_{1f}]$, $N_1 = (\tau_{1f}, \tau_{1e})$, $B_2 = [\tau_{2e}, \tau_{2f}]$ and $N_2 = (\tau_{2f}, \tau]$. The observations $\tau_{1e} = \lfloor Tr_{1e} \rfloor$ and $\tau_{1f} = \lfloor Tr_{1f} \rfloor$ are the origination and termination dates of the first bubble; $\tau_{2e} = \lfloor Tr_{2e} \rfloor$ and $\tau_{2f} = \lfloor Tr_{2f} \rfloor$ are the origination and termination dates of the second bubbles; and τ is the last observation of the sample. After the collapse of the first bubble, X_t resumes a martingale path until time $\tau_{2e} - 1$ and a second episode of exuberance begins at τ_{2e}. The expansion process lasts until τ_{2f} and collapses to a value of $X^*_{\tau_{2f}}$. The process then continues on a martingale path until the end of the sample period τ. The expansion duration of the first is assumed to be longer than that of the second bubble, namely $\tau_{1f} - \tau_{1e} > \tau_{2f}, -\tau_{2e}$. Obvious extension of the system includes models where the mildly explosive coefficient δ_T takes different values in regimes B_1 and B_2 and models where the transition mechanisms to martingale behaviour over N_1 and N_2 take more graduated and possibly different forms, thereby distinguishing the bubble mechanisms in the two cases.

The date-stamping strategy of PWY suggests calculating r_{1e}, r_{1f}, r_{2e}, r_{2f} and r_{2f} from the following equations (based on the ADF statistic),

$$\hat{r}_{1e} = inf_{r_2 \in [r_0, 1]} \left\{ r_2 \colon ADF_{r_2} > cv_{r_2}^{\beta_T} \right\} and$$

$$\hat{r}_{1f} = inf_{r_2 \in [\hat{r}_{1e} + \log(T)/T, 1]} \left\{ r_2 \colon ADF_{r_2} < cv_{r_2}^{\beta_T} \right\},$$

$$\hat{r}_{2e} = inf_{r_2 \in [\hat{r}_{1f}, 1]} \left\{ r_2 \colon ADF_{r_2} > cv_{r_2}^{\beta_T} \right\} and$$

$$\hat{r}_{2f} = inf_{r_2 \in [\hat{r}_{2e} + \log(T)/T, 1]} \left\{ r_2 \colon ADF_{r_2} < cv_{r_2}^{\beta_T} \right\},$$

where the duration of the bubble periods is restricted to be longer than $\log(T)$. The new strategy recommends using the backward sup-ADF test and calculating the origination and termination points according to the following equations,

$$\hat{r}_{1e} = inf_{r_2 \in [r_0, 1]} \left\{ r_2 \colon BSADF_{r_2}(r_0) > scv_{r_2}^{\beta_T} \right\},$$

$$\hat{r}_{1f} = inf_{r_2 \in [\hat{r}_{1e} + \delta \log(T)/T, 1]} \left\{ r_2 \colon BSADF_{r_2}(r_0) < scv_{r_2}^{\beta_T} \right\},$$

$$\hat{r}_{2e} = inf_{r_2 \in [\hat{r}_{1f}, 1]} \left\{ r_2 \colon BSADF_{r_2}(r_0) > scv_{r_2}^{\beta_T} \right\},$$

$$\hat{r}_{2f} = inf_{r_2 \in [\hat{r}_{2e} + \delta \log(T)/T, 1]} \left\{ r_2 \colon BSADF_{r_2}(r_0) < scv_{r_2}^{\beta_T} \right\}.$$

An alternative implementation of the PWY procedure is to use that procedure sequentially, namely to detect one bubble at a time and sequentially re-apply the algorithm. The dating criteria for the first bubble remain the same. Conditional on the first bubble having been found and terminated at $\hat{r}_{1f}$, the following dating criteria are used to date stamp a second bubble,

$$\hat{r}_{2e} = inf_{r_2 \in [\,\hat{r}_{1f},1]} \left\{r_2 :_{\hat{r}_{1f}} ADF_{r_2} > cv_{r_2}^{\beta_T}\right\} \; and$$

$$\hat{r}_{2f} = inf_{r_2 \in [\hat{r}_{2e}+\log(T)/T,1]} \left\{r_2 :_{\hat{r}_{1f}} ADF_{r_2} < cv_{r_2}^{\beta_T}\right\},$$

where $\hat{r}_{1f}ADFr_2$ is the ADF statistic calculated over $(\hat{r}_{1f}, r_2]$. This sequential application of the PWY procedure requires a few observations in order to re-initialize the test process after a bubble.

The asymptotic behaviour of these various dating estimates is developed in PSY (2015b) and summarized as follows.

(i) The PWY procedure: Under (2.26) and the rate condition (2.24), the ADF detector provides consistent estimates $(\hat{r}_{1e}, \hat{r}_{1f}) \xrightarrow{p} (r_{1e}, r_{1f})$ of the origination and termination of the first bubble, but does not discover the second bubble when the duration of the first bubble exceeds that of the second bubble $\tau_{1f} - \tau_{1e} > \tau_{2f}, -\tau_{2e}$. If the duration of the first bubble is shorter than the second bubble $\tau_{1f} - \tau_{1e} \leq \tau_{2f}, -\tau_{2e}$, than under the rate condition

$$\frac{1}{cv^{\beta_T}} + \frac{cv^{\beta_T}}{T^{1-\alpha/2}} \to 0, as\; T \to \infty \qquad (2.27)$$

PWY consistently estimates the first bubble and detects the second bubble but with a delay that misdates the bubble – specifically $(\hat{r}_{2e}, \hat{r}_{2f}) \xrightarrow{p} (r_{2e} + r_{1f} - r_{1e}, r_{2f})$.

(ii) The backward sup-ADF procedure: Under (2.26) and the rate condition (2.25), the backward sup-ADF detector provides consistent estimates $(\hat{r}_{1e}, \hat{r}_{1f}, \hat{r}_{2e}, \hat{r}_{2f})$ $\xrightarrow{p} (r_{1e}, r_{1f}, r_{2e}, r_{2f})$ of the origination and termination points of the first and second bubbles.

(iii) The sequential PWY procedure: Under (2.26) and the rate condition (2.24), sequential application (with re-initialization) of the ADF detector used in PWY provides consistent estimates $(\hat{r}_{1e}, \hat{r}_{1f}, \hat{r}_{2e}, \hat{r}_{2f}) \xrightarrow{p} (r_{1e}, r_{1f}, r_{2e}, r_{2f})$ of the origination and termination points of the first and second bubbles.

When the sample period consists of successive bubble episodes the detection strategy of PWY consistently estimates the origination and termination of the first bubble but does not consistently date stamp the second bubble when the first bubble has longer duration. The new backward sup-ADF procedure and repeated implementation of the PWY strategy both provide consistent estimates of the origination and termination dates of the two bubbles. PSY (2015b) also examine the consistency properties of the date-stamping strategies when the duration of the first bubble is shorter than the second bubble. In this case, the PWY procedure fails to fully consistently date-stamp the second bubble whereas the new strategy again succeeds in consistently estimating both the origination and termination dates of the two bubbles.

The reason for detection failures in the original PWY procedure lies in the asymptotic behaviour of the recursive estimates of the autoregressive coefficient. Under data generating mechanisms such as (2.26), a recursive estimate $\hat{\delta}_{0,t}$ of $\delta_T = 1 + \frac{c}{T^\alpha}$ that is based on data up to observation $t \in B_2$ is dominated by data over the earlier domain $N_0 \cup B_1 \cup N_1$ and it turns that that $\hat{\delta}_{0,t} \sim 1 + \frac{c}{T^\alpha} < 1$. It follows that right sided unit root tests generally will not detect explosive behaviour with such asymptotic behaviour in the coefficient estimate. This difficulty is completely avoided by flexible rolling window methods such as the new backward sup-ADF test or by repeated use of the original PWY procedure with re-initialization that eliminates the effects of earlier bubble episodes. To consistently estimate the second bubble using PSY and sequential PWY detectors, the minimum window size needs to be small enough to distinguish the different episodes. Particularly, r_0 should be less than the distance separating the two bubbles, i.e. $r_0 < r_{2e} - r_{1f}$.

Appendix 5.8: Price-dividend ratios in response to selected variables within the Pre-Dotcom bubble period with 100 weeks.