An Empirical Investigation of Bubble and Contagion Effects in the Thai Stock Market

by

Jumpon Kluaymai-Ngarm

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Abstract

This thesis examines stock price bubbles in the Stock Exchange of Thailand (SET) from its establishment in April 1975 until December 2012 using regime-switching bubble models, on the main aggregated market index, called the “SET Index,” and several disaggregated stock indices by industrial sector. The results suggest some evidence of bubble-like behaviour in these indices, most especially when a structural break is included at July 1997, the date when Thailand switched to adopting a managed floating exchange rate system. Given the limitations of published stock price indices in Thailand – a new, consistent index was computed – the K-NI. The econometric test results using this new index indicate strong evidence of stock price bubbles in several industrial sectors and at least some evidence of bubbles in all industry groups in the SET. Finally, the standard model is extended to study the transmission of bubbles between industry groups. The results indicate some levels of contagion in the Technology sector, as well as, in several other industry groups, while the Resources sector seems to be relatively isolated.

Key words: asset pricing, stock market bubble, bubble test, regime-switching model, bubble contagion, Thai stock market

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Chapter 1: Introduction

According to IMF's World Economic Outlook Database: October 2014 Edition, the 2014 Thai nominal gross domestic product (GDP) was estimated to be around US$380 billion, ranking 32nd in the world, or ranking 22nd based on the purchasing-power-parity valuation of approximately US$990 billion. Thailand's principal stock market is the Stock Exchange of Thailand (SET), the domestic market capitalisation of which was about US$430 billion at the end of December 2014, ranking it 22th out of the 64 exchanges, according to the World Federation of Exchange (WFE) statistics. These figures illustrate the significance of the Thai economy and the Thai stock market in both the South East Asian region and the global economy in 2015. This position, however, has been achieved over a relatively short time period, given the stock market was not opened until 1975.

There have been several periods of rapid expansion in the Thai stock market. For example, the market index more than doubled from 400 points to about 900 points during 1988-1989. It slowed down during 1990 until mid-1992 and then soared to above 1700 points in 1993. Market capitalisation rose about 25 times during these six years from 138 billion baht to 3,325 trillion baht. During the Asian Financial Crisis in 1997-1998, the Thai market was heavily hit. The Stock Exchange of Thailand's SET Index plummeted from 850 points to 370 points, and the market capitalisation shrank to just a third of the previous year's valuation. More recently the global crash of 2007-08 also impacted the Thai stock market which saw the index plunged by more than 50% from the October 2007 high at around 900 points to the November 2008 low at roughly 400 points. However, the index had rebounded strongly to about 1400 points at the end of 2012.

It is this record of growth and volatility in the Thai stock market that provides the motivation for this thesis. Since the long-term growth of the Thai economy depends in part on the ability of local and international firms to grow by raising capital, it is important to examine the extent to which the true fundamental value of the assets governs the level of the stock price index or if there exist periods of dramatic price rises followed by remarkable sharp price corrections - a phenomenon known as bubbles. In these bubble phases, market transactions are motivated by expectations of future price increases, with little regard to the fundamentals. This study, therefore, aims to investigate in presence and importance of stock price bubbles in the Thai stock market.

This study of bubbles is a topical issue and has motivated asset-pricing research to understand its developments to produce sensible forecasts for future decisions. Although some authors, such as Garber (1990), may have doubted the validity of claims for the widely cited events as bubbles, it is clear that asset mispricing is typically associated with crashes and crises, which pose serious challenges to the financial stability of the economy. At least, the resulting loss of investor confidence would hurt the economy through the rise in the cost of capital for businesses. Given these implications, it begs the question whether policy makers should actively try to break the bubbles. At first glance, it seems desirable for the central banks or the government to restrain the bubbles or burst them when preventions failed. In the real world, however, the issue is much more complicated. First of all, the true models for explaining asset price behaviour are far from settled, and it is almost impossible to conclusive identify bubbles as the economy is going through different periods. Furthermore, large asset price drops are not necessarily coincided with economic recessions. Expansive economic measures can help alleviate the severity of any potential downturn, although the use of such policies is questioned to have contributed to form the next bubble (Jones, 2014; Meltzer, 2002). On the other hand, speculations in stock markets could provide potential economic benefits as well. Consider a case where financing is limited to borrowing from banks. Companies with innovative but risky projects may never obtain the funding required. However, with its capability of risk-sharing and diversifications, stock markets could help enable the implementation of new technology, which consequently lead to better long-run economic growth (Komaromi, 2006). Nevertheless, the asset prices would deteriorate if investors' expectations of future profits do not materialise, due to mal- or over-investments, for example. In addition, an economy could realise long-run benefits from institutional or regulatory change, triggered by the collapse of bubbles.

Apart from winners and losers in the stock market, bubbles are also in the interests of financial intermediaries, such as brokerage firms, mutual funds, and investment banks. A boom in the stock market means more trading activities and potential fees to be collected by these parties. Money managers, in particularly, would gain from understanding the behaviour of asset price for their portfolio optimisation and hedging decisions. Specifically, they could profit from trading rules that allow them to successfully ride the bubbles and exit just before the burst, for instance.

Finally, the issue of financial bubbles has also attracted a great deal of consideration from the academics. Similar to the investors, researchers seek to formulate models suitable for pricing assets as well. They aim to improve the knowledge of investor behaviour and resulting bubbles – in particular, the dynamics of bubbles in different asset classes, and in different groups or sectors, and whether they are contagion between them. Most importantly, the analysis of bubbles help improve the understanding of determinants of asset prices and whether they are driven by fundamentals, as well as, other non-fundamental factors.

The thesis makes four identifiable contributions to the literature. First, this study focuses on bubble behaviour in the Thai stock market from its establishment in April 1975 until December 2012. Even though it stands as one of the largest stock markets in the South-east Asian region with strong linkages to other more advanced markets, the amount of research on bubbles in the Thai market is very limited. Only a few frequently cited papers exist: for example, Jirasakuldech et al. (2008), who examined whether Thai stock price deviated from fundamental values, and Watanapalachaikul and Islam (2007) who considered rational speculative bubbles in the Thai stock market using the Weibull Hazard model, but with data spanning only from 1992 to 2001. Other work on the Thai market usually appears as a part of broader studies of Asian markets, such as that by Chan et al. (1998).

A second contribution of the thesis is that in addition to the main market-wide index, disaggregated indices were also examined. They provide a more detailed insight as to which industry or sector contains bubbles and may be regarded as an informal test of the claim by Jung and Shiller (2005) that results based on the aggregated market index would be more obscure than any derived from the disaggregated sectors. The idea is that in aggregate bubbles in different sectors might offset each other, or a bubble in one sector of the market may drive a bubble in another sector. Although disaggregated sector data is available from the SET's industry group and sectoral indices and Thomson Reuters' Datastream, both of these sets of data have limitations. For example, there were many sectoral indices which make estimation and interpretation less manageable, while the official industry group indices were only available for a limited sample period. At the same time, the bubble calculations based on Datastream-calculated indices were not completely reliable.

Consequently, a new index – referred to as the K-NI – was computed; it overcomes these limitations by replicating the SET's industry group indices and extending them to start as far as 1988.

The third contribution of this thesis is to apply a regime-switching model approach to the Thai market. This model is intuitively very appealing and has been applied in other contexts, such as van Norden and Schaller (1993) who analysed the Toronto Stock Exchange, and Anderson et al. (2010) who studied the S&P500. For studies on Thai market, only Pongsutinart (2000) used this particular technique with the SET Index. Nonetheless, his sample size, covering only the data during 1989-1999, was far too short – especially when compared to a more extended coverage in this research. Moreover, Pongsutinart (2000) adopted the basic Van Norden-Schaller model, while this thesis considered the volume-augmented model which also includes abnormal trading volume as an indicator to help identify the possible timing of bubble collapse.

Additionally, one of the specific features of the Thai market over the period of study is the switch in exchange rate regime during 1997, which is one example of a potential structural break. Other examples may be the financial liberalisation policies by the Thai government in the early 1990s or the recent global financial crises. Experimentation with endogenous breakpoints and multiple structure breaks are therefore a feature of the modelling approach employed in this thesis. As the inclusion of structural breaks improves the results from estimations, this method suggests that significant changes in the behaviour of Thai market returns took place. Particularly, the model allowing for two structural breaks picked up the breakpoints at September 1996 and August 1998, consistent with splitting the period up to pre-crisis, the Asian Financial Crisis, and post-crisis sub-periods.

Finally, the baseline bubble model was also extended to capture potential bubble transmission between industry groups within the Thai stock market. Three models were investigated, namely the model for contagion with all other industry groups (Model A), the model for contagion with the market-wide index as a proxy (Model M), and the model for contagion between two industry groups (Model J). The comparison of results between models shows that the technology stocks were the most contagious, while stocks in resources industry were rather isolated. Several other industry groups were found to be heavily interlinked as well. The findings of the Granger Causality tests partly reinforced these results.

This thesis is organised as followed. Chapter 2 critically reviews the theoretical and relevant empirical literature on stock market bubbles and contagion. The institutional structure of the Thai stock market is elaborated in Chapter 3, together with documentation of its historical development and performance. Chapter 4 describes the econometric methodology used in the thesis to test the bubble hypothesis, the results of which are reported in the following three chapters. Chapter 5 presents the results from the aggregate market index, Chapter 6 the results from the disaggregated (industry group and sectoral) indices and Chapter 7 the results from the inter-sector contagion models. Overall conclusions from the empirical analysis and potential implications for policy are noted in Chapter 8.

Chapter 2: Review of the Literature on Asset Bubbles

2.1. Introduction

Historically, episodes of extreme movements of asset prices, such as the Tulipmania in the early 1960s in the Netherlands, Japan during 1980s, or the dot-com bubble in the late 1990s in the US, were observed every once in a while. Prices significantly rose which sometimes continued for an extended period, and then followed by sharp corrections. Such phenomena motivated much research. The fact that the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2013 – commonly referred to as the Nobel Prize in Economics – were awarded to three laureates who have contributed to the understanding of asset pricing only helps show the significance of the field.

Still, economists diverge in their opinions as to what actually determine prices. Many believe that prices are driven by fundamental factors, such as expected future dividends streams, however, there exists plenty of evidence that suggests otherwise. That led researchers to search for other factors, one of which is the possibility of bubbles. The question whether a bubble exists in the financial market in a particular period has significant implications for the economy and market participants. Specifically, asset prices serve to allocate economy's limited resources to the best use. A bubble could potentially distort decisions to consume, save, and invest. Damages caused by the collapse of a bubble were substantial and demanded a large amount of attention by regulators and policy makers. Investment managers would also monitor the development of asset prices and try to form optimal trading rules to obtain highest returns. Finally, as mentioned earlier, the issue draws massive attention from the academic community as well.

There have been many theoretical models, empirical tests, experiments proposed by countless of authors. From the early works in the 1960s, researchers were focusing on the fundamental factor as a key determinant of prices with discount rates which include the risk premium assumed to be constant, as well as, whether bubbles will be prohibited or broken if occurred by market forces. When that appeared to be unconvincing, economists also investigated the possibility of time-varying discount rates. Lately, many assumptions were further relaxed, and concepts brought over from the field of psychology were introduced. In short, the bubble literature has experienced considerable advancements. There are still many unresolved issues. While the role of behavioural biases of traders seems to help further complement the understanding of bubbles, they are still relatively underexplored. The review of the earlier literature includes, for example, Camerer (1989) and Stiglitz, (1990), while a survey of more recent approaches is offered by Scherbina (2013).

Several economists have offered their descriptions of a bubble, but there is no universally agreed definition (see, for example, Kindleberger and Aliber, 2005; Brunnermeier, 2008). Most of them emphasised on a situation where prices deviate from the fundamental value, or that they move independently of the fundamental value or cannot be explained by any reasonable future changes in fundamental factors. This definition allows for a simple mathematical representation of bubbles as a difference between actual price and fundamentals. The sharp rise of price and the divergence from fundamentals typically believed to be caused by the expectations of continued price increase or the possibility of reselling at higher prices. This resale optionality stresses the importance of anticipations and self-fulfilling nature of future price movements. Kindleberger and Aliber (2005) also mentioned that the price surge from the bubble is a continuous process whose initial rise leads to an expectation of further advances and drawing in new buyers. The new players represent excess demand and result in demand-side inflation or bubble. Many economists, as early as Keynes (1936), recognised the impacts of emotions and psychological biases of investors. Keynes made a distinction between the more legitimate enterprise investment and the speculation under the influence of mass psychology. He also further described speculation as the activity of predicting market’s psychology. More precisely, investment decisions are not made based on the intrinsic value but rather the prediction of what average opinion expects average opinion to be. Episodes of trade frenzy or volatile price were thought to be caused by over-confidence and panic – or change in animal spirits which Alan Greenspan referred to as irrational exuberance – in the market. Shiller (2014) also pointed out the epidemic nature of bubble where investing ideas based on exaggerated beliefs of one investor can be contagious to others, as well as, the important role of news media in spreading and suppressing the information. Finally, some authors focused on the social dimensions of bubbles, regarding members of the general public who has little interest or understanding in the financial markets being drawn into participating the bubble and suffer the eventual burst. However, this aspect is less practical for formal testing.

Bubbles in the different context could mean slightly different things, and their properties are also inconclusive. In general, it usually begins with prices deviate from fundamental value explosively and persistently then reversals follow. Most papers concentrated on overvaluation or positive bubbles because it is more common, due to relatively more limit on short selling activity. The expectation for higher sale price in the future was typically assumed to initiate a bubble. Alternatively, others suggested they can be artificially made by the incorrect model of fundamental values, or violations of assumptions included in the fundamental model such as information asymmetry, or created by exogenous factors uncorrelated with fundamental factors like psychology or behaviour of investors. For instance, the models that include the role of feedback traders interacting with rational investors, or behaviour of institutional investors under different limitations were proposed. On the other hand, the collapse of bubble often regarded by theories as caused by a change in investors' beliefs about the future or by exogenous events. Moreover, although the term seems to suggest a drama of sudden burst, like the US market in 1929 or 2000, it is not required, and a bubble could gradually deflate and even reflate again or not instead, for example, the periods between 2003-2007 and 2009 until recently (Shiller, 2014). In addition, it is frequently observed that the run-up time and the crashes tend to be at different speeds, where collapses are shorter than the build-up, and when a bubble episode involved speculative attacks or regulatory change, its reversal is quicker than a sentiment change. Finally, there was evidence of different recovery time in different markets. Scherbina (2013) discussed that the real estate market took longer to bounce back than equity.

There are three main methodologies for analysing bubbles. The first is the mathematical approach, which involves specifying mathematical models to explain various market characteristics. It includes conventional rational bubble models, the new generation of rational models where the assumption of perfect rationality is relaxed, and behavioural models. Proposed models are, for instance, models with asymmetrical information, or models with heterogeneous beliefs. However, with exact modelling, the approach is criticised regarding its generality, as it is only valid in certain specific contexts. Necessary and sufficient conditions are sometimes left unelaborated. An alternative approach is to conduct laboratory-based experiments to examine different factors, referred to as experimental approach. Finally, the literary approach qualitatively discussed properties, causes and effects, of different historical bubble incidents. It is interesting to note that although the terms bubble and asset price bubble are used interchangeably, Komaromi

(2006) discussed a fine distinction between them. Specifically, the former refers to an unqualified form of the bubble in the overall market, while the latter analyses a bubble formed in each specific asset which can be generalised into the entire market. In this sense, the mathematical and experimental approaches are more suitable for investigating asset price bubble, whereas with the literary approach can analyse a bubble phenomenon better.

Analysing bubble phenomena face a number of challenges. Firstly, not all explosive price movements are bubbles, and an eventual price correction does not necessarily mean a breaking of bubbles if they reflect a systemic response by market participants which is entirely rational. For instance, if oil price surged due to scarcity, and when the petroleum substitute was discovered, the price could drop markedly (Stiglitz, 1990). In contrast, bubbles could arise but not detected. Jones (2014) discussed an example of when prices do not change or decrease just marginally, but expectations of future dividends become more pessimistic which results in lower fundamental values. Furthermore, even when it can be established that bubble exists, there are many competing theories attempting to explain the causes and developments of the bubbles. It is hard to determine unambiguously whether a bubble was caused by informational issues forbidding agents to act with perfect rationality, by institutional settings that limit the ability of rational investors to break the bubbles through arbitrage, or by irrational behavioural errors of market participants. To put it differently, the split between those holding the rational expectations assumptions and those who believe in behavioural finance is somewhat unreal (Shiller, 2014). It could only be known with a reasonable level of certainty ex-post, which also implies real-time monitoring as the bubble is in progress would be exceptionally tricky if not impossible. This problem of inference, together with the unsettled definition of a bubble result in many empirical tests ignoring to elaborate on theoretical existence problem and treating bubbles as empirical issues (Gürkaynak, 2008). Finally, given that the perfect arbitrage does not really exist, prices would almost never be equal to the fundamental value. In other words, with a strict definition of a bubble, there is asset price bubble all the time. Thus, some researcher doubts whether bubble investigation is still relevant (Komaromi, 2006).

The following sections elaborate on the theoretical arguments of rational bubble models, behavioural models, and related discussions. After that, the results drawn from the experimental approach are discussed. Next, the insights from the literary approach are explored. Finally, the last section focuses on empirical evidence from bubble detection tests.

2.2. Rational Bubble Models

The standard asset pricing models assuming rational expectations normally start at what the fair price is. In principles, the fair price should reflect the intrinsic value of the asset. For a stock, it represents the present value of all the future dividends and the future price when the stock is to be sold or a terminal price. In a way, the future price will also be dependent future dividends further forward, thus, it implies expected dividend streams are the only systematic force driving the price movements. The implication is that there cannot be any bubbles. This is because investors are rational, and when they observe price deviates from the fundamental value, they will intervene such that the mispricing will be eliminated.

However, this conclusion is based on such a simple model which relies on several assumptions. For example, there has to be no informational asymmetry, such that there are no uninformed momentum traders who infer information from others' trades and amplify price movements away from the equilibrium. The representative consumer is assumed to be risk neutral or that there is no risk premium, implying that the discount rate is constant over time. Finally, to have the unique equilibrium price, dividends must grow at the rate lower than the discount rate so that the present value of future dividends in distant future are approaching zero and are negligible.

The last assumption is also known as the transversality condition. If it is relaxed, there are an infinite number of possible relationships between price and fundamentals, or that price could have multiple equilibria. That could even include a path where actual price diverges from the fundamental value due to the existence of a bubble. In other words, actual price could have two components, which are the systematic fundamental part, and a bubble. That means the case where price is equal to fundamental value is only a special case, where a bubble is zero, out of many more general settings. The bubble can derive from different generating mechanisms, and there is no generally accepted view. The only condition for it to be consistent with rational expectations behaviour is that the bubble must be expected to grow at the rate equal to the discount rate. The intuition is that if the bubble grows at a rate lower than the discount rate, it would also be insignificant in the distant future, and the transversality condition applies so that price would converge to the fundamental value. On the other hand, if the growth rate is higher than the discount rate, the bubble would explode infinitely, and asset price would exceed the aggregate wealth of the economy.

Another condition for the possibility of a bubble depends on the arbitrage opportunity. A bubble could exist if there are short-sale constraints in place, or the market is not complete such that not all instruments are available, or the asset does not have a close substitute. Maturity or investment period also matters. Bubbles could only exist with an asset with infinite periods. This is because if the asset has a fixed maturity, say, at time *t*, investors would know it cannot grow after a specific time and would, therefore, try to offload the assets in the period before. That means the price will not contain bubbles in the period *t*-1. It is only rational for investors to foresee this and decide to sell the assets before that. This backward induction repeatedly occurs until a conclusion is reached that there must never be a bubble in the first place. A similar result can be obtained if non-infinitely-lived decision makers replace the finite asset or that there are only limited number of players in the market. Rational investors are thought to prohibit the existence of a bubble. However, if they do not live forever or have overlapping generations to continue, there is no guarantee that there will be someone to break the bubbles. However, these results are based on the backward induction which implicitly implies complete information that the timing of the collapse is known. Allen et al. (1993), for example, showed that a bubble could exist for a finitely-lived asset when there is no common knowledge, and short-sale constraints are imposed. Lastly, Tirole (1982) discussed another type of common knowledge. If all agents regard the initial allocation as Pareto efficient, they will not trade the assets, and thus, rational bubbles cannot be present.

There are many tests for rational bubble detection in the literature, and they will be discussed in the following sections. However, the results are not compelling (see, for example, Flood and Hodrick, 1990). Meltzer (2002) explained that part of the reasons was the inability for a researcher to observe expectations, and the models are, consequently, prone to misspecification. More critically, the broader issue is the joint hypothesis problem where the bubble hypothesis is tested against a maintained hypothesis of fundamental price valuation. Investors are assuming to have rational expectations and thus exploit all available information, but it is limited to what included in the maintain model. Bubbles would account for whatever remain explained or act as a catch-all. The fundamental value models had been under extreme scrutiny. The literature documented failures of the standard present value model to capture certain characteristics. They include, for instance, non-linearity, long-memory in dividends series – which refers to persistent deviations from the equilibrium condition (Caporale and Gil-Alana, 2004; Cuñado et al., 2005; Koustas and Serletis, 2005), and the impact of low probability but high impact event of a policy change such as currency regime or tax law – especially when they were expected but did not materialise (Flood and Hodrick, 1986; Flood et al., 1994). In these cases, the behaviour of prices would look like a bubble, though they are arguably not one, and thus complicate the identification of bubbles.

Moreover, the standard model viewed the investors as practising buy-and-hold strategy and having an infinite investment period. However, in reality, data of terminal price extended into infinity are not available which means the fundamental value cannot be determined in advance (Stiglitz, 1990). Plus, there are several other trading motives which could lead to current price to include some interim returns as well. The assumption of perfect information is also crucial. There are several instances of financial markets that are incomplete, such that precise payoffs cannot be assigned or that investors have different information or interpretations. For example, Brunnermeier (2001) showed that asset price increase could happen because of the ability for investors with different prior opinions to trade as compared to the case where they cannot. Finally, although some authors argued that it would require extreme beliefs for the standard models to produce estimates of fundamental values that justify movements observed in the data, Jones (2014) proved that a small change in fundamental assumption could lead to significant impact on the assessed price as well.

In addition, some authors also questioned the validity of fundamental models when applied to assets that do not typically pay dividends like technology stocks. Anderson et al. (2010) and Anderson and Brooks (2014) argued that the use of alternatives measures such as earnings, or soft variables like human resources, patents, or web traffic were not proved to represent fundamental values better by previous studies. In addition, their tests detected bubble in several sectors and not just the technology sectors, which led them to conclude that the fundamental model based on dividends are equally applicable, and the approach allowed for direct comparisons between sectors as well. Furthermore, Damodaran (2002) also showed that the conventional fundamental valuation is still valid with growth stocks although it tends to be quite noisy. All these issues illustrate how complicated the problem of fundamental price estimation could be and the impact it has on the identification of bubbles.

The rational bubble model implied that price would explode to be infinitely large. However, this is not observed in the data. Froot and Obstfeld (1991) proposed an alternative type of bubble, which is determined by evaluation of dividends instead of being stochastic, and referred to it as an intrinsic bubble. The approach yielded some promising results that are more closely aligned with empirical observations and could help explains several puzzles, such as why prices are more volatile than dividends or overreact to dividend changes (Scherbina, 2013). Furthermore, it could replicate a bubble burst, as a bubble would disappear when the fundamentals are zero.

The next issue regarding rational bubbles is about the conditions on initiating and terminating bubbles. Several authors had pointed out that the models are providing very little clues on these matters. Brunnermeier (2008), for example, concluded that rational bubbles must already exist when the trading of the asset started, as they can never emerge within the asset-pricing model. Moreover, it is quite inconclusive with regards to negative bubbles. Some papers allowed for the existence of such bubble, while others argued against such possibility. For instance, Brunnermeier (2008) explained that it is not possible as it suggests that, at some point in time, the expected asset price has to become negative.

Lastly, it is also difficult to separate between rational and non-rational or behavioural bubbles. The main difference between the two explanations is the rational bubbles are related to rational response based on some structural hypothesis, while the collapse of a bubble based on irrational exuberance works independently from such kind of hypothesis. However, this issue is complicated by uncertainties in determining the fundamental value. For example, a change to fundamentals could happen, but investors cannot distinguish with certainty the type of the shocks whether it is temporary, permanent in level, or permanent in growth rate (Meltzer, 2002). Investors could form different views regarding price prospect, and the correctness of their predictions would only be confirmed ex-post. This could be applied in the case of new technology innovations or liberalisation of monetary policy of central banks (Zeira, 1999).

In conclusion, the initial focus on rational bubbles did not produce convincing explanations due to both the failure of the standard models, as well as, the questionable assumptions of perfect rationality. The new generation of rational models introduces more realistic features, such as non-standard preference, incentive structure, and market frictions. It allows the researcher to explain movements of price without having to resort to irrational behaviour. Scherbina (2013), for instance, discussed three examples: herding, limited liability, and perverse incentives.

The first aspect is herding, which is when investors follow the actions of others. Herding is deemed to be an important mechanism for starting and spreading bubbles. Theories of herding suggested that investors have incomplete information and thus try to improve their trading strategies by looking for hints from other investors (Shiller, 2001). Alternatively, it could be the outcome from other settings with non-standard preferences or different incentive structures as well. They are, for example, relative wealth model (DeMarzo et al., 2008), interaction between 'smart' and 'dumb' money managers (Scharfstein and Stein, 1990), the cost of going against the herd by investment managers in terms of fund outflows, and the role played by popular media in attracting investors to a particular asset.

Secondly, a situation where investors only faced limited downside risk but enjoy the full benefits of rising price is referred to as limited liability. It could contribute to the existence of bubble as it increases willingness for money managers to 'ride the bubble' instead of breaking it. The means, for instance, unskilled managers would participate in a bubble and hope they can sell it in time before the burst. They would not mind taking this risk since they could earn high profits if it works out well, while the losses are limited if they do not manage to. This is particularly notable for risky assets. The higher the risk, the more money is drawn into the bubble, thus the larger the size.

Lastly, many important market players who are supposed to provide correct information and could help prevent bubbles have perverse incentives. Equity analysts, rating agencies, accounting auditors have the role of disseminating information to other market participants. However, they are sometimes motivated by badly-structured incentives to not tell the truths. For example, equity analysts issuing sell recommendations would risk hurting their connections with the companies and be cut off from future communications, or auditors and rating agencies faced conflicts of interests as they are paid by the firm and would be concerned about losing future businesses.

2.3. Behavioural Explanations

Since the 1990s, there have been several hundred papers presenting empirical evidence of inconsistencies with investors' rationality (Shiller, 2014). Instead of assuming rational expectations, the alternative approach of behavioural finance also incorporated psychological patterns of investor behaviour to explain asset price movements. The behavioural models assume that at least one group of investors is irrational. These non-rational investors follow typical behavioural patterns with assumptions based on psychological evidence or make decisions based on rules of thumb instead of being perfectly rational. Some authors argued that they are not entirely wrong but rather quasi-rational (Komaromi, 2006). As opposed to rational models which concentrate on possibility and conditions for bubble formation under perfect rationality, behavioural approach attempt to model the observed price dynamics by taking into account certain behavioural specifics. Behavioural approach can explain some anomalies in asset returns and also finds support from experimental studies (Scherbina, 2013). Moreover, in the original rational bubble models, investors would hold the assets as they grow in expectations ad infinitum, while more recent models would include an option to resell to others, sometimes referred to as 'greater fools'. Lastly, the rational bubble models cannot really explain how bubbles are initiated or assume that they must already be present, while the behavioural models suggest some possible causes, for example, bubbles arise when investors overreact to information or money illusion (Brunnermeier and Julliard, 2008).

In any case, there are also issues in analysing bubbles with the behavioural models. Firstly, this approach still has the fundamental value as a benchmark for the existence of bubbles. However, as argued in the case of rational models, the validity of fundamental value is disputed. It is still not possible to test and exclude all possible explanations to conclude the existence of bubbles irrefutably. There are always alternative explanations for bubble-like episodes. For example, the rational story of 1929 bubble in the US is along the line of the new economy and new era beliefs, together with the monetary policy by the Federal Reserves, or that technological innovations are bringing significant changes in productivity but do not result in substantial changes in profits of companies (Meltzer, 2002). Reinhart and Rogoff (2009) also described many cases of bubbles in emerging markets led by the expansion of credit resulting from financial liberalisation. It is difficult to identify as the economy is experiencing a bubble whether which explanation is correct and it could potentially take years before conclusive evidence is available. In addition, Meltzer (2002) and Komaromi (2006) pointed out that the behavioural approach only explores the issues in general terms. This means, for example, it does not precisely analyse the dynamics of investor behaviour over different time periods, or does not explain the behaviour of sellers thoroughly. If it is assumed that there will be someone predicting the collapse of bubble and would have sold the assets out earlier, the volume of short sales is too small, or if it is assumed that the holders of assets turn into sellers who increasingly offload the assets at different price levels, more concentrated holdings are not always observed.

In terms of an example of specific models, Scherbina (2013) discussed behavioural bubbles in four settings.

2.3.1. Model 1: Differences in opinions and short sale constraints

This first setting is based on a combination of disagreement among investors and short sale constraints. The model incorporates some uncertainty such that there are investors who interpret information positively, and others who are more pessimistic. Alternatively, the model could start from investors started with different prior belief distribution but would not try to infer from each other due to psychological biases like overconfident, such that they agree to disagree even when they share all information (Brunnermeier, 2008). The pessimistic investors are limited by short sale constraints and consequently are not able to sell their assets, while the optimistic investors are very rigid in their view such that they ignore the possibility of others who may think differently but cannot offload the asset. With the optimistic investors pushing up the price and pessimistic investors not being able to counterbalance, the result is that price would be higher than the fair price. Harrison and Kreps (1978) developed a model with this foundation in a dynamic setting. They concluded that differences in opinion and short sale constraints could cause a bubble. A bubble of this type would usually coincide with high price volatility and trading volume. Scheinkman and Xiong (2003) showed that it should be accompanied by active trading and that the bubble size increases with the degree of overconfidence but decrease with trading costs. The validity of this model is also confirmed by several empirical studies based on analyst earnings forecasts or mutual fund ownership as a proxy for different opinions of investors

(Chen et al., 2002; Diether et al., 2002). Finally, under this setting, a bubble will collapse when the uncertain is resolved or that short sale constraints become less binding. This prediction is supported by evidence based on price declines observed around the time of earnings announcements, and the expiration of the lock-up provisions imposed by many technology companies' initial public offerings (Ofek and Richardson, 2003; Scherbina, 2008).

2.3.2. Model 2: Feedback trading

Feedback traders refer to a group of investors whose trade demand is exclusively determined by past movements of price. They can lead to bubbles by the following process. Suppose there is a positive news regarding the asset's future cash flow which would result in price increase. This initial return attracts feedback traders who expect the return to continue and push prices up further beyond justified by the initial news. The extra return would draw in subsequent investors who buy the asset and result in price rising even further and so on. Although it is difficult to forecast the exact point of sentiment reversal, it usually corresponds to the decelerating of bubble growth after new inflows start to slow down, which is sometimes indicated by the participation of poor households or those who do not generally take part in financial markets, or caused by credit tightening such as capital control or tax policy (Scherbina, 2013). Investment funds would begin to flow out and thus leading to bubble deflation or collapse. Instead of exhaustion of new capital, an alternative mechanism that could potentially cause a bubble to deflate is the introduction of a new supply of the assets, for example, seasonal equity offerings in the case of stocks. This would also reduce pressure on price to keep on rising. Shiller (2001) also discussed the role of new media in attractive new investors into the bubble, which keeps the bubble growing for some time before the eventual burst. In some way, this setting is comparable to a Ponzi scheme where it is sustained by new inflows and those who are in early hope to get out just before it deflates. Another interesting feature of this model is the action of rational investors if introduced. Recall that rational investors are expected to break the bubbles. However, in this case, because they predict the action of feedback traders which will result in an even higher price, they would, in fact, participate in the bubble, rather than trading against it. Moreover, the interaction between returns and trading volume could signal different stages of bubbles in this model. Trading volume is a natural outcome from investors contributing to the bubble. Finally, Scherbina (2013) also discussed the possibility of frauds to prevent returns from falling which will lead to outflows of investments at the later stage of the bubble.

2.3.3. Model 3: Biased self-attribution

Biased self-attribution is one of the heavily examined behavioural phenomena in psychology. In the context of the stock market, it is related to the situation where investors become selective in interpreting the signals they received by only paying attention to those supporting the views they hold and ignoring those that contradict. Daniel et al. (1998) constructed a model with this setting. In their model, investors first obtained a noisy private signal by, for instance, conducting their own research, and formed their initial prediction of the asset price. Then, they also received a noisy public signal. Because they suffer this biased self-attribution, they are dogmatic to the view they established earlier. If the public signal support what was interpreted from their private signal, they would become ever more confident and, consequently, revise their expectations further in the direction of their initial valuation. However, if they are conflicting, the investors will dismiss the public information and price will be unaffected. A bubble is registered when the price is revised further beyond what is justified by fundamentals in the first case. Eventually, when sufficient amount of public signal convinced the investors to become less confident in their interpretation of the private signal, the bubble would begin to deflate.

2.3.4. Model 4: Representativeness heuristic and conservatism bias

The last model is based on two behavioural biases from psychology concerning how information is processed. Representativeness heuristic is when investors make decisions on the rule of thumb based on information that stands out more than others, for example, overreacting to an attention-grabbing news. On the other hand, conservatism bias is a mistake in information process where investors value the initial information used to form an opinion but deem new information received after the opinion is formed that may be conflicting as not important. In other words, investors put too little weight on relevant information and underreact as they look as if they are just regular evidence. An example of a model in this setting is by Barberis et al. (1998). In their model, investors mistakenly assume a wrong asset pricing model based on a few realisation of earnings data that occur by chance. They detected a pattern and assumed it to continue into the future. That means they suffer representativeness heuristic. Alternatively, if investors hold a certain incorrect model to be true and fail to revise their model based on recent realisations of earnings, they would have suffered conservatism bias. When investors conduct their trades based on a false model, their price predictions could be incorrect. This mispricing is a bubble, and it will continue until the investors revise their pricing model once they have accumulated sufficient evidence that they have made a mistake. In other words, the bubble would collapse when the sentiment is reversed. Besides, a strong negative signal could also lead to a burst of the bubble. For instance, stock market crash in 1929 may have acted as a negative signal for real estate market (Nicholas and Scherbina, 2013).

Regarding a comparison between these four behavioural models, there are several similarities as well as difference among them. For instance, Model 1 with heterogeneous beliefs among investors and short sale constraints could only result in positive bubbles, while both positive and negative bubbles are possible for the other three models. Secondly, Model 1, Model 3 and Model 4 are more appropriate for assets that are difficult for valuation and judgement is critical, but Model 2 could also work with more basic assets. Thirdly, the accompanied trading volume can be conjectured for Model 1 and Model 2. However, the same is not possible for Model 3 and Model 4 as the investors could be aggregated into representative agent settings. Finally, Model 3 would only produce a result in the form of overreaction, while Model 4 could yield a resulting bubble with initial underreact and then overreaction.

2.4. Limit to Arbitrage

Based on efficient market hypothesis, rational investors should take advantage of arbitrage opportunity when prices deviate from fundamentals and bubble cannot survive. Even with the existence of behavioural investors, when sufficient amount of short sales by arbitrageurs attacks the bubble, it would be undone. However, there are plenty of evidence against this prediction. Sophisticated investors like hedge funds were found to be participating in the bubbles, instead of correcting the mispricing, during the 1990s (Brunnermeier and Nagel, 2004). Xiong and Yu (2011) also discussed a bubble in Chinese warrants in the late 2000s. Assuming a case of bubble existence has been established, the literature on limits to arbitrage offers explanations on what might prohibit arbitrageurs from breaking the bubbles, apart from constraints from regulations on short selling.

The first channel is the fundamental risk. Fundamentals may have changed positively such that the asset is no longer overvalued. Availability of close substitutes or other assets that are not overvalued but closely correlated to the bubbly asset is also an issue. The lack of such instrument would complicate the hedging strategy.

Secondly, rational investors also interact with other behavioural investors who suffered psychological biases or noise traders. These irrational traders may keep pushing the price up further and cause the price to deviate from fundamental value even further. In other words, bubbles may continue to grow instead of collapsing. In that case, arbitrageurs would incur losses and may even have to cut back on their investments to meet margin calls. Shleifer and Vishny (1997) discussed how money managers are affected by these short-run price movements in terms of possible fund outflows. Consequently, they might trade less aggressively against the bubbles.

Thirdly, as each investor represents only a small fraction of the total investment in the market, breaking the bubble requires coordinated efforts. Abreu and Brunnermeier (2003) considered a bubble model without a synchronisation mechanism for arbitrage attack. The model assumed sequential awareness of bubble existence by investors. This means each investor does not know what others know or how many of them have already recognised of the bubble. This lack of common knowledge dismisses the argument against the existence of bubble using backward induction process. Also, there is a trade-off faced by each player. If they attempt to bring the price down too early, they miss out on a further potential upside. However, if they are too late, they would suffer from the crash. The result is that rational investors could decide not to trade against the bubble since it is to their advantage to participate in the bubble for some time before breaking it in the end. The time it takes before the arbitrage is exercised depends on the level of disagreement among investors, and the size of investors required to attack the bubble successfully.

Finally, arbitrage against bubble could be costly. When new information about the asset was difficult to interpret, it can lead to a mispricing. Investors have different skills and knowledge, and they might evaluate the effect of the new information on the fair price differently. This information asymmetry means individual investors who correctly observed that price are overvalued and decided to attack the bubble may encounter liquidity issues, and trading costs could be high. Moreover, as arbitrageurs typically trade with large volume, they risk eliminating or reducing potential profits. Therefore, they may decide to defer their actions under bubbles burst by other exogenous factors, especially when the growth rate of the bubble is high and they can still enjoy the price surge.

2.5. Policy Implications

One of the most important aspects of bubble analysis is about policy implications. The issue is whether government inventions are required. Many authors supported the role of the government or the central bank in deflating or, failing that, breaking the bubbles. However, bubble identification cannot be with sufficient accuracy. For example, some economists argued that asset prices are consistent with distributions with fat tails. Moreover, policy makers do not have superior information and face the same uncertainty encountered by market participants in terms of detecting and predicting the future of bubbles. Moreover, any errors in interpretation will only be confirmed ex-post. In any case, Meltzer (2002) pointed out that a collapse of a bubble does not need to be followed by a recession. Economic policies could still be useful. Specifically, expansionary policies after the decline of the Nasdaq index in 2000 helped offset the resulting economic downturn in the US. Nonetheless, there are doubts whether the extended use of such policy could be provoking the next bubble in asset price (Jones, 2014). Meanwhile, Scherbina (2013) suggested several initiatives, such as removal of short sale constraints and limited liability incentive structure by exposing investors to downside risks as well, or providing better financial education to reduce irrationality.

2.6. Experimental Approach

An alternative approach to the mathematical modelling of a bubble is the experimental approach. It directly investigates different factors affecting investor behaviour in artificial market settings. Several simulations were conducted with the different focus on various conditions based on the pioneering work of Smith et al. (1988). Researchers attempt to assess the size of the bubble and the probability of bubble initiation based on a particular aspect of the setting while keeping other conditions constant. The main weakness of this methodology is the issue of how the findings obtained can be related to real world asset markets since the participants might be influenced by the specific circumstances set in the simulation (Komaromi, 2006). That is, they might act differently in their real life outside of the laboratory. Given the possible distortions, the evidence still reaffirms some of the factors for bubble formation discussed in the literature. For instance, bubble in assets with fixed maturity is possible. Moreover, investors are prone to mistakes, for example, in their discounting calculation, and may not make every decision rationally. Besides, the fact that bubbles do not disappear quickly implies participants might assume that not everyone is acting rationally. Lastly, bubbles were also found to be accompanied by high trading volume and high volatility of price relative to fundamentals, which is consistent with the existence of feedback traders.

In general, the findings from several experiments revealed that there are two groups of factors determining the bubble formation. The first type is the uncertainty factors. The lack of common knowledge of rationality causes players to ride with the bubble, instead of breaking it (Lei et al., 2001). This is consistent with the investors assuming the existence of other noise traders which may allow them to resell the asset at a higher price in the future. The inclusion of experience players helped eliminate or reduce the number of bubble incidents as well (Dufwenberg et al., 2005). The uncertainty caused by the lack of information regarding the number of rounds the experiment is to be conducted was also found to lead to higher price deviations from the fundamental value (Stanley, 1997). Finally, if transaction information, such as the bid-ask details, are not provided, that also coincided with a larger bubble (Caginalp et al., 2001). The second set of factors involves liquidity. Caginalp et al. (2001) also documented the impacts of initial cash relative to price, and the liquidity caused by whether dividends are paid immediately or deferred on the size of the bubble. However, the evidence on the effect of short sale constraints was mixed. Ackert et al., (2002) concluded that permitting short selling resulted in price closer to fundamentals, while Haruvy and Noussair (2006) found that relaxing short sale constraints did not make the market more efficient.

2.7. Literary Approach

The previous sections reviewed the mathematical approach including rational and behavioural bubble models and the experimental approached. They examined deviations of actual price from the fundamental value and how a bubble of an individual asset could occur. On the other than, the literary economics is the third approach that considers the same phenomena but with a broader perspective of why a bubble in the whole market emerge and what its impacts on the economy are. Rather than analysing quantitatively, this approach discusses bubbles in more qualitative terms. The main tools employed in the literary approach include historical examples and comparisons of their similarities.

The typical development of a bubble process starts with the assets, or the economy experiences a positive shock which leads to a distinct price rise for an extended period. Uninformed investors, troubled with deducing the causes of the price change, interpret the initial price increase as a positive sign and expect it to continue with a further rise. The particular stocks or sectors then attract more and more of buyers to participate in the market. Most of the investors do not aim to receive dividend payments but rather speculate on the capital gains. The increase in activity of these new players is accompanied by a surge in trading volume. The existence of feedback traders, together with information asymmetry, magnify the influence from noise trading before the eventual collapse. In addition, economists generally only refer to a period of a stock market bubble when the probability of a sudden reversal in price pattern grows and that real macroeconomic impacts or regulatory changes are observed after the crash.

The literature chronicled many incidents of bubble episodes. Detailed discussions can be found in, for instance, Galbraith (1994), Kindleberger and Aliber (2005), Komaromi (2006), and Scherbina (2013). The famous examples include the Dutch tulip bulb bubble in 1634-1637, the South Sea bubble in the UK and the French Mississippi bubble – which are often considered as the first stock market bubbles – in 1720, the Latin American debt boom in 1820s, the railway manias in the UK during 1840s and the US during 1870s, the so-called Roaring Twenties in the US ending with a big crash in 1929, the rise in bank loans to Mexico and other developing countries in the 1970s, the bubbles in equity and real estate markets in Japan, Finland, Norway, and Sweden during 1980s, the collapse of the US equity price in 1987, the rise in foreign investment in Mexico during 1990-1993, real estate and stock market bubbles in Thailand, Malaysia, Indonesia, and many other Asian countries in 1990s, the bubble in real estate and the dot-com bubble ending in 2000, and the recent subprime mortgage crisis in the US starting from 2008. It suffices to say the main feature of the stock market bubbles is arguably the crash, which is normally caused by a change in investor behaviour. However, the review of these notable examples did not show a causal relationship between a bubble and a crisis, although they tend to coincide. There were cases where the economic crisis overlaps or precedes a bubble collapse, while a burst of a bubble could worsen the crisis, in other occasions. Moreover, the market participants generally regarded a period of excessive speculation as a bubble. However, the literary approach to bubble does not offer a definite conclusion on conditions for qualifying such episode, which led to the difficulty in identifying a stock market bubble and separating it from other phenomena.

Still, there are certain traits commonly found before the eventual stock market bubble crash. A collapse of the stock market bubble is typically not caused by the arrival of new shock, or that price has reached a certain level. Rather, it mostly happens due to a radical change in investor behaviour which is usually when noise traders dominate the market. Komaromi (2006) listed several signals that could point to the intensification of noise trading. The indicators include the use of leverage, an increase in policymakers' activity, the incidents of corporate scandals, frauds and corruptions, and unjustifiable co-movement of prices.

Finally, as mentioned earlier, stock market bubbles typically refer to the boom with the eventual collapse which have lasting impacts on the economy. The obvious consequences of a crash are a possible economic recession, and consumption and investment decline in the short run. In the longer run, however, there could be positive impacts in terms of institutional or regulatory advancements or developments of better financing systems, which could lead to better resource allocation and economic growth.

2.8. Empirical Evidence

2.8.1. Test of Bubble: Overview

Economists have been fascinated by the notion of bubbles for a long time. Several strands of models were developed since the 1980s and early 1990s (Daoud and Antolin-Diaz, 2014). The majority of the studies focus on the detection of the rational bubbles. That is when investors expect asset price to go up even higher and, consequently, are willing to pay above the value warranted by discounted future dividends. This pricing will still be considered as rational if there are no arbitrage opportunities. Examples of influential survey papers include West (1988) and Camerer (1989).

Essentially, most bubble tests examine whether the standard asset pricing model is valid. In cases where the assumption is refuted, they investigate whether it can be reconciled with the existence of bubbles. Since the seminal paper by Shiller (1981), numerous methodologies have been proposed to infer bubble-like behaviour in equity, commodities, and currency markets and in other macroeconomic time-series. There is no standard convention on how to categorise them. As a start, they can be separated roughly into indirect and direct tests.

Asset prices are assumed to behave in certain ways in the absence of a bubble. They can be used to test for the presence of bubbles indirectly. More specifically, indirect tests identify bubbles by assessing distributions of fundamental values, actual prices, or returns (Blanchard and Watson, 1983; LeRoy and Porter, 1981; Shiller, 1981), conducting cointegration test of fundamental values and actual prices (Campbell and Shiller, 1987; Diba and Grossman, 1988), or evaluating hypothesised and actual relationship between dividends and prices (Dezhbakhsh and Demirguc-Kunt, 1990; West, 1987). As these tests rely on having the correct present value model in the first place, they are occasionally regarded as providing only clues, rather than solid evidence of bubbles. In contrast, direct tests specify a particular form of a bubble and assess how it fits with the actual data. The specifications are, for instance, deterministic bubbles (Flood and Garber, 1980) or periodically collapsing speculative bubbles (Bohl, 2003; van Norden and Schaller, 1993).

Regarding the empirical evidence, the literature offers mixed conclusions, although there tend to be more papers supporting the existence of bubble than against it (Anderson and Brooks, 2014). However, none of the tests can convincingly prove or refuse the presence of bubbles (Flood and Hodrick, 1990; Jones, 2014). This is because they cannot satisfactorily differentiate between bubbles and misspecified fundamental values. That is, as pointed out by Evans (1991), the tests only have power against certain bubble types. While some of them might be able to illustrate that the data do not support the notion of a bubble in some aspects, but those that reject the null hypothesis of the present value model cannot do so in a manner that bubble explanation is the only alternative. Gürkaynak (2008) concluded that, for every proposed test, there is always a paper that challenges it, and this is not just a theoretical issue.

Many tests reach their conclusions by ruling out possible explanations of asset price movements, before inferring whether a bubble exists. However, this approach may not be valid. The issue is referred to as the joint hypothesis problem. It means the test combines both the hypothesis of having a correctly specified present value model and the bubble hypothesis. The fundamental value models are subject to misspecification, as they are often based on unobserved estimates. When a test rejects a particular model, it does not automatically imply the presence of a bubble, as there might be other alternative models. In other words, it could be mistaken to presume a bubble exists, as it may well be just a catch-all or a residual of what not captured by the reference model. Moreover, many models were built on concepts of equilibrium prices in an efficient market, which is a very controversial topic on its own.

Other issues for the bubble detection tests include the fact that bubble crash is taken to be exogenous. For example, many models assume it could be caused by the change of investors' beliefs that the bubble will no longer survive (Anderson et al., 2010). Most tests impose very little structure on the bubble process and do not produce a time series of the bubble term, which prohibit assessment of its properties (Gürkaynak, 2008).

Furthermore, the tests may have to overcome many estimation and measurement issues, such as small sample size distortion, estimated coefficients' stability, quantifying irrational behaviour (Jones, 2014). Thus, the development of tests – especially, for real-time monitoring purpose – was also limited by the advancements in econometrics techniques.

Moreover, as pointed out by Meltzer (2002), the rational bubble tests did not generate convincing results because there may be other unobserved variables. They include, for example, investors' rational expectations – such as anticipated inflation, the possibility of joining an integrated market like the European Monetary Union, or a change in economic structure (Daoud and Antolin-Diaz, 2014).

Apart from the difficulties dealing with measurement and inference problems, one last issue of bubble test for policy purpose is about the threshold. There are still ongoing debates with regards to how large the deviations of prices must be for an intervention to be required. Jones (2014) discussed the trade-off between the probability of not foreseeing the coming bubble collapse (Type I error) and the likelihood of observing too many false warnings of bubbles (Type II error). However, a price correction can still take place even if the bubble is not detected. For instance, when investors form overly optimistic expectations of future growth, and it later appears to be no longer viable, the share price could return to the previous level. In other words, failing to detect a bubble does not guarantee no risk of a large price drop (Daoud and Antolin-Diaz, 2014).

It may seem that bubble tests are not very informative about whether the bubble definitely exists. Many stylised facts about asset pricing have been discovered in the process. For example, the variance bounds tests show that there is something more volatile what is already included in the standard present value model. Non-linearity and possible regime-switching nature of fundamental values were detected with papers investigating intrinsic bubble and collapsing bubble (Gürkaynak, 2008).

Finally, it is important to note that the methodologies surveyed in this review are tests of rational bubbles. More recently, the behavioural approach offers an alternative set of models that allow for irrational bubbles. Vissing-Jorgensen (2004), for example, discussed such models.

The following sections will elaborate and critically review the different types of bubble tests applied in the literature. They include variance bounds or excess volatility test, West's two-step approach, cointegration-based tests, intrinsic bubble test, regime-switching models, bubble premium test, the test based on the change of persistence, and quantity-based test.

The final section discusses the importance of analysing data on the different level of aggregation, namely, market index, and sectoral or firm-level data.

2.8.2. Bubble Premium Test

In general, asset returns comprise of the risk-free return, the risk premium which rewards investors for the asset-specific risks they assume, and a random disturbance. With the presence of bubbles, the asset return will be even higher to compensate for the additional risk of bubble exploding. The excess return is referred to as bubble premium.

Hardouvelis (1988) split sample period 1977-87 into two samples at 1985 and used the first sample as a base to calculate bubble premium in the second sample. His analysis picked up excess return before the crash in 1987. However, with this methodology, he implicitly assumed that absence of a bubble in first sample and stability of parameters across two samples, which were unproven (Brooks and Katsaris, 2003a). Rappoport and White (1993) indirectly tested for bubble premium by investigating the interest rate and deduced that there was an increase in market risk in 1928 and 1929. However, the conclusion was challenged by Liu et al. (1995) as the similar phenomenon was observed in 1919-20 and the market did not experience a bubble collapse. They also indicated that the premium detected was influenced by the change in monetary policy, and there was no bubble in 1929 when that was controlled for. Wu (1997) used a model with the bubble as an unobserved variable and found that it influences stock prices, but Gürkaynak (2008) argued that it was a catch-all for model misspecification. More recently, Anderson and Brooks (2014) developed a cross-sectional regression model based on Fama and French (1996) to include bubble risk and found supports for the presence of a bubble in the UK stock market.

2.8.3. Variance Bounds Test

Tests of bubble premium had encountered some critical issues and could not offer conclusive evidence whether bubbles exist. One of the alternative methods is to assess the assets' return variances and check for excess volatility. Shiller (1981) and LeRoy and Porter (1981) initiated this approach. The test compares the variance of actual prices with the variance of fundament prices which were typically computed using ex-post data and observed whether the observed prices were too volatile to be justified by dividend flows. As the actual prices are only determined by expected dividends and not their forecast errors, the ex-post rational price should be at least variable as the actual prices. The violation of this theorised relationship suggests rejection of the standard present value model, and, thus, could also be interpreted as a sign of a bubble, although the tests were not initially intended to be used for bubble detection.

In terms of empirical results, Shiller wrote a seminal paper rejecting efficient markets model based on U.S. stock data. Shiller (1981) showed that volatility of actual prices exceeds the bound imposed by the variance of the fundamental prices. LeRoy and Porter (1981) also arrived at the same conclusion that the standard present value models do not hold. The main difference between the two papers was that the former only produced a point estimate while, the latter views prices and dividends as a bivariate process which allows for construction of standard errors as well (Gürkaynak, 2008). In contrast, Dezhbakhsh and Demirguc-Kunt (1990) analysed volatility of fundamental values based on dividends series forecasted with an ARMA model and found that both sets of price had the same volatility. Thus, the no-bubble hypothesis cannot be rejected.

Overall, the test type offered additional indirect evidence, which was generally in support of the existence of bubbles (Brooks and Katsaris, 2003a). However, its actual implementation is problematic, and its validity was not without disagreements. Gilles and LeRoy (1991) surveyed the literature and discussed several concerns. The first issue is about the terminal price. As dividends are not realised out to infinity, the ex-post rational price is never observed. Shiller (1981) approximated a terminal price by sample average of de-trended real price. However, that proxy is unreliable since the cut-off period is chosen arbitrarily. Also, it implies some strong assumptions, such as the market is efficiently pricing the future dividend flows when it might actually contain bubble and will not be detected, or the dividend process would remain unchanged throughout, which could potentially lead to wrong inference about the presence of bubble (Marsh and Merton, 1986). Flavin (1983) showed that it would be biased towards rejection in small samples and proposed the use of last observed price instead. However, that approach is also not suitable as a test of a bubble, because the bounds will not be violated when there is a rational bubble, and thus, not detected (Mankiw et al., 1985).

Secondly, the original test was based on a constant discount rate, which means it unrealistically assumed investors' risk preference and market risk to stay the same through time. When this assumption is relaxed, the results are more ambiguous. For instance, Cochrane (1992) explored whether there is a discount rate that would justify the dividend and price volatility. The finding showed that there exists a time-varying process that would fit the data without having to resort to bubble explanations.

Next, Flood and Garber (1980) asserted that excess volatility tests are unreliable on the basis that the fundamental prices are misspecified, as they were based on information set different from one used by investors, and relevant variables were not included. Moreover, the variance estimates are biased because dividend and price are not stationary (Marsh and Merton, 1986).

Lastly, the violation of variance bounds can be caused by, not only misspecification of the fundamental price but also by the irrationality of investors (Kleidon, 1986). Moreover, the same paper also pointed out that the cross-sectional variances, not time-series estimates, should be tested and the non-stationary time-series could lead to observed results of excess volatility.

2.8.4. West's Two-step Test

Although they are related, the test of a bubble and the test of the present value model validity are slightly different undertakings. As discussed earlier, the joint hypothesis problem means it cannot be automatically inferred that there is a bubble when the present value model fails. A good bubble detection test should at least have a bubble explanation explicitly included in the alternative hypothesis. The first of such test was West (1987).

West proposed a test derived from the fact that parameters required for the calculation of price from expected dividends can be obtained from two different ways. His insight was that the Euler equation based on consumers' optimisation problem could be estimated on its own to produce an implied discount rate, which can, in turn, describe the theoretical relationship between prices and dividends. This analysis is independent of the existence of a bubble. On the other hand, the relationship between actual prices and dividends, which could be affected by a bubble, can also be estimated. In the absence of bubbles, the actual and the constructed relationships should be the same and, hence, the two estimates are expected to coincide. West used the Hausman specification test to determine whether they are different. If the discrepancy between the two estimates is found, specification tests can also be applied directly to the Euler equation and the dividend process assumed. If misspecification of the models is dismissed, evidence of bubble will be supported. West found that no-bubble hypothesis is rejected with the US stock data.

Although it is very appealing conceptually, there were some concerns with this methodology. Firstly, Gürkaynak (2008) showed that this test will only identify a particular type of bubble which is correlated with dividends. He also pointed out that the set of information included in the expectation of future dividends by investors may be different from what is assumed in the dividend process. Moreover, it is not feasible to test for all possible specification to give a definite evidence of a bubble. Flood et al. (1994) indicated that the test could have picked up the influence of other factors, such as how investors assign a probability of large impact event like a tax law change (Flood and Hodrick, 1986) or other expected regime change that did not occur. They also questioned the validity of the Euler equation with risk neutrality and constant discount rate assumed. Indeed, when the time-varying discount rate is allowed, evidence of bubbles is less clear-cut (Gürkaynak, 2008). The next issue is stationarity. As non-stationarity would affect the test and it is difficult to detect with reasonable certainty, the test should be conducted with data both in levels and differences. Finally, Dezhbakhsh and Demirguc-Kunt (1990) challenged the test on the basis of small sample distortion and developed an alternative test which considered small sample properties and found no evidence of bubbles.

2.8.5. Non-stationarity and Cointegration Tests

Even though bubble theories suggest that bubbles have explosive nature, the earlier tests did not exploit this knowledge. Specifically, West's test eliminates other alternative explanation in order to identify a bubble, while the variance bounds tests simply showed that there is something other than the fundamental factors. There were other authors who developed tests based on concepts of stationarity and cointegration.

Diba and Grossman (1988) examined the present value model with unobserved fundamentals and analysed whether the deviations from fundamentals can be attributed to a bubble. Precisely, as the stock price is determined by future dividends, when there is no bubble, both should have the same level of stationarity. That is, if dividends are stationary in levels, then price should also be stationary in levels, or, if dividends are stationary after differencing *n* times, the price should be stationary after differencing *n* times as well. However, the relationship will not hold, when there is a bubble. This suggests a natural way to identify a bubble, which is by testing whether the price is more explosive than dividend process. On the other hand, the present value model also suggests an equilibrium relationship between price and dividend. That means, even if they are non-stationary, they will be cointegrated. Then, if they are cointegrated, the bubble hypothesis is not supported. So, testing for cointegration between price and dividend flows is another way to detect a bubble.

Diba and Grossman applied the Dickey-Fuller unit-root tests to both prices and dividends as their first test of a bubble. The result was that they are difference stationary, which implies that bubble was not present in the data. They reaffirmed the result by conducting the cointegration tests which found evidence of cointegrating relationship between the two series and concluded that the bubble hypothesis can be rejected. Donaldson and Kamstra (1996) constructed fundamental prices based on nonstationary, non-linear discount rates and dividends and expected dividends forecasted with ARMA-GARCH, Artificial Neural Network model, and showed that they seemed to replicate to actual price observed in the U.S. stock market in 1929; thus there was no bubble. They also checked the series for cointegration and the result showed that they are cointegrated. Therefore, the no bubble hypothesis was not rejected. In contrast, Campbell and Shiller (1987) presented evidence that the linear combination of prices and discounted dividends is not stationary and that there may be bubbles, although they warned that the methodology is very sensitive to the discount rate. However, Campbell and Shiller (1988) discovered weak cointegration between prices and dividends. This shows how unreliable the evidence of a bubble is. Moreover, Fama and French (1988) argued that price is stationary in the short run, but it could change in the longer time frame. This was partly because asset price is more predictable in the long run, but also that there could exist collapsing and regenerating bubbles that were not detected. Finally, Brooks and Katsaris (2003a) investigated explosive bubble in the London Stock Exchange with the cointegration test, and reported that prices were driven, but other factors did not have an equilibrium relationship with dividends in the late 1990s. They suggested it could potentially be a speculative bubble.

There are certain issues when interpreting results from this approach. Firstly, its validity is greatly questioned, due to difficulties testing stationarity and detecting cointegration between variables. The econometrics literature offers many competing methodologies with differing properties and power, and they do not always give unambiguous results. Worse, there is also an issue of small sample distortion. The study of Diba and Grossman included less than 100 observations, which the Dickey-Fuller tests would not give reliable results (Evans and Savin, 1984).

A very influential criticism of this test was presented by Evans (1991). Although the paper did not prove the presence of a bubble, it illustrated that the standard unit-root tests are not sufficient to reject the bubble hypothesis. In a simulation study, Evans showed that the tests would not detect prices containing periodically collapsing bubbles. Because the collapsing feature makes it mean-reverting over time, and, hence, does not appear explosive, but rather like stationary process. Moreover, cointegration tests have low power against intrinsic bubbles whose development is tied to dividend process. Therefore, when the test fails to reject the no-bubble hypothesis, it does not mean that the data is free from a bubble. However, it would rule out any monotonically increasing bubbles (Gürkaynak, 2008).

On the other hand, lack of cointegration does not prove the presence of bubbles as the model could be misspecified in some aspects by excluding other factors or making unrealistic assumptions. For example, Craine (1993) showed that discount rate for the S&P500 has unit-root. So, even if dividends are stationary, actual prices will not be stationary. Therefore, when the test suggests the existence of a bubble, it actually indicates there is something else non-stationary, which may or may not be a bubble.

After the critique by Evans (1991), there were many subsequent attempts to improve the usefulness of the test. However, there was no agreement regarding methods or results. Taylor and Peel (1998) proposed a cointegration test that would be robust for a collapsing bubble and found that bubble did not exist in their data. Wu and Xiao (2008) developed a test based on an insight that although residuals from periodically collapsing bubbles would be stationary, they would still be large. They also did not find evidence of a bubble.

One of the most popular techniques to model for periodically collapsing bubbles was to allow for regime switches. Some examples of papers include van Norden and Schaller (1993), Driffill and Sola (1998), Hall et al. (1999), Bohl (2003), and McMillan (2007). This type of studies will be discussed in the following section.

2.8.6. Regime-switching Test

Motivated by the Evans critique regarding collapsing bubbles, many regime-switching models were built to explain the relationship between prices and dividends, and possibility of bubbles. Several papers adopted the Markov switching process, for instance, Hall et al. (1999) considered Evans' collapsing bubble as a separate regime with constant probabilities of switching, while others analysed bubbles with other functional forms, for example, van Norden and Schaller (2002) (hereafter VNS).

The origin of the VNS model started from Blanchard (1979) and Blanchard and Watson (1982). They constructed a speculative bubble model such that in each period, the bubble may survive and continue to grow into the next period with a constant probability q or completely burst with probability $1 - q$. With the Blanchard and Watson model, a couple of very restrictive assumptions were imposed, and VNS attempted to fix them. Firstly, the bubble was assumed to disappear abruptly when it crashes. VNS allowed for partial collapses, which means a bubble may deflate over a period of time, and that bubble could regenerate or there could be more than one bubble in the series. And, secondly, the probability of bubble surviving was assumed to be constant. VNS formulated that it would depend on the absolute size of the bubble, which suggests a time-varying probability and a possibility of a negative bubble was also permissible. Using the U.S. stock market data, they found support for their regime-switching model and evidence of bubbles.

Still, the probability of collapse was assumed to be dependent only on the bubble size. However, bubble deviation could be prolonged before it crashes. Brooks and Katsaris (2003b) and Brooks and Katsaris (2005a) extended the VNS model by including the abnormal volume term as an indicator of a collapse, in order to form trading rules. Anderson et al. (2010) applied the volume-augmented model with S&P500 series and presented evidence of bubble-like dynamics in the S&P500 as a whole, as well as, several sectoral indices. In addition, Brooks and Katsaris (2005b) further relaxed the assumption that a bubble had to always be explosive and extended the model by allowing for a third regime where the bubble only grows steadily in the dormant state.

Another modelling technique adopted by McMillan (2010) was the asymmetric logistic smooth-transition (LSTR) model. He claimed that the approach offers improvements in three ways. Firstly, McMillan argued that rational bubble model could not explain how a bubble initially forms, while his research allows for either rational or non-rational grounds. Secondly, the LSTR model permits more than two regimes. More specifically, it includes two extreme regimes and one transitional phase. Lastly, unlike VNS sudden change between regimes, the transition in the LSTR approach is smooth and observable. Investigating UK sectoral indices, he concluded that there was evidence in support of bubbles in the majority of sectors.

Moreover, under the two regimes, the bubbles behave very differently. That is, when the bubble is small, the price is close the fundamental value. Changes in dividends affect the asset return, as predicted by the present value model. Also, when this small bubble increases, the next-period return will be higher too. This market sentiment shows the confidence of investors, which could potentially be an over-confidence as well. In this regime, it is interpreted as the fundamental traders dominate.

A different behaviour was observed when the bubble is large. The estimated coefficients for dividend yield were small and largely statistically insignificant, suggesting no relationship with fundamentals. That is, prices were disconnected from dividends. By then, the market was dominated by noise traders. In fact, the fundamental traders would foresee and take advantage of this situation. More specifically, when there is a positive news regarding dividend development, it would warrant a price rise. However, as fundamental traders are aware that the noise traders would chase the trend, they push price up beyond what can be justified by the initial news, and start selling when noise traders began to be active. In other words, the fundamental investors would, in fact, ride the bubble and destabilise the market. Furthermore, in some case like the Technology and Telecoms sector, the estimates of dividend yields on returns were unexpectedly negative. This suggests that investor might be concerned about the possible collapse of the bubble and start offloading the asset which pushes the price down.

On the whole, the regime-switching tests also face problems. van Norden and Vigfusson (1998) compared the performance in detecting tests periodically collapsing speculative bubbles of the models proposed by Hall et al. (1999) and van Norden and Schaller (2002) and concluded that size distortion was occasionally found even with hundreds of observations. Furthermore, they also pointed out the issue of the exact switching process, since they observed that both models have significant power, even though the former assumed a constant probability and the latter assumed it was determined by the bubble size.

2.8.7. Intrinsic Bubble Test

Generally, bubbles do not have to be correlated with fundamentals. They are only required to grow at the rate $(1 + r)$ to be consistent with the no-arbitrage condition. If they do not, the deviations from fundamentals will have explosive nature. In contrast, there is a large category of bubbles that are assumed to have the same evolution with the expected dividends. As the process of this bubble depends completely on dividends, it will not just rise independently, and, consequently, will not be detected by many tests. These bubbles are referred to as intrinsic bubbles.

Froot and Obstfeld (1991) proposed one such setup. To tie bubble to fundamentals, they explicitly modelled the dividend process as a random walk with drift. Given the standard present value model, prices are a linear combination of expected future dividends. Alternatively, when there is an intrinsic bubble, prices would be extra responsive to any change in dividends. That is, intrinsic bubbles cause the relationship between prices and dividends to be non-linear. The behaviour of the price/dividend ratio will be different as well. Specifically, it would be a constant in the absence of a bubble, and it will be a function of dividends when there is a bubble. Froot and Obstfeld used this understanding to develop a test for intrinsic bubbles. It was done by estimating a regression of price/dividend ratio on a constant and dividends. If the estimated parameter of dividends is found to be statistically significant, that will suggest a non-linear relationship between prices and dividends. In other words, it would point to the existence of a bubble. However, if only the constant term is found to be statistically significant, it would imply there was no bubble.

Froot and Obstfeld reported a statistically significant and positive value for the estimated coefficient of dividends, which indicates that the data may contain a bubble. However, they cautioned that the evidence was not conclusive as other explanations were possible as well. Gürkaynak (2008) explained that the result only showed that there is non-linearity in the relationship between prices and dividends. It could be interpreted as a bubble because the model was assumed to be linear. However, it is possible the true relationship between them is non-linear. In fact, a remarkable example is Driffill and Sola (1998) who incorporated both regime-switching fundamental and intrinsic bubbles into their analysis. They found that the explanatory power of the combined model was low, but the model with just either the regime-switching feature or the intrinsic bubbles worked equally well.

On a separate note, Gürkaynak (2008) also pointed out that West's test actually investigated bubble that is correlated with dividends as well, but Froot and Obstfeld imposed more structure on the bubble process.

2.8.8. Test based on Change in Persistence

Bubbles represent deviations from the fundamental price. When they exist, prices would contain an explosive component in them. Some researchers have exploited this intuition and attempted to identify episodes of a bubble by detecting the change in characteristics of price/dividend ratio from a random walk to an explosive phase, which is a higher degree of non-stationarity. This type of bubble detection procedure derived from the literature on change-in-persistence tests developed by, for example, Kim (2000) and Busetti and Taylor (2004). The change-in-persistence test assessed between the hypotheses of time series being stationary the entire period or that it change between being stationary and non-stationary. Examples of papers with this approach are Phillips et al. (2011) who employed sequential unit-root test to timestamp the start date of bubble formation and reported a bubble in the Nasdaq index at the end of the 1990s, and Homm and Breitung (2012) who compared different bubble detection tests based on classic break date tests and presented evidence of bubbles in several markets.

The tests based on a change in persistence have some advantages over the other conventional tests. Firstly, the most obvious benefit is that the old approach could only tell whether there was any trace of a bubble in the data series, while the change-in-persistence bubble tests would be able to estimate the time when the bubbles start and burst. In other words, it offers live monitoring capability as well. Secondly, although the other tests may fail to detect the periodically collapsing noted by Evans (1991), these new bubble detection test with the sub-sampling or break-test procedures, will be able to do so. Finally, the classic tests would require approximation of the price/dividend ratio by converting into logarithms. In contrast, the bubble test based on change-in-persistence can be formulated to test data in levels and do not have to face uncertainty whether the relationship of the logarithm of the price/dividend ratio is a good approximation, for example, a version of the test by Phillips et al. (2013).

However, there are also points of concern, such as, even when the test shows no evidence of a bubble in a certain time, a bubble can always start in a relatively short period. More importantly, Homm and Breitung (2012) showed that the number of breaks caused by episodes of a bubble is also a critical issue. Tests have different power based on assumption. Specifically, a sequential Chow test and a modified version of Busetti and Taylor (2004) had the highest power when only a single switch is assumed, while the Phillips et al. (2011) procedure was the most robust when multiple phases of bubbles were allowed.

2.8.9. Quantity-based Framework

All the test discussed so far have been based on price or return of assets. However, as noted by Jones (2014), not only the volatility of risk premium or the require rate of return, but also changes in other non-price information were observed during some of the largest booms and busts in the history of asset markets. Therefore, he argued that the quantity data should also be considered to enhance understanding asset price behaviour and detect for signs of bubbles, particularly in four aspects: quantity and quality of issuance, trading volumes, fund flows, and investor surveys.

Firstly, Myers and Majluf (1984) put forward the pecking order theory which suggests the management of the firm have and will exploit their information advantage as an insider. That is, they would choose to issue new securities to raise capital over other alternative methods of financing when they consider the cost of capital to be low or that prices are high relative to fundamental value. Thus, quantity and quality of issuance could be a sign for overvaluation. Secondly, abnormal trading activity should also be watched as trading frenzy was seen in practically every episode of asset price bubble from the Tulipmania in 1620 to the dot-com bubble in the late 1990s and the recent housing bubble in the U.S. market. Thirdly, Jones presented evidence of trend chasing in the asset market, where the positive correlation between asset returns and fund flows were witnessed. More specifically, debt and equity returns in emerging market appeared to lead fund flow by one quarter. Therefore, the pattern of investor fund flows is another tool to monitoring bubble evaluation as well. Finally, surveys of return expectations show how investors estimate future returns and measure market sentiment. It must be included in the surveillance framework too.

2.8.10. Test based on Co-movement of Price

When investors herd after each other and trade with positive feedback, meaning buying an asset with a high previous return in hopes for the price to continue even higher, their opinions are converging and so do prices of different assets. Komaromi (2006) proposed monitoring any unjustified co-movements of asset prices, for example, when prices of assets not affected by a common factor begin to move in the same direction, as it implies noise traders are dominating and, thus, a sign of a bubble. This is consistent with, for instance, investors becoming very optimistic about the future during the boom, not able to tell apart good and bad investments, and causing excitements over all assets in a particular market. (Kindleberger and Aliber, 2005). He used the average coefficient of determination (R^2) between returns of a particular asset and the market return as a measure of co-movement. The changes of such time-series show the strength of the level of convergence and periods of high variability would indicate a possible shift towards more non-information trading.

Moreover, Komaromi also explained that co-movement is mainly determined by the level of market maturity. Markets that are less-developed, not so integrated, and have weak corporate governance, tend to not attract many institutional investors like investment funds or hedge funds and the information content in prices will be limited. Investors would consequently have to trade with more noises. Thus, in such a market, using co-movement index as an indicator of possible bubble collapse is probably appropriate. However, a more complexed index might be required for more advanced markets.

2.8.11. Results on Data with Different Level of Aggregation

As discussed previously, the empirical evidence of bubble detection tests is extensive. However, a majority of them assessed the market-wide index. Recently, an increasing number of papers has looked into more disaggregated data. Examples of studies based on sectoral or industry level include McMillan (2010) and Anderson et al. (2010), while investigations on firm-level were conducted by Nasseh and Strauss (2004), Goddard et al. (2008), and Anderson and Brooks (2014).

Utilising disaggregated data not only let researchers compare results based on different level of aggregation, but it could help them gain a deeper understanding of how bubbles may be formed, which sectors contain bubbles, and whether it only concentrates on particular grouping, like technology-related stocks. Moreover, it also allows for contagion or transmission of bubbles between different sectors to be investigated.

In general, the results based on index-level data tend to find limited support for the standard present value model, while they are more likely to hold at firm-level. This is because aggregation averages out information from dividends from its constituents (Jung and Shiller, 2005). In other words, it disguises information context of dividends, which makes impacts of any change in individual asset less pronounced and harder to predict. At the same time, that also leads to effects of factors other than fundamentals becoming more significant in determining price movements. Evidence from sectoral-level appears to lie in between (McMillan, 2010).

Anderson et al. (2010) studied the evolution of S&P500 indices and showed that the augmented model that includes effects of the bubble from other sectors is preferred to the standard model. Their test detected bubble-like behaviour in many sectors and not just from the Information Technology (IT) as put forward by popular opinion or as concluded by

Cochrane (2002) that the bubble was concentrated on tech and internet stock. Similarly, McMillan (2010) worked with UK sectoral indices and found that evidence of a bubble, in the form of large and persistent deviations from fundamental values, appeared in most of the sectors, although there exists a long-run relationship between dividends and prices, which means the present value model is also justified.

More specifically, Anderson et al. (2010) concluded that there were strong evidence in favour of periodically collapsing speculative bubbles in Financials, General Industrials, Information Technology and Non-Cyclical Services. They also detected some evidence in the Cyclical Services, Basic Industries and Utilities sectors. Working on data with Datastream's classification system, McMillan (2010) found supports for bubbles in Technology, and Telecoms, as well as, other consumer product sectors like Financials, Health Care, Oil and Gas, and Utilities. Sectors that revealed limited evidence of bubble included Cyclical Consumer Goods, Non-Cyclical Consumer Goods, and Resources (Anderson et al., 2010), or the Basic Materials and Industrials sectors (McMillan, 2010). In other words, the traditional or old-economy sectors seem to be more immune to bubbles.

For evidence of transmission of bubbles across sectors, Anderson et al. (2010) indicated that the Basic Industries, Cyclical Services, Financials, and General Industries are highly responsive, while the highly contagious sectors include the Basic Industries, Cyclical Consumer Goods, Information Technology and Resources. It thus led them to conclude that the linkages were multi-directional. They considered Non-cyclical Consumer Goods and Utilities as relatively isolated. Based on the graphical analysis, McMillan (2010) also discussed the linkages of technology bubbles to other sectors and inferred that it spread to many but not all other sectors. In addition, there was also evidence of the increase of deviation from the fundamental price in sectors with relatively low level of a bubble before the bursting of a so-called dot-com bubble around March 2000. This implies that investors may have recognised that the bubble was collapsing and shifting their investments to relatively safer sectors. A comparable pattern was also observed by McMillan (2010). The Basic Materials and Industrials sectors were regarded as immune from bubbles. However, they led the recovery after the crash in 2000, which suggested fund-shifting activities by investors. These two sectors appeared to contain bubble-like behaviour starting from 2006 and later collapse in 2008.

Lastly, there are also results showing impacts of the market as a whole on the disaggregated data. For instance, the bubble in the market-wide index was found to increase the probabilities of the collapse of the bubble in certain individual sectors. They are the Cyclical Services, Information Technology, Non-Cyclical Services, Resources and Utilities (Anderson et al., 2010). Also, the covariance between bubbles at the individual firm and the market level was found to influence stock returns (Anderson and Brooks, 2014).

Chapter 3: The Thai Stock Market

3.1. Introduction

In the early days of stock trading in Thailand, the activities were initiated by foreign players. Bird Co. Ltd was the first securities brokerage who began operating in 1953. Other companies with similar business were, for example, Houseman & Co., Ltd, Siamerican Securities Ltd., and Z&R Investment and Consultants. However, securities trading in a public market was not very popular at the time. Most activities were done in private dealings. Later in 1962, the Bangkok Stock Exchange was founded by a group of Thai and foreign investors as the first organised stock exchange in Thailand. Nonetheless, it was also with limited success and finally ceased operations in the early 1970s (Stock Exchange of Thailand, 2015a).

Since 1961, Thailand's economic growth objectives and directions have been defined in the National Economic and Social Development Plans. The Second Plan for 1967-1971 included a plan for a new market for securities trading. The Third Plan for 1972-1976 introduced the Stock Exchange of Thailand Act in May 1974. The bill gave rise to the Securities Exchange of Thailand, which started the trading operations on 30th April 1975. The exchange's official name was changed to the Stock Exchange of Thailand (SET) in 1991. Later in 1992, the Securities and Exchange Act (SEA) was enacted to replace the early Stock Exchange of Thailand Acts. The SEA is a comprehensive legal framework for regulating the capital market, including issues of disclosure, investor protection, fund management, takeover procedures, and securities company regulations. It also established the Securities and Exchange Commission (SEC) as the sole supervisor of the securities business.

The SET is a secondary market. It attracts business to be listed on the bourse with the benefit of having an expanded investor base. Once the firm is registered with the exchange, the SET facilitates trading, settlement, and delivery of the securities, as well as, regulates trading, listed companies, and member brokerage firms. It is a self-regulatory organisation which operates under the supervision of the SEC, who is, in turn, overseen by the Ministry of Finance. Moreover, the SET has also expanded operations and included many subsidiary companies over the years. For example, it introduced a computerised trading system and set up the Thailand Securities Depository who offers post-trade services in 1995, and Settrade.com who provides the internet trading platform from 2001. The Market for Alternative Investment (mai) which is the exchange for small and medium enterprises with registered capital more than 20 million baht (approximately US$0.55 million) but less than the required 300 million baht (approximately US$8.3 million) in the SET's main board, the Bond Electronic Exchange (BEX) and the Thailand Futures Exchange (TFEX) are also part of the SET group. They began operations from 1999, 2003 and 2006, respectively.

The SET's primary objectives include operation efficiency regarding facilitating liquidity, risk-sharing opportunities and reducing volatility, and information efficiency by ensuring timely and accurate disclosure of information which leads to low costs of capital and transaction costs. It serves several duties in the economy, for instance, promoting savings and fund raising activities, creating liquidity, enabling businesses to restructure and obtain the optimal balance between debt and equity financing, serving as an organised exchange with appropriate supervisions, supporting participations of investors as part of the ownership, protecting the benefits of all related parties, disseminating relevant information, helping expand tax base for the government, and offering a leading indicator for the economic performance of the country.

An alternative channel for savings and fund raising to the securities market would be through financial institutions, especially banks. The differences are that spread between the interest rate paid to depositors and charges to borrowers is earned by banks, while the cost of capital can be reflected more clearly via equity financing. Business risks would also be pooled to financial institutions, instead of being shared among investors. Furthermore, expected returns for investors are higher in the stock investment than savings at banks. Finally, the government by means of taxpayers' money has to offer implicitly guarantee for the solvency of financial institutions in case of defaults. In other words, the SET plays a major role in the development of the Thai economy.

The main market-wide index of the Stock Exchange of Thailand is called the "SET Index". Moreover, the SET also provided two blue chip indices: the "SET50 Index" and the "SET100 Index". Besides, two disaggregated indices – the industry group indices and the sectoral indices – are also published by the bourse.

Information about the SET can be found via the official website at www.set.or.th, while further information regarding trading and investing in the SET, including investor knowledge resources, are available at www.settrade.com. Other public relations and education activities are done via the Thailand Securities Institutes (TSI), various publications, and a television programme on economics and investment news called “Money Channel”. Lastly, the SET also offers historical data in a database called “SETSMART” as well.

3.2. Trading Systems

The financial products registered with the SET include equity instruments, such as ordinary shares, preferred share, warrants, unit trusts, and non-voting depository receipt (NVDR), and other instruments, such as debenture, and convertible bonds, as well. In May 1991, the SET introduced a fully computerised system called the “Automated Trading System for the Stock Exchange of Thailand” (ASSET). It was then upgraded to the “Advance Resilience Matching System” (ARMS) in August 2008. The latest system, called “SET Connect” was implemented to cope with new financial innovations and international standard protocol. Normally, the trading unit or board lot contains 100 units of the security or 50 units of security priced at 500 baht (approximately US$14) or more for six consecutive months.

The market is open on all bank business days, typically Monday to Friday. The morning session pre-opens at 9:30 and the random opening time is between 9:55 to 10:00. The intermission is between 12:30 to 14:00 when it pre-opens again for the afternoon session. The second random opening time is between 14:25 to 14:30. The market pre-closes at 16:30 and the random closing time is between 16:35 to 16:40. Off-hour trading is still allowed until 17:00 when the market is closed. The closing price is calculated based on the random auction method to prevent manipulation. Table 1 summarised the possible movement of prices stipulated by the SET’s regulations. Floor and ceiling limits on the price of typical instruments are also set to be at 30 percent of the previous closing price of local shares or a not more than one price spread. Foreign shares can move up to 60 percent of the previous closing price of domestic shares. Share price on the first trading day can move up to three times the Initial Public Offering (IPO) price but not below 0.01 baht. Warrants can have up to 100 percent movement in price from the previous close. There are also circuit breakers for unusual trading volatility. Transactions are halted for 30 minutes if the aggregated market index or the SET Index falls by 10 percent from the previous close. If it falls further to 20 percent from the previous close, trading would be stopped again for one hour.

Table 1: Price Spread in the Stock Exchange of Thailand

Market Price (Baht)	Spread
Less than 2	0.01
2 up to less than 5	0.02
5 up to less than 10	0.05
10 up to less than 25	0.10
25 up to less than 100	0.25
100 up to less than 200	0.50
200 up to less than 400	1.00
400 up	2.00

Source: Stock Exchange of Thailand, effective from 30th March 2009

The only clearinghouse, securities depository, and registrar in the Thai stock market is the Thailand Securities Depository Co., Ltd (TSD), which is a subsidiary of the SET. It was established in November 1994 and began operations in January 1995 to develop and promote back-office systems for after-trade services for all equity and debt instruments. Clearing and settlement of equity instruments are completed three business days after the transaction (T+3).

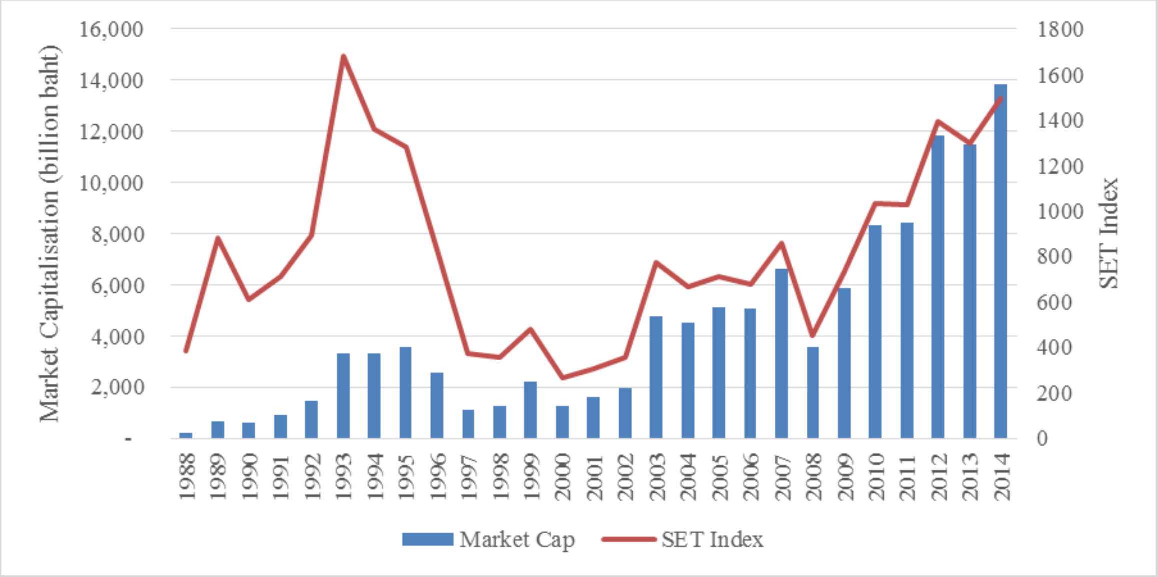
3.3. Performance of the Thai Stock Market

The performance of the Thai stock market can be analysed from various aspects. The first view is in terms of the market size. The SET Index’s monthly close since the establishment in April 1975 until December 2014 are plotted in Figure 1, and the measurement of the market size by market capitalisation from 1988 are shown in Figure 2, while the major events affecting the Thai stock market are listed in Table 2.

Figure 1: Monthly SET Index (April 1975 – December 2014)

Source: Stock Exchange of Thailand

Figure 2: Annual SET Index and Market Capitalisation (1988 –2014)



Source: Stock Exchange of Thailand

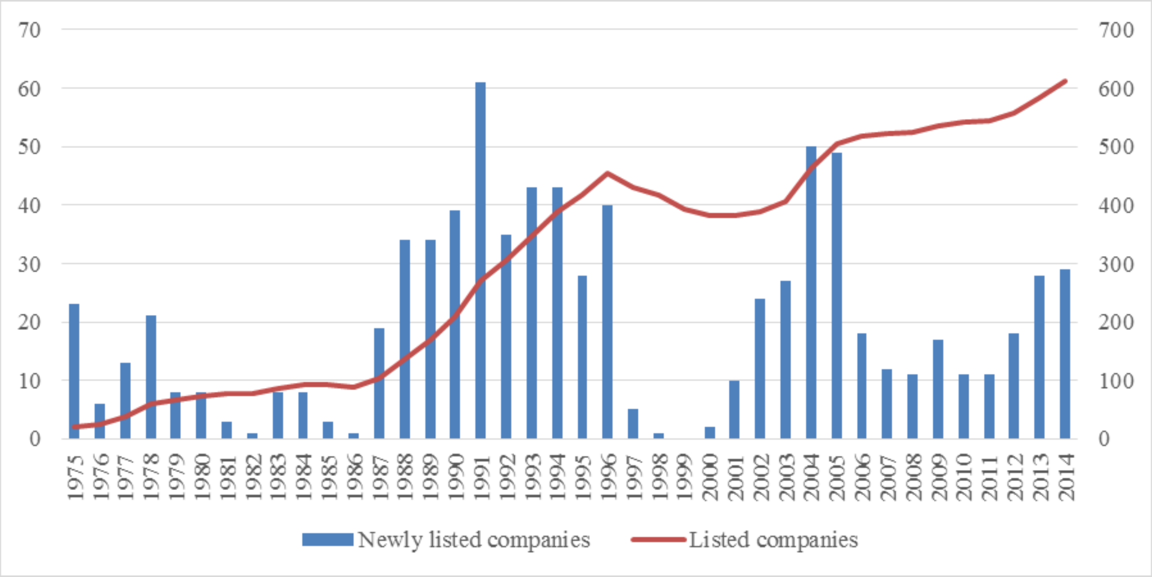
Table 2: Major Events affecting the Stock Exchange of Thailand during 1975-2014

Apr 1975	First trading day of the SET on 30th April 1975
Mar 1976	SET Index closed at historical low at 76.44 points on 17th March 1976
1979	Oil crisis
1981	Global liquidity squeeze and high interest rate
Apr 1981	Coup d'état
Sep 1985	Coup d'état
May 1986	Dissolution of parliament
Oct 1987	Black Monday
1989	Speculation in real estate market
Oct 1989	Mini Black Monday
Aug 1990	Persian Gulf War
Feb 1991	Coup d'état
May 1992	Public demonstration leading to the Black May incident
Jan 1994	SET Index was at its all-time high closing price at 1753.73 points on 4th January 1994 with a price-earnings ratio of 31 times
Jan 1995	Mexican peso crisis
Feb 1995	Losses in derivatives investment by Baring Securities Singapore
1997	Asian Financial Crisis
Jul 1997	Thailand abandoned the currency peg regime and adopted a managed float system
Aug 1997	Granted IMF Reform Package
Dec 1997	Closure of finance companies
Sep 1998	SET Index closed at the second lowest level in the history at 207.31 on 4th September 1998
Mar 1999	Introduction of economic stimulation measures
Aug 1999	Measures on private consumption stimulation and financial institution rehabilitation
Jan 2001	General election
May 2001	Thai market underweighted by the MSCL
Sep 2001	September 11 attacks
Jun 2002	WorldCom scandal
Jul 2002 - Apr 2003	Iraq War
Mar 2003	SARS outbreak
Jan – Dec 2003	Thailand’s economic recovery
Jan – Feb 2004	Avian Influenza outbreak
Feb – Apr 2004	South Thailand insurgency
Feb – Mar 2004	Demonstration against the privatisation of the Electricity Generating Authority of Thailand (EGAT)
May – Jul 2004	Increasing trends of oil price and interest rates
Sep 2006	Coup d'état

Dec 2006	Introduction of the unremunerated reserve requirement (URR) on short-term capital flows by the Bank of Thailand (BOT)
Feb 2008	Lifting of the URR measure
May 2008	Public demonstrations with the People's Alliance for Democracy seizing the airport
Oct 2008	The second and third implementations of the first-stage circuit breaker after the SET Index fell by more than 10 percent during trading hours, as a result of the Subprime Crisis in the US on 10th and 27th October 2008.
Nov 2008	US Federal Reserve introduced Quantitative Easing measure (QE1)
Feb 2009	Thailand’s Administrative Court suspended the development of sixty-five projects in the Map Thaput Industrial Estate, worth an estimated US$8 billion, due to inadequate health impact assessments
May 2009	The Government of Dubai requested for delayed debt repayments of Dubai World company
Mar 2010	Morgan Stanley changed recommendation for Thai stock market to overweight
Apr 2010	Emergency Decree imposed in Bangkok, Thailand’s capital city
Jul 2010	Most European banks passed the stress test
Nov 2010	Second round of Quantitative Easing measure by the US Federal Reserve (QE2)
Feb 2011	Egyptian Revolution
Mar 2011	Tsunami in Japan
Jul 2011	Investor confidence in the Thai market improved
Oct – Dec 2011	Severe flooding in Thailand
Sep 2012	US Federal Reserve’s QE3 and the ECB’s asset purchase programme
May 2013	Public demonstration against an amnesty bill in Bangkok
May 2014	Coup d'état by the National Council for Peace and Order (NCPO)

From the beginning of the bourse in 1975 until 1977, the development of the SET had been rather gradual. Then, the first noticeable boom period was during 1977-1979. The number of newly listed companies rose as business owners raised funds to support the economic expansion as presented in Figure 3. However, the oil price crisis in 1979 led to high inflation, and the Thai baht was devalued in 1981. The index was consequently relatively steady during 1979-1982.

Figure 3: Number of List Companies and Newly Listed Companies (1975 –2014)



Source: Stock Exchange of Thailand

The index then advanced during 1986-1988 as a result of a further devaluation of the Thai baht in 1984 which led to strong exports. The market gradually turned bearish after the Black Monday in October 1987. From 1990, economics policies aiming at financial liberalisation and deregulation were increasingly introduced. Volatility in the market also increased in 1990 due to the Persian Gulf War. The index was affected again by the coup d'état in 1991 and the following Black May incident, which was the clash between police and military officers and protestors leading to loss of lives and many injured in 1992. Excess liquidity in the market helped the index regained from late 1993 and saw the index reached all-time high in January 1994.

However, speculation in both real estate and stock markets, together with speculative attacks on the Thai baht led to Thailand switching from fixed currency regime to a managed floating system on 2nd July 1997, which signalled the start of the Asian Financial Crisis. The index plummeted as far 207.31 points in September 1998, before the various economic programmes led to a recovery in 2003.

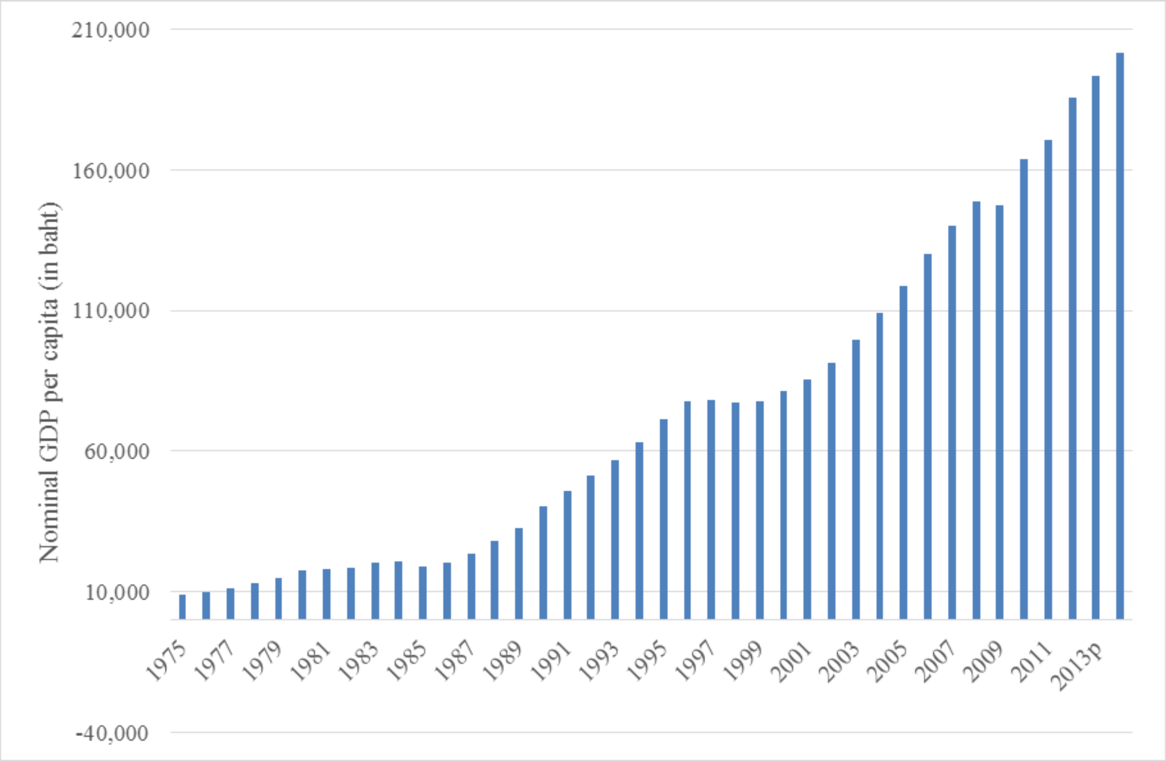
Thailand had another coup d'état in September 2006. Later that year, the Bank of Thailand introduced the unremunerated reserve requirement (URR) on short-term capital flows. The measure required 30 percent of all capital inflows into Thailand to be held in non-interest bearing deposits at the central bank for one year. The SET Index closed at 730.55 on 18th December 2006. The URR was announced in the evening that day and led the SET Index to plunge by more than 20 percent during trading hours of 19th December 2006. The circuit breakers were triggered for the first time at both 10 percent and 20 percent stages. The Index rebounded and closed at 14.84 percent loss, marking one of the worst trading days in the SET's history. The global crash led by the Subprime Crisis in the US resulted in circuit breakers with 30-minute trading halt being activated on two occasions in October 2008.

In 2011, Thailand faced one of the most severe floodings in the history. Sixty-five out of 77 provinces in Thailand were declared disaster areas, including part of Bangkok – the capital city – was inundated. The World Bank (2011) estimated this flooding to be the world's fourth costliest in 2011 with US$45.7 billion in economic damages and losses due to this flooding.

From the establishment of the Stock Exchange of Thailand 1975 until 2014, Thailand had enjoyed the compounded annual growth rate (CAGR) of 8.1 percent in nominal GDP per capita based on Figure 4. Compared to other markets, the total market capitalisation of the SET and the mai had the CAGR of 22.4 percent, while the debt market and the total credit extended by commercial banks had CAGR of 18.5 percent and 13 percent, respectively (Stock Exchange of Thailand, 2015b).

Figure 5 presented the combined total market capitalisation of the SET and the mai and comparison to the nominal GDP. Overall, it showed the Thai stock market has been growing strongly relative the economic growth and its market capitalisation represented approximately 154 percent of nominal GDP in 2014.

Figure 4: Thailand's Nominal GDP per capita (1975 – 2014)



Source: International Monetary Fund, World Bank, and the Office of the National Economic and Social Development Board of Thailand

Figure 5: Total Market Capitalisation (SET and mai) and Percentage of Nominal GDP (1990 – 2014)

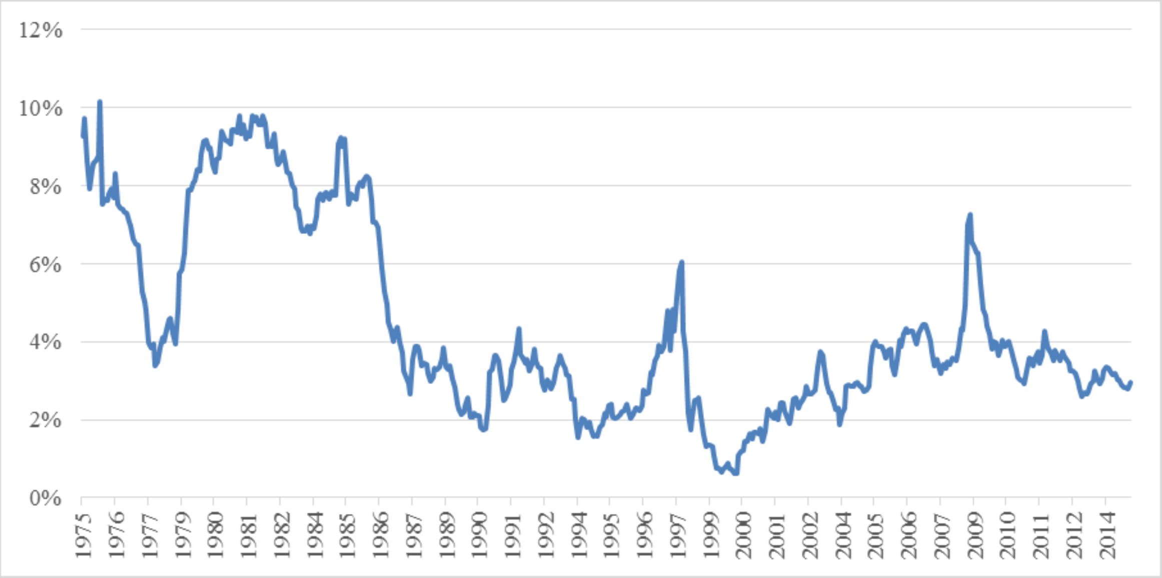
Source: Bank of Thailand and Stock Exchange of Thailand

Next, the returns on investment in the SET is considered. Over the period of 40 years from establishment, the market had experienced various crises such as the Persian Gulf War, the Asian Financial Crisis, the dot-com bubble, and the Subprime Crisis. It yielded a CAGR of approximately 8.86 percent, while saving deposits and gold would earn 6.50 percent, and 5.62 percent, respectively (Stock Exchange of Thailand, 2015b). In other words, investing in the stock market, saving deposits, or gold for 40 years would have generated nominal returns of about 27, 11, and 8 times of the initial investment, respectively. Historical market dividend yields, price-earnings (P/E) ratios, and price-to-book-value (P/BV) ratios were also reported in Figure 6, Figure 7, and Figure 8.

Regarding liquidity, the SET's average daily total turnover and foreign investors' turnover were displayed in Figure 9. Participation of foreign investors in the SET have been significant in terms of percentage of total turnover shown in Figure 10. It represented roughly between 20 to 30 percent of transaction value by all types of investors. The position of foreign investors also appeared to somewhat correlate with the performance of the SET. This is illustrated in Figure 11.

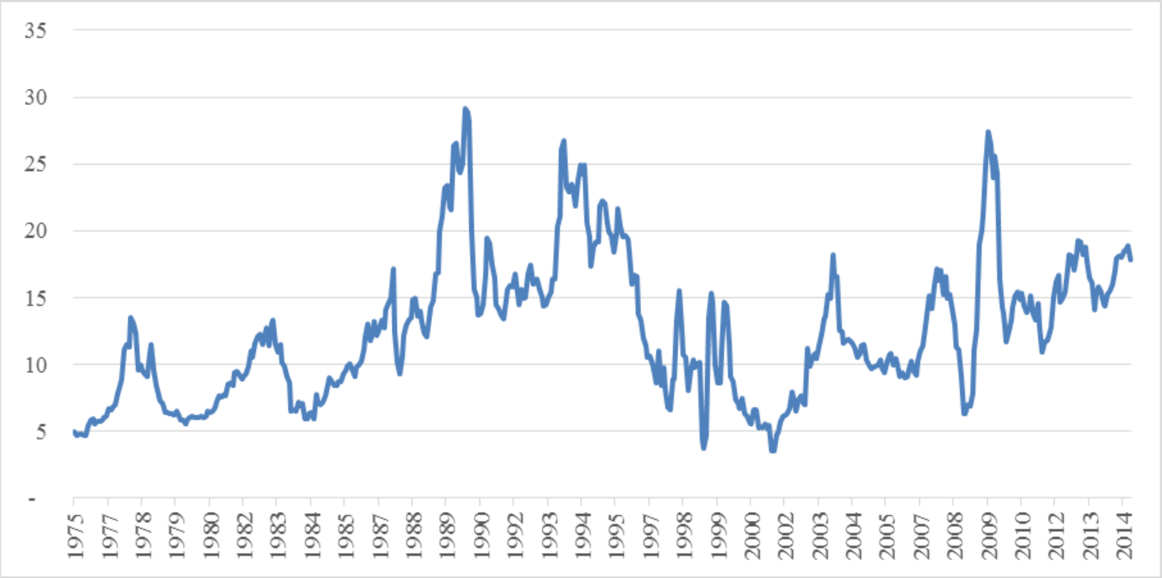
Finally, the number of listed companies and the total market capitalisation by industry group demonstrated the level of concentration in the SET. They can be referred to from Figure 12 and Figure 13.

Figure 6: SET's Monthly Market Dividend Yield (1975 – 2014)



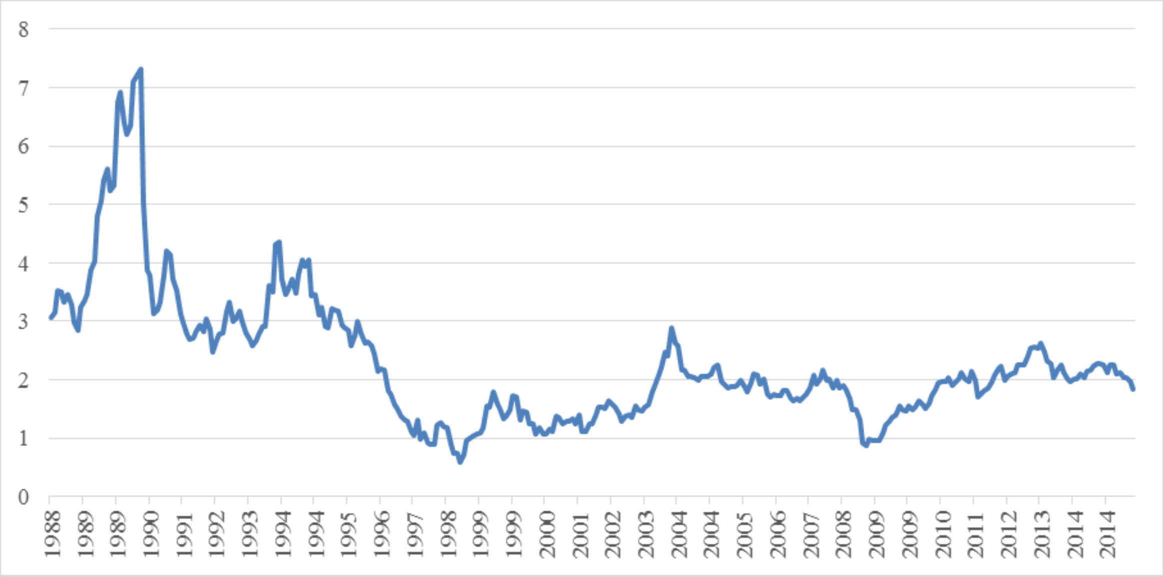
Source: Stock Exchange of Thailand

Figure 7: SET's Monthly Price-earnings Ratios (1975 – 2014)



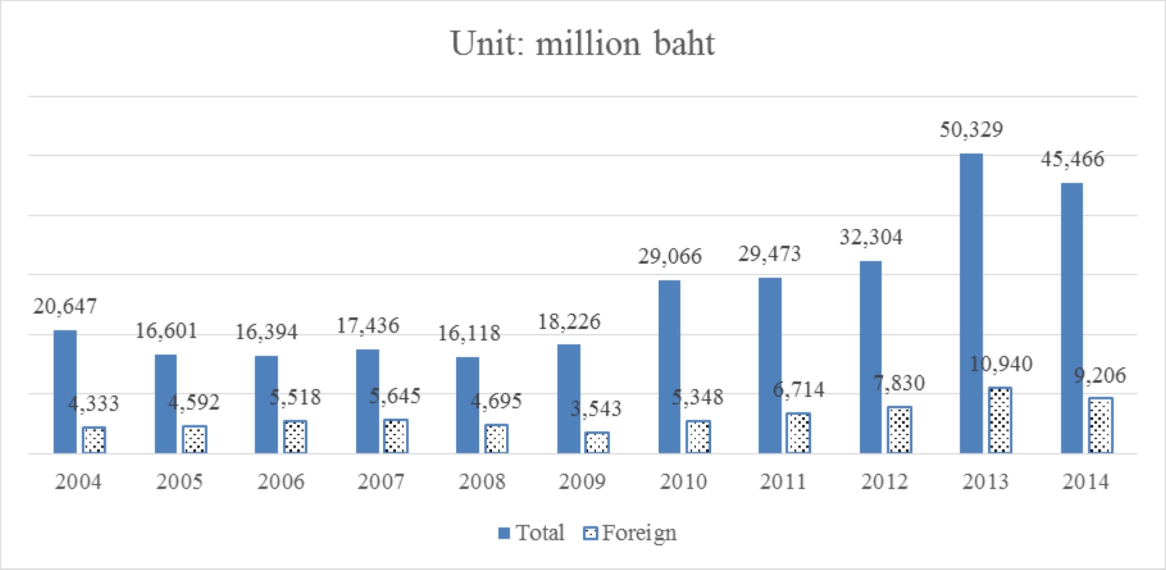
Source: Stock Exchange of Thailand

Figure 8: SET's Monthly P/BV Ratios (1975 – 2014)



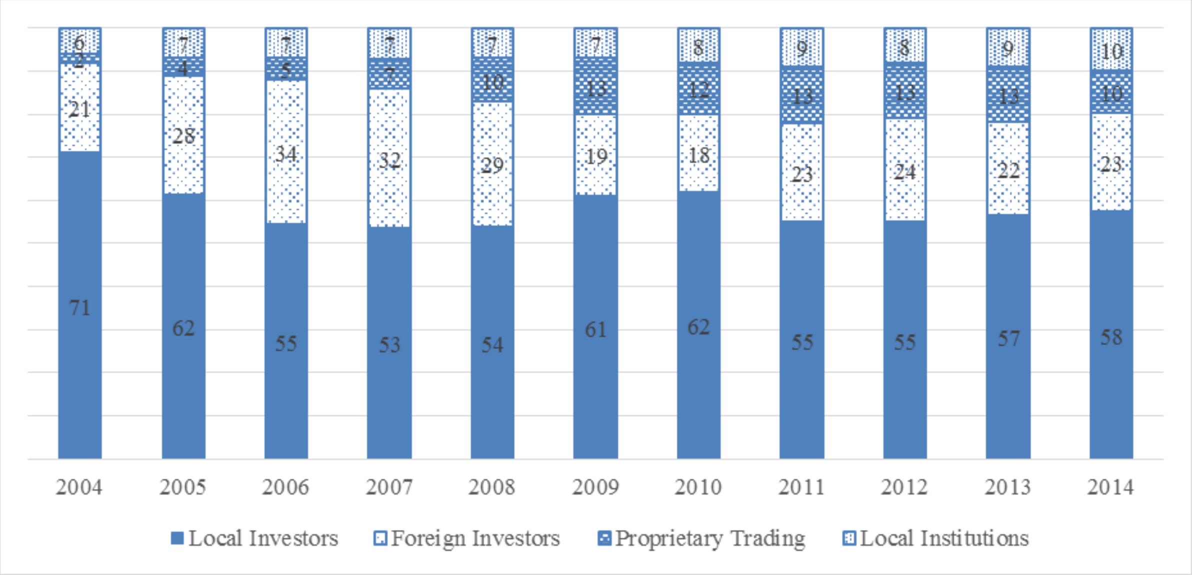
Source: Stock Exchange of Thailand

Figure 9: Average Daily Turnover in the SET (2004-2014)



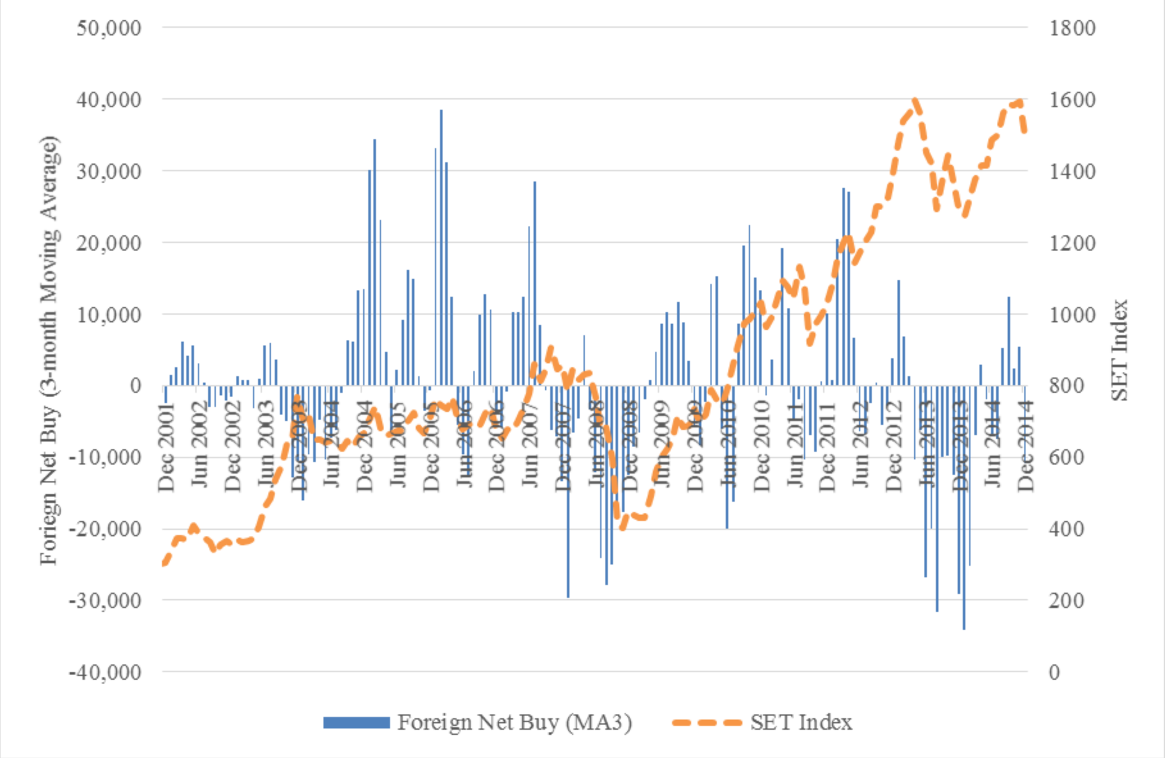
Source: Stock Exchange of Thailand

Figure 10: Transactions by investor type in the SET during 2004- 2013 (%)



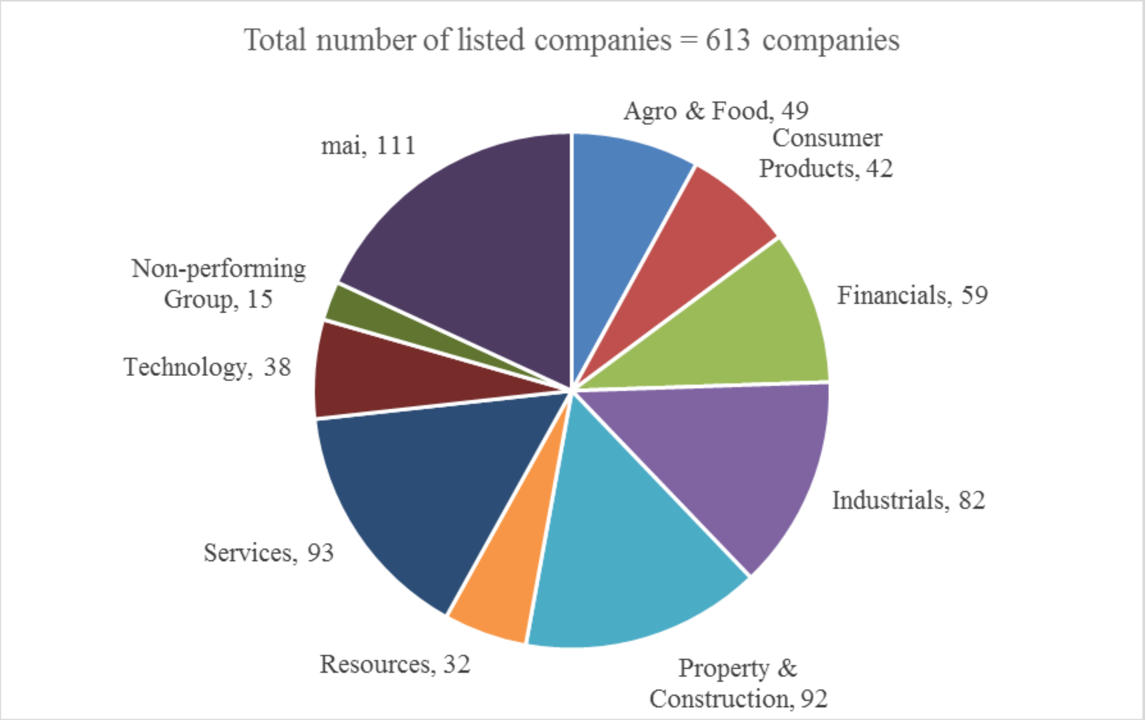
Source: Stock Exchange of Thailand

Figure 11: Monthly Foreign Net Buy (3-month Moving Average) and the SET Index (2001 –2014)



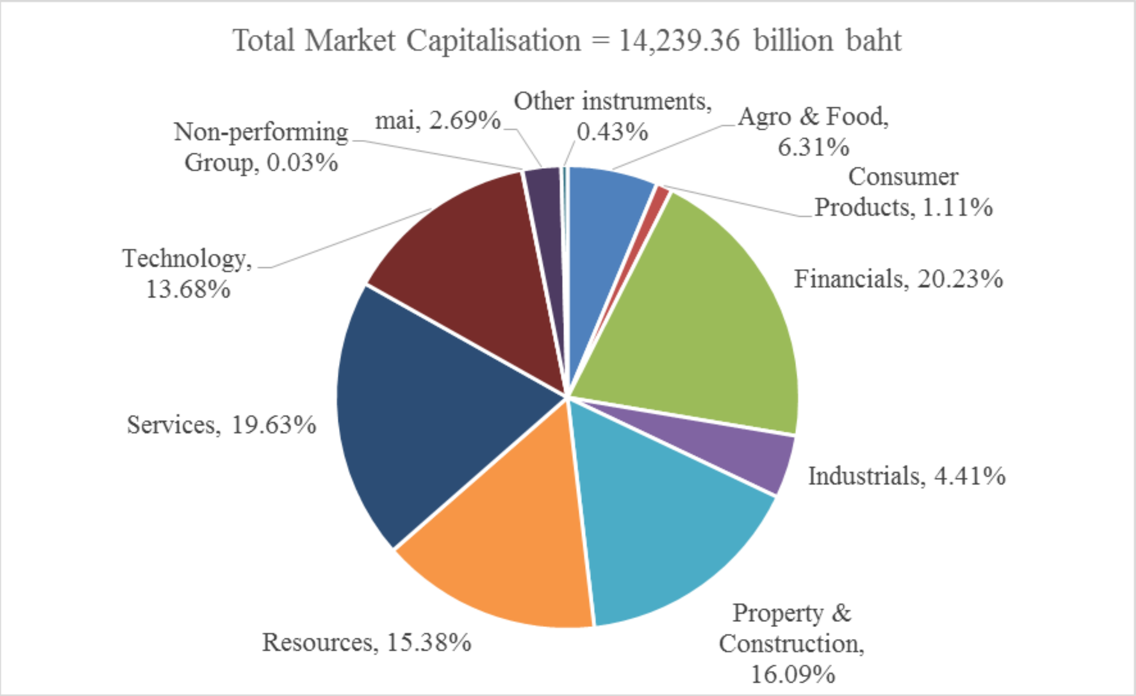
Source: Stock Exchange of Thailand

Figure 12: Listed Companies by Industry Group (As of December 2014)



Source: Stock Exchange of Thailand

Figure 13: Total Market Capitalisation by Industry Group (As of December 2014)



Source: Stock Exchange of Thailand

3.4. Thai Stock Market's Presence in Asia and the World

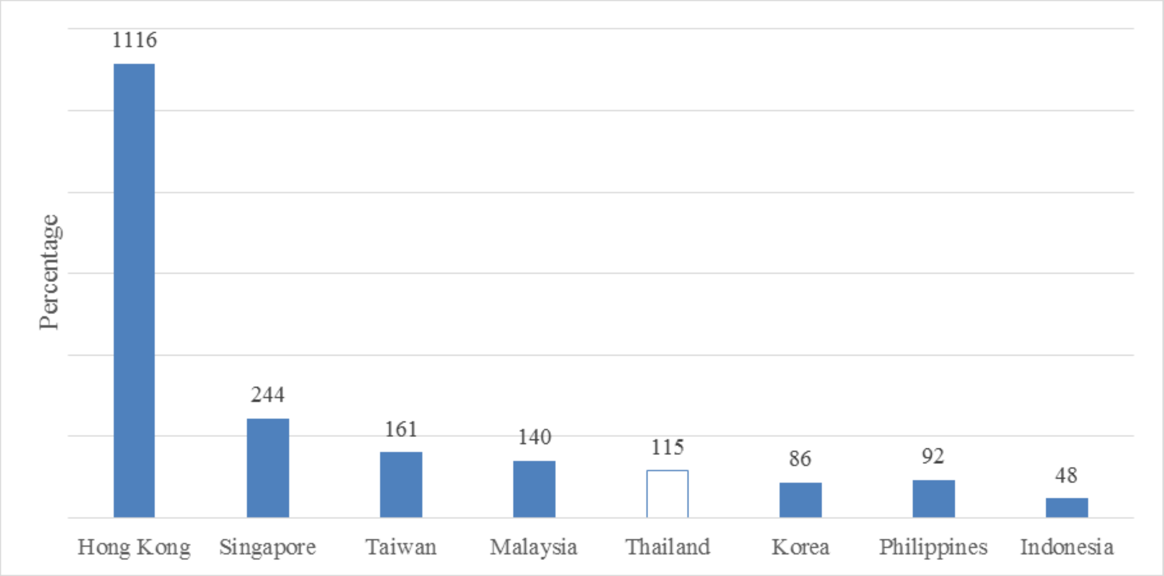
The SET's total market capitalisation to GDP ratio, the number of listed companies, and the total market capitalisation in billion US dollar as compared to selected Asian markets were presented in Figure 14, Figure 15, and Figure 16, respectively. Overall, they suggested the Thai stock market was still comparatively small in terms of the absolute market size, the market size relative to the size of the economy, and the participation of listed firms. The SET had fairly high liquidity when share turnover velocity was considered in Figure 17.

Figure 18 reported the market share of the SET out of selected exchanges in Asia ex-Japan. It suggested that the market share of the Thai stock market based on market turnover had been in decline since 2012, while the share based on market capitalisation in 2013 dropped from the 2012 level with the share in 2014 also remained unchanged.

Historical P/E ratio and market yields of selected Asian stock exchanges as of November 2014 were illustrated in Figure 19 and Figure 20. They implied that the profitability of Thai stocks was quite poor, although the dividend yield was on part with other stock markets. In terms of the broad index performance, Figure 21 showed that the SET was one of the markets that did well in 2014 with a one-year return of approximately 15 percent, although that was still far from top markets, like, Shanghai Stock Exchange or BSE India, who generated 53 and 37 percent return, respectively.

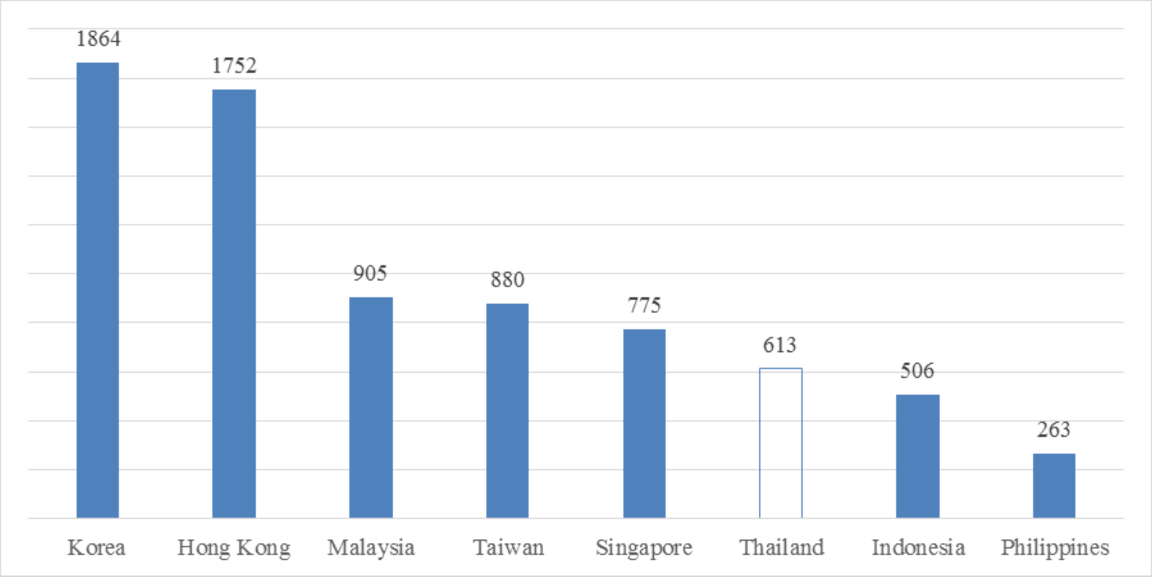
Lastly, Figure 22, Figure 23, and Figure 24 compared the position of the SET in the global market in terms of domestic market capitalisation, the total value of share trading in billion US dollar, and the number of listed companies, respectively. The results indicated that the Thai stock market ranked 25th out of 64 exchanges in terms of market capitalisation, 22nd out of 64 in terms of trade value, and 22nd out of 74 in terms of the number of listed companies.

Figure 14: Market Capitalisation to GDP (As of December 2014)



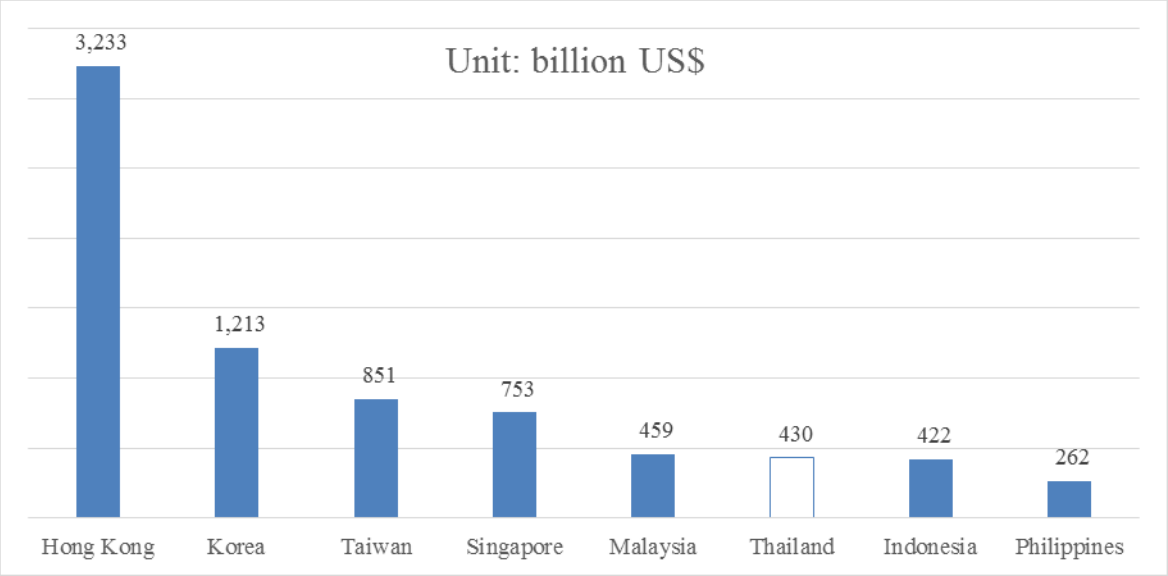
Source: World Federation of Exchanges (WFE) and IMF's World Economic Outlook Database

Figure 15: Number of Listed Companies (As of December 2014)



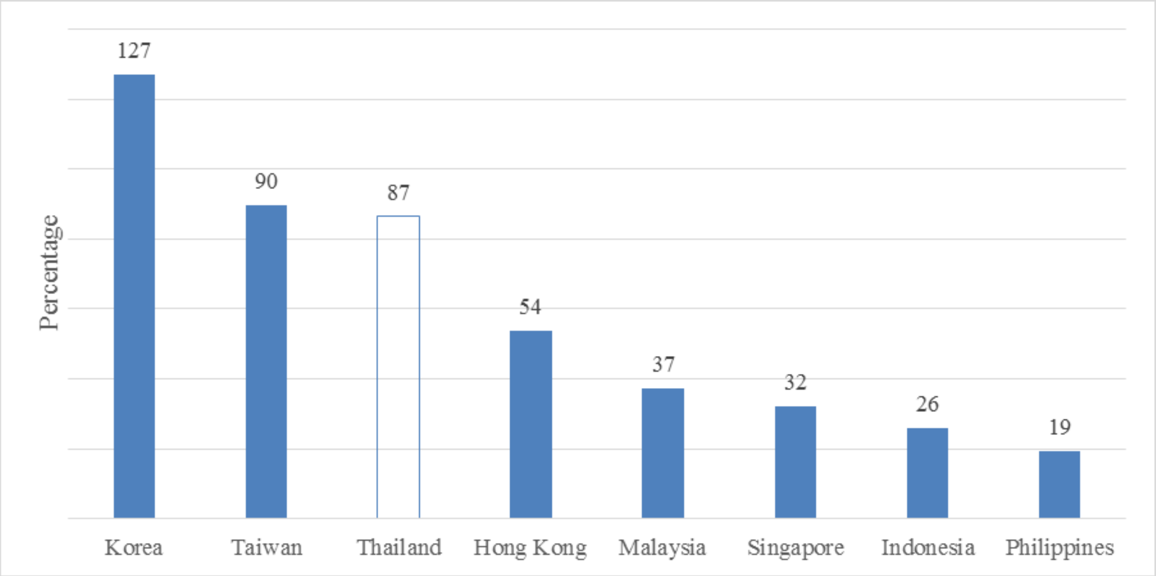
Source: World Federation of Exchanges (WFE)

Figure 16: Market Capitalisation (As of December 2014)



Source: World Federation of Exchanges (WFE)

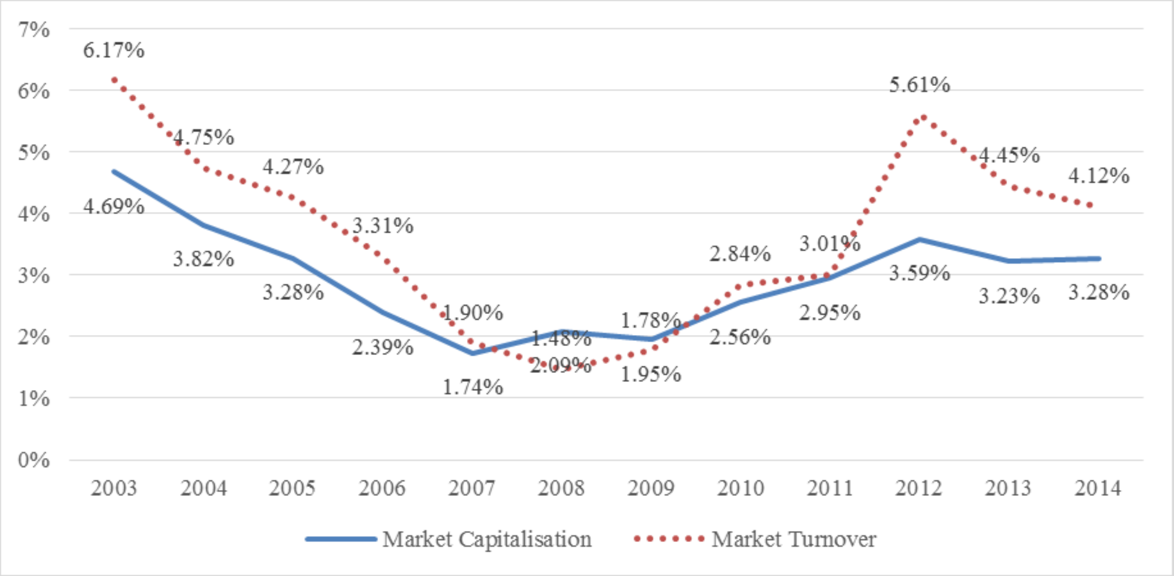
Figure 17: Share Turnover Velocity (As of December 2014)



Note: Share velocity is calculated by share turnover/market capitalisation*12

Source: World Federation of Exchanges (WFE)

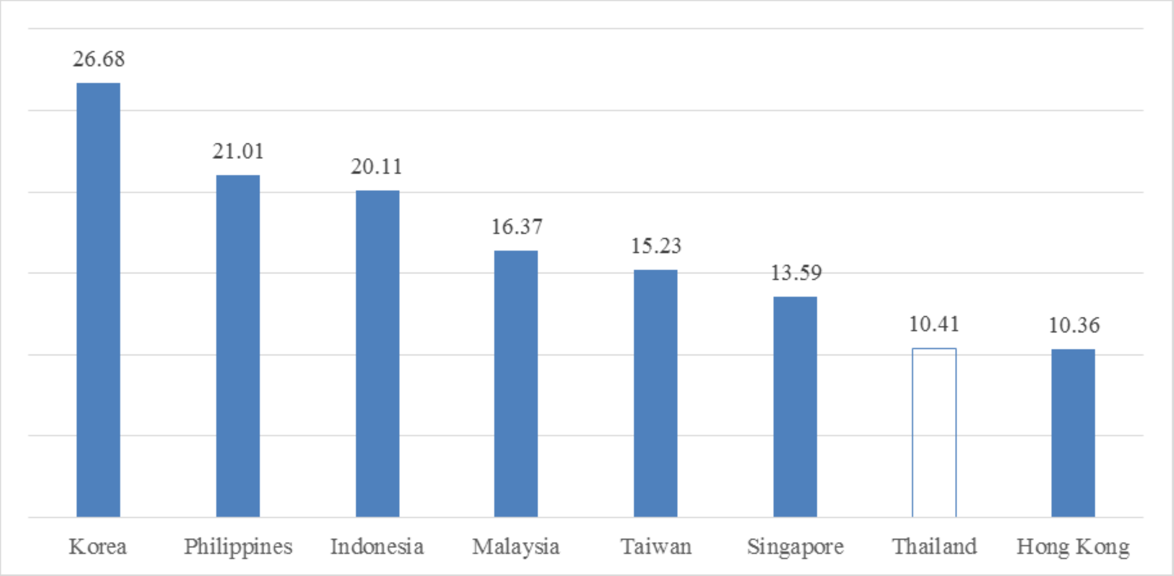
Figure 18: Market Share of the Thai Stock Market in Asian Markets (As of December 2014)



Note: Asian markets included China, Hong Kong, India, Indonesia, Korea, Malaysia, the Philippines, Singapore, Sri Lanka, Taiwan, and Thailand.

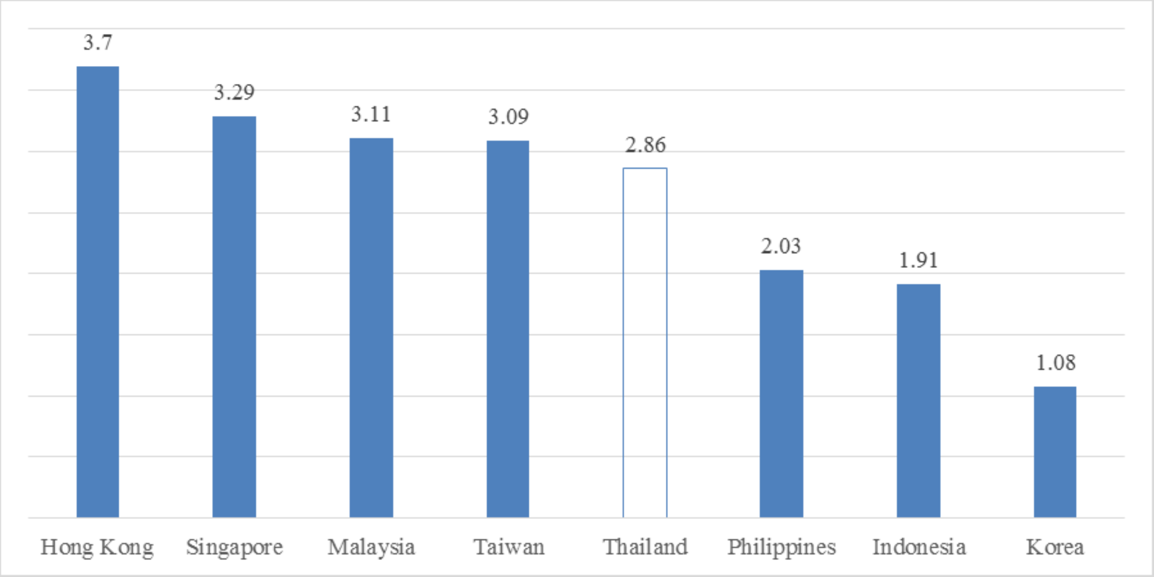
Source: World Federation of Exchanges (WFE)

Figure 19: Historical P/E ratio (As of November 2014)



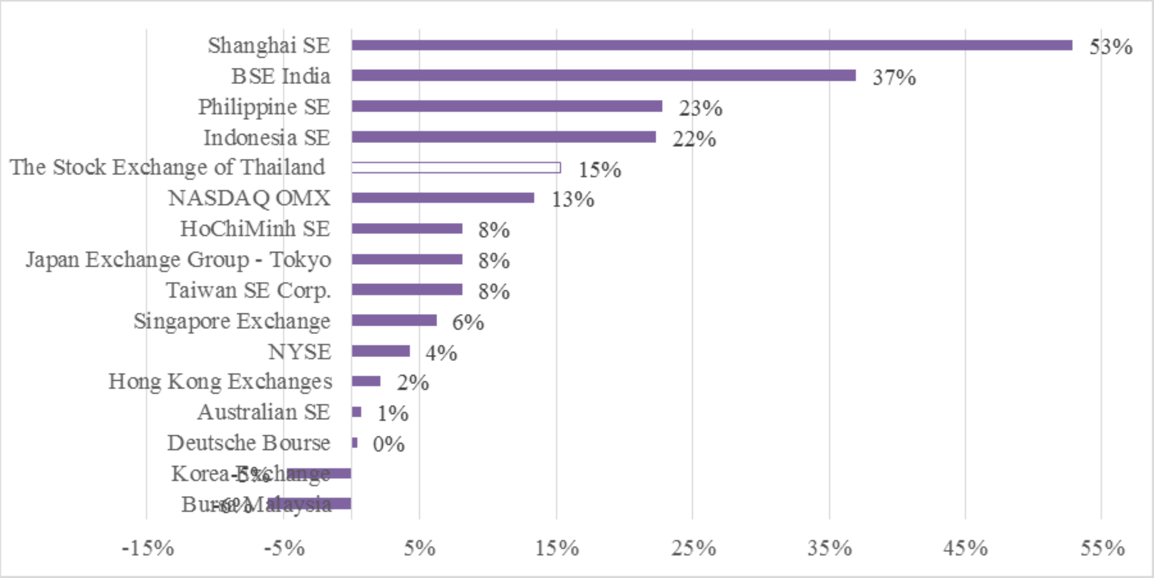
Source: Stock Exchange of Thailand (2014)

Figure 20: Market Yield (As of November 2014)



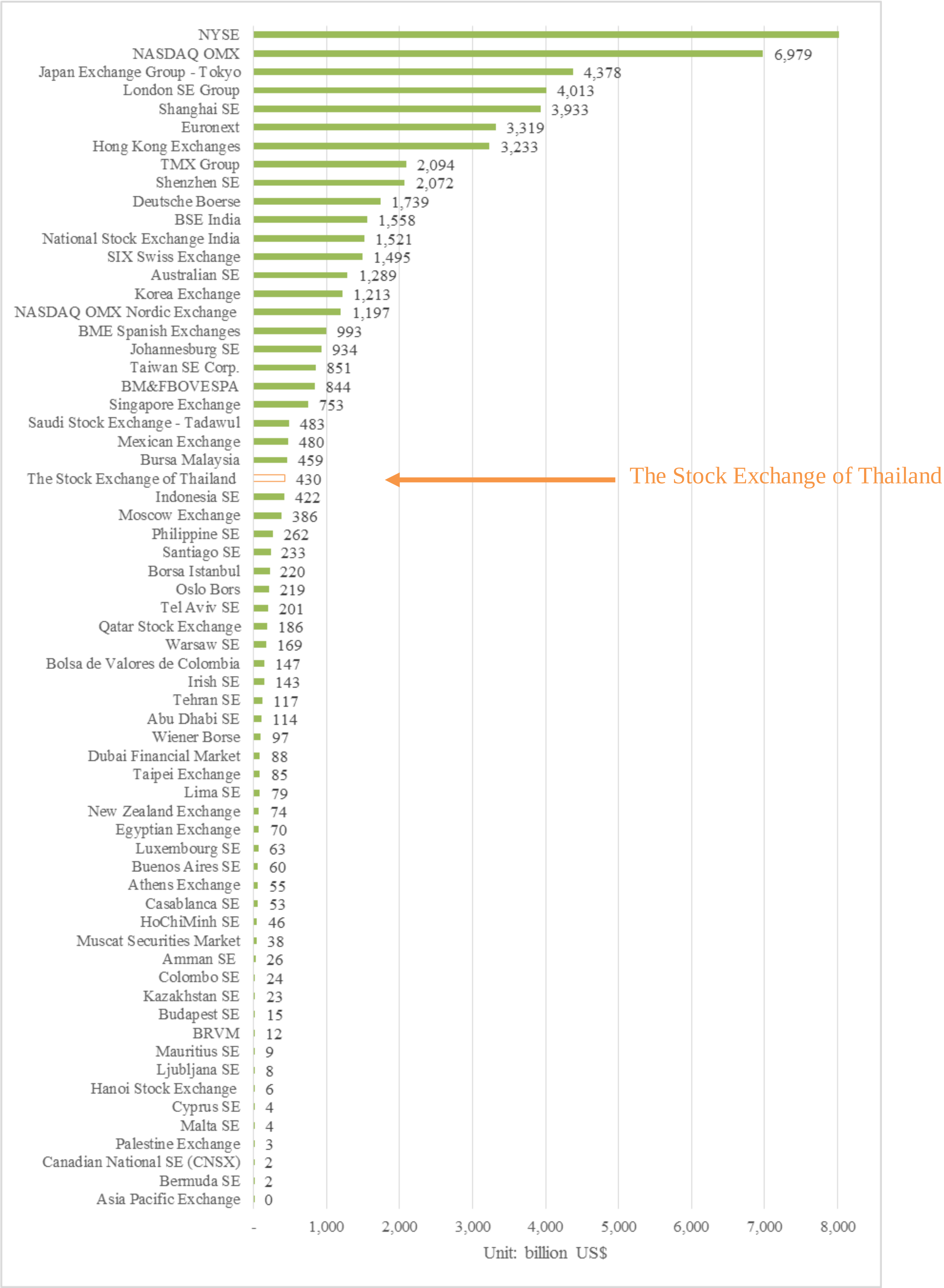
Source: Stock Exchange of Thailand (2014)

Figure 21: One-year Return on the Index (As of December 2014)



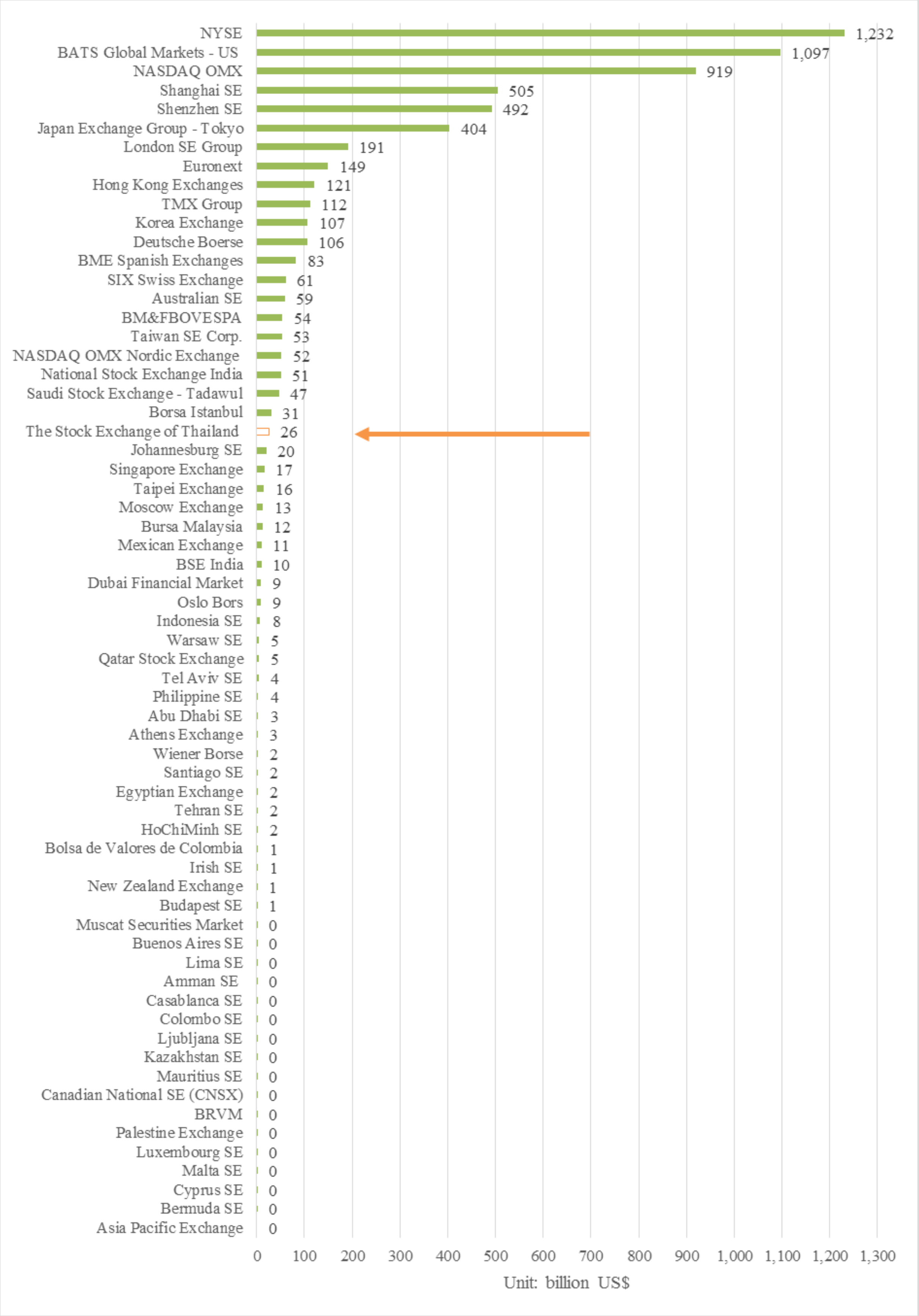
Source: World Federation of Exchanges (WFE)

Figure 22: Domestic Market Capitalisation (As of December 2014)



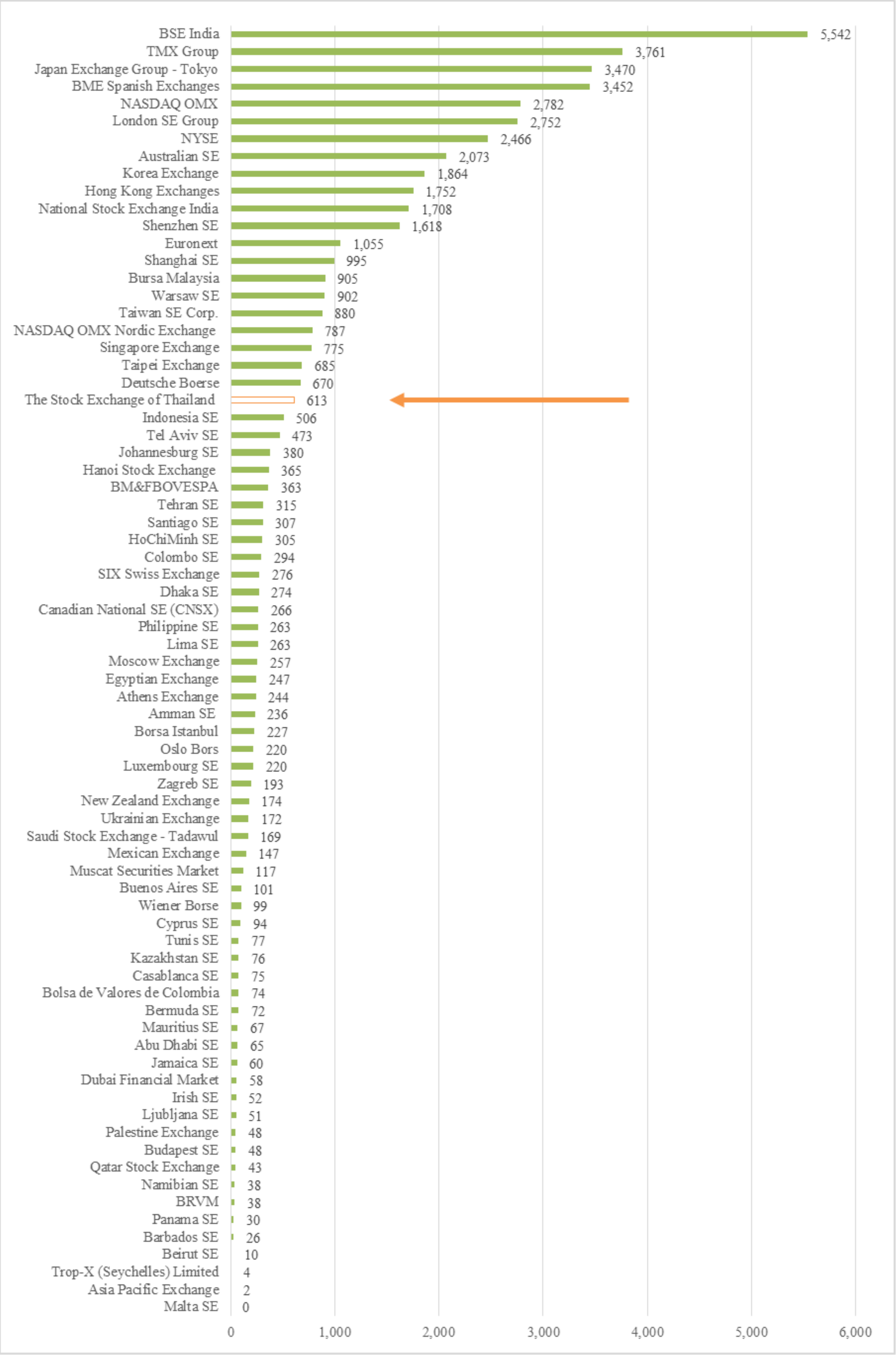
Source: World Federation of Exchanges (WFE)

Figure 23: Average Monthly Total Value of Share Trading (For the year 2014)



Source: World Federation of Exchanges (WFE)

Figure 24: Number of Listed Companies (As of December 2014)



Source: World Federation of Exchanges (WFE)

Chapter 4: Methodology and Models

This chapter elaborates on the methodology and data used in the following empirical chapters. The first section develops the speculative bubble models, namely, the Blanchard-Watson model, the van Norden- Schaller (VNS) model, and the volume-augmented model. It is important to note that, by adopting these models, this thesis focuses on employing a direct test, where the behaviour of bubbles is assumed and checked for. That means when an evidence of a bubble is detected; it suggests that the data appears to contain the bubble of the kind developed by the model. In contrast, when no evidence of a bubble is discovered, it implies that only the type of bubble described in the model is not found, and there could still be a bubble in other forms.

The next two sections then describe the restriction tests to determine the validity of the bubble hypothesis and the robustness checks against simpler simplification. The following section shows how the fundamental values are computed. Then, the next section explains the construction of the K-NI, which is an author's calculated index. Finally, last two sections discuss the models of bubble transmission and the Granger-causality tests used to investigate contagion effects.

4.1. Speculative Bubble Models

Consider a simple asset-pricing model with the assumptions that investors are risk-neutral with rational expectations, discount rates are constant, and the market is in equilibrium. The period-to-period arbitrage condition would hold, such that the stock price is determined by the present value of its expected future cash flows received by investors which include future price and dividend to be paid in period $t + 1$. This can be expressed as:

$$p_t = \frac{E_t(p_{t+1} + d_{t+1})}{(1 + i)} \tag{1}$$

where p_t is the actual stock price at time t, d_t is the cash dividend paid in period t, $E_t(\cdot)$ is conditional expectation operator with respect to information set available at time t, i is the discount rate or the equilibrium expected rate of return.

From equation (1), expected future stock prices in period $t+1$ and beyond can be worked out and substituted back into the equation recursively. Given the assumption of rational expectations, the expectation of the future expected value implies the expectation as formed now or at $E_t\left(E_{t+1}(\cdot_{t+2})\right) = E_t(\cdot_{t+2})$. This gives the fundamental stock price of:

$$p_t^f = \sum_{g-1}^{\infty} \frac{1}{(1+i)^g} E_t\left(d_{t+g}\right) \tag{2}$$

The actual stock price in period t is equal to its fundamental price plus the bubble component b_t, and the error term, v_t, which has a mean of zero and a constant variance:

$$p_t = p_t^f + b_t + v_t \tag{3}$$

In other words, the deviations of actual prices from their fundamental values are caused by the bubble term. Note that $\hat{b}_t$ can then be simply estimated as the difference between actual price and the corresponding fundamental value of a particular stock. All assets must satisfy the arbitrage condition. This suggests that the bubble component should also follow equation (1):

$$E_t(b_{t+1}) = (1+i)b_t \tag{4}$$

4.1.1. The Blanchard-Watson Model

A speculative bubble model was developed by Blanchard (1979) and Blanchard and Watson (1982). Each period in this model, the bubble component may survive and continue to grow (state S) or burst and collapse completely (state C) with the probability that next-period return would be in the bubble surviving regime of $P(r_{t+1}|S) = q$, with $0 < q < 1$, or that it could be in the bubble collapsing regime with the probability of $P(r_{t+1}|C) = 1 - q$. When the bubble crashes, it will disappear and stock price will revert to the fundamental level. If the bubble survives, the investor needs to be additionally compensated for the extra risk taken. Therefore, the stochastic process generating the expected bubble in period $t + 1$ will be as followed:

$$E_t(b_{t+1}|S) = \frac{(1+i)b_t}{q} \tag{5}$$

$$E_t(b_{t+1}|C) = 0 \tag{6}$$

Note that when the bubble does crash, it will collapse completely in a single period, which is a rather strong assumption. Furthermore, the fact that it would deflate completely, this implies that the bubble can never grow again and that there can be only one bubble in the entire period covered in the data. Lastly, the probability of collapse is assumed to be constant over time. These issues present some challenges to the model.

4.1.2. The VNS Model

Van Norden and Schaller (2002) (hereafter VNS) then developed a model for periodically partially collapsing speculative bubbles allowing for both positive and negative bubbles and a time-varying probability of collapse. They made two extensions to the Blanchard-Watson model.

First, they noted that the probability of a bubble surviving reduces as bubble size increases and that bubbles could be either positive or negative ones. They consequently revised the probability function by adding the absolute value of relative bubble size $(B_t = b_t/p_t)$ to be:

$$P(r_{t+1}|S) = q(B_t) \tag{7}$$

where $dq(B_t)/d|B_t| < 0$. For this, they adopted the following Probit models to ensure that the estimates of q is between 0 and 1:

$$q(B_t) = \Omega(\beta_{qo} + \beta_{qb}|B_t|) \tag{8}$$

where Ω is the standard normal cumulative density function, $\Omega(\beta_{qo})$ is the mean probability of a bubble surviving in next period, and β_{qb} is the sensitivity of the probability to survive to the absolute value of relative bubble size.

Secondly, VNS let the expected bubble component in state C be a function of relative bubble size to allow for partial collapse, so

$$E_t(b_{t+1}|C) = u(B_t) \cdot p_t \tag{9}$$

It is further assumed that $u(B_t)$ is a continuous and everywhere differentiable function, such that the model can be linearised for estimation purpose and $u(0) = 0$, $0 \leq du(B_t)/d(B_t) \leq 1$ which shows that, in the collapsing state, the expected relative bubble size in period $t + 1$ will shrink. Specifically, it cannot be larger than the relative bubble size in period t and must be smaller than the surviving state bubble.

Given this new setup, the expected bubble size in surviving regime will then be:

$$E_t(b_{t+1}|S) = \frac{(1+i)}{q(b_t)} b_t - \frac{1-q(B_t)}{q(B_t)} u(B_t) \cdot p_t \tag{10}$$

This implies that the expected bubble size in state S is a decreasing function of probability q (increasing function of probability of collapse, $1 - q$) and probability q is an increasing function of absolute relative bubble size. In other words, as the bubble grows and the probability of collapse increases, investors need larger compensation for their risk. Note that, if $q(B_t) = q$ and $u(B_t) = 0$, this model reverts to Blanchard-Watson setup.

Under certain assumptions about the dividend process, the gross return for stock in the VNS model is determined by the non-linear switching model:

$$E_t(r_{t+1}|S) = \left[M(1 - B_t) + \frac{MB_t}{q(B_t)} - \frac{1-q(B_t)}{q(B_t)} u(B_t)\right] \tag{11}$$

$$E_t(r_{t+1}|C) = [M(1 - B_t) + u(B_t)] \tag{12}$$

where M is the expected growth rate of explosive bubble component, $E_t\ (b_{t+1})/b_t$.

For estimation purpose, the model can be linearised by taking the first-order Taylor series approximation of $E_t(r_{t+1}|S)$ and $E_t(r_{t+1}|C)$ with respect to B_t around some arbitrary B_0. This yields a linear regime-switching model:

$$r_{s,t+1} = \beta_{so} + \beta_{sb}B_t + \varepsilon_{s,t+1} \tag{13}$$

$$r_{c,t+1} = \beta_{co} + \beta_{cb}B_t + \varepsilon_{c,t+1} \tag{14}$$

with a single state-independent probability switching regimes:

$$q(B_t) = \Omega\big(\beta_{qo} + \beta_{qb}|B_t|\big) \tag{15}$$

where:

$$\beta_{sb} = -\frac{1}{q(B_0)^2}\cdot\frac{dq(B_0)}{dB_t}\cdot\left[(1+i)B_0 - u(B_0) + \frac{1-q(B_0)}{q(B_0)}\cdot\left[1+i-\frac{du(B_0)}{q(B_t)}\right]\right] \tag{16}$$

$$\beta_{cb} = \left[\frac{du(B_0)}{dB_t} - (1+i)\right] \tag{17}$$

and $\varepsilon_{s,t+1}$ and $\varepsilon_{c,t+1}$ are the unexpected gross returns in period $t+1$ in the surviving and collapsing state, respectively. The two disturbance terms are assumed to have a zero mean, constant variance and i.i.d. normal random variables. Assuming that $i \geq 0$, it can be proved that $\beta_{sb} \geq 0$ and $\beta_{cb} \leq 0$, thus, $\beta_{sb} \geq \beta_{cb}$.

4.1.3. Volume-augmented Model

Brooks and Katsaris (2005) noted that investors could regard an increase in volume traded as a sign for other investors trying to unload their ‘bubbly’ assets to avoid the next burst of the bubble, which will, in turn, result in the realisation of the bubble collapse. The unusual volume is then negatively correlated with the probability of a bubble surviving in the next period. Also, investors need to be further compensated for these signals of possible change in the long-run trend in stock prices as well. Brooks and Katsaris (2005), therefore, extend the model by including also the abnormal volume terms in both the surviving-regime gross returns equation and the probability function, such that the expected bubble size is:

$$E_t(b_{t+1}) \\ = \begin{cases} \frac{(1+i)b_t}{q(B_t, AV_t)} - \frac{1-q(B_t, AV_t)}{q(B_t, AV_t)} u(B_t) \cdot p_t & \text{with probability } q(B_t, AV_t) \\ u(B_t) \cdot p_t & \text{with probability } 1 - q(B_t, AV_t) \end{cases} \tag{18}$$

where AV_t is a measure of abnormal volume in period t and $\partial(B_t, AV_t)/\partial AV_t < 0$. Assuming dividends follow a geometric random walk with drift, it can be shown that the expected gross return in period $t+1$ can be written as:

$$E_t(r_{t+1}|S) = \left[M(1-B_t) + \frac{MB_t}{q(B_t, AV_t)} - \frac{1-q(B_t, AV_t)}{q(B_t, AV_t)} u(B_t) \right] \tag{19}$$

$$E_t(r_{t+1}|C) = [M(1-B_t) + u(B_t)] \tag{20}$$

$$P(r_{t+1}|S) = q(B_t, AV_t) = \Omega\big(\beta_{qo} + \beta_{qb}|B_t| + \beta_{qv} AV_t\big) \tag{21}$$

where β_{qv} is the sensitivity of the probability to survive to the measure of unusual trading volume. This can again be linearised by taking first first-order Taylor series approximation around arbirrayarbitrary B_0 and AV_0 which yields a linear switching regression model:

$$r_{s,t+1} = \beta_{so} + \beta_{sb} B_t + \beta_{sv} AV_t + \varepsilon_{s,t+1} \tag{22}$$

$$r_{c,t+1} = \beta_{co} + \beta_{cb} B_t + \varepsilon_{c,t+1} \tag{23}$$

$$P(r_{t+1}|S) = q(B_t, AV_t) = \Omega\big(\beta_{qo} + \beta_{qb}|B_t| + \beta_{qv} AV_t\big) \tag{24}$$

The model is estimated using maximum likelihood approach with the assumption that the disturbance is normally distributed. The log-likelihood function is:

$$\ell(r_{t+1}|\xi) = \sum_{t=1}^{T} ln\left[P(r_{t+1}|S)\frac{\omega\left(\frac{r_{t+1}-\beta_{so}-\beta_{sb}B_t-\beta_{sv}AV_t}{\sigma_s}\right)}{\sigma_s} + P(r_{t+1}|C)\frac{\omega\left(\frac{r_{t+1}-\beta_{co}-\beta_{cb}B_t}{\sigma_c}\right)}{\sigma_c}\right] \quad (25)$$

where ξ is the set of parameters including $\beta_{so}, \beta_{sb}, \beta_{sv}, \beta_{co}, \beta_{cb}, \beta_{qo}, \beta_{qb}, \beta_{qv}, \sigma_s, \sigma_c$ and ω is standard normal probability density function, , σ_s and σ_c are the standard deviations of the disturbances in surviving and collapsing state, respectively, and $P(r_{t+1}|C) = 1 - P(r_{t+1}|S)$. The estimations of the all models are performed using MATLAB. Particularly, as σ_s, σ_c cannot be negative, these estimations are essentially constrained optimisations where the constraints are that the two standard deviation parameters are non-negative. However, it is more efficient to work with unconstrained optimisation problems. The objective function was therefore modified to include the exponentials of σ_s and σ_c instead. The estimated parameters of $\sigma_s$and σ_c are later obtained by taking the logarithms of the estimated values from the optimisation process. The standard errors for hypothesis testing were taken from the inverse of the Hessian matrix at the optimum.

4.2. Speculative Bubble Model Restrictions LR Tests

Apart from testing the significance of the parameters, there are some additional conditions for this model of periodically collapsing speculative bubbles to have explanatory power for stock market returns, in other words, for the null hypothesis of no bubble to be rejected. The restrictions are:

$$\begin{aligned} \beta_{so} &\neq \beta_{co} && (R1)\\ \beta_{cb} &< 0 && (R2)\\ \beta_{sb} &> \beta_{cb} && (R3)\\ \beta_{qb} &< 0 && (R4)\\ \beta_{qv} &< 0 && (R5)\\ \beta_{sv} &> 0 && (R6) \end{aligned}$$

Firstly, the model assumes two distinct regimes and restriction (R1) specifies that the average return of the two regimes should not be the same. However, it does not require that the mean return in the bubble-collapsing regime must be smaller than that in the bubble-surviving regime. This is because the equations for the two regimes are basically derived based on two independent distributions. Although the bubble-collapsing state may be thought to have higher volatility than that of the bubble-surviving state, it does not warrant that the average return must be lower. Realisations of next-period return following bubble collapses are typically low, but that due to the effects coming from both the average return and the relative bubble term, and not necessarily just the average return itself. Thus, the restriction test only requires the two average returns to be different – so that they are indeed two distinct regimes – and not that one is higher than another.

Next, restriction (R2) ensures that the expected return should be negative if the bubble collapses. Restriction (R3) means the return compensating for the existence of bubble when it survives should be larger than in the case where the bubble collapses. Restrictions (R4) and (R5) imply that the probability of the bubble surviving in the next period will be lower as the size of bubble grows and the abnormal volume increase, respectively. Lastly, as investors would require a higher return to compensate for the higher risk signalled by the increase in unusual volume, restriction (R6) is needed. Likelihood ratio (LR) tests can be performed to test all of these restrictions on the estimated parameters. The tests are two-tailed for restriction (R1) and one-tailed for restrictions (R2) to (R6).

These six restriction tests describe the sign and relative size of the coefficients as postulated by the volume-augmented model. If the data contains a bubble of the kind proposed by the model, the estimated parameters should satisfy these conditions. Therefore, for this thesis, they will serve as a decision criteria for concluding whether a particular set of data displays any evidence of bubble-like behaviour. Specifically, adopting the approach of Anderson et al. (2010), the result will be interpreted as showing some signs of bubble when at least two restriction tests are rejected. When three or more tests are refuted, the result will be taken as strong evidence. In other words, to detect a bubble, it is necessary for the data to have at least two of the hypothesised characteristics, but it will only be sufficient when three or more conditions are met.

4.3. Robustness against Stylised Alternatives LR Tests

The ability of the models to explain the variability of stock returns can be further checked by testing them against simpler models that are already nested within this more general framework. This is also done by likelihood ratio tests.

4.3.1. Volatility Regimes Model

First, a tested against a simple model of changing volatility can be performed. This model can be expressed as followed:

$$r_{s,t+1} = \beta_o + u_{s,t+1} \quad , u_{s,t+1} \sim (0, \sigma_s) \tag{26}$$

$$r_{c,t+1} = \beta_o + u_{c,t+1} \quad , u_{c,t+1} \sim (0, \sigma_c) \tag{27}$$

$$P(r_{t+1}|S) = q = \Omega(\beta_{qo}) \tag{28}$$

This suggests that the next period mean returns are the same in both regimes, the bubble component has no predictive ability for returns in next period, and the probability of switching between regimes is fixed. However, the two regimes are different in terms of disturbance variances. These assumptions can be translated into the following joint restrictions: $\beta_{co} = \beta_{so} = \beta_o, \beta_{cb} = \beta_{sb} = \beta_{sv} = \beta_{qb} = \beta_{qv} = 0$, and $\sigma_s \neq \sigma_c$.

4.3.2. Mixture of Normals Model

An alternative is to allow for next period mean returns, as well as, the residual variances, to be different in two regimes:

$$r_{s,t+1} = \beta_{so} + u_{s,t+1} \quad , u_{s,t+1} \sim (0, \sigma_s) \tag{29}$$

$$r_{c,t+1} = \beta_{co} + u_{c,t+1} \quad , u_{c,t+1} \sim (0, \sigma_c) \tag{30}$$

$$P(r_{t+1}|S) = q = \Omega(\beta_{qo}) \tag{31}$$

This can be referred to as a mixture of normal distributions model, which means the restrictions are only $\beta_{cb} = \beta_{sb} = \beta_{sv} = \beta_{qb} = \beta_{qv} = 0$.

4.3.3. Fads Model

Cutler et al. (1991) proposed a model with a mean reversion in prices or fads model:

$$r_{s,t+1} = \beta_o + \beta_b B_t + u_{s,t+1} \quad , u_{s,t+1} \sim (0, \sigma_s) \tag{32}$$

$$r_{c,t+1} = \beta_o + \beta_b B_t + u_{c,t+1} \quad , u_{c,t+1} \sim (0, \sigma_c) \tag{33}$$

$$P(r_{t+1}|S) = q = \Omega(\beta_{qo}) \tag{34}$$

In this model, the next period mean returns are the same across regimes. The bubble components determine returns in both regimes with the same linear function, but do not have explanatory power over the probability of regime switching. Lastly, the two regimes have different disturbance variances. The restrictions are thus: $\beta_{so} = \beta_{co} = \beta_o$, $\beta_{sb} = \beta_{cb} = \beta_b$ and $\beta_{sv} = \beta_{qb} = \beta_{qv} = 0$.

4.3.4. VNS Model

Finally, the volume-augmented model by Brooks and Katsaris (2005) can be tested against the VNS model. This is equivalent to testing whether the unusual trading volume adds any explanatory power to the speculative bubble model. The restriction is: $\beta_{sv} = \beta_{qv} = 0$.

These results were investigated to compare the different model of bubbles and find out the specification that fits best with the available data. It could also help justify the use of the volume-augmented model if the likelihood ratio tests against the more parsimonious models are rejected. Nevertheless, they were not conducted to check for the existence of bubbles. Precisely, the volatility regimes and the mixture of normals models do not include any bubble term, and if these two non-bubble models provide a better fit to the data, there may indeed not be any bubbles in the Thai stock market. However, following the approach of Anderson et al. (2010), when these two simpler models were not rejected, the evidence was still judged to contain evidence of bubbles.

4.4. Measure of Fundamental Values

In order to obtain the series of bubble components, the fundamental prices needed to be constructed first. The literature suggests a number of approaches for that. For example, it can be done by considering the classic Gordon (1982) model:

$$p_t^f = \frac{d_t}{r - g} \tag{35}$$

where g is the growth rate of dividend. This method assumes that the fundamental price is a function of current dividends, their expected rate of growth, and expected rate of return. Many previous studies assumed further that log dividends follow a random walk with drift process:

$$D_t = \alpha + D_{t-1} + \epsilon_t \tag{36}$$

where D_t is log dividends. It is possible to show that the fundamental price is then a function of multiple of current dividends:

$$p_t^f = \rho d_t \tag{37}$$

where

$$\rho = \frac{1 + r}{e^{(\alpha + \sigma^2/2)} - 1} \tag{38}$$

Under this approach, the relative bubble size is constructed as:

$$B_t = \frac{b_t}{p_t} = \frac{p_t - p_t^f - \nu_t}{p_t} = 1 - \frac{\rho d_t + \nu_t}{p_t} \tag{39}$$

Following the approach of van Norden and Schaller (2002) and Anderson et al. (2010), this research will use the sample mean of historical price/dividend ratio as a proxy for ρ. In order to ensure that calculations were made with a sufficient data, the first sample mean of price/dividend ratio – which will be used to compute estimates of fundamental price and the relative bubble term – would start from the 12th observation to allow for one year of data points. As the sample mean is calculated separately for each period, using data from the first observation up to the current one, the sample size for computation of sample mean in the following periods will be updated and expanded by the recent observations. That is, this research does not use the mean of entire sample in all estimations, rather the sample mean of historical price/dividend ratio for each estimation period would vary.

In any case, it could be argued that more recent observations might carry more relevant information and should, thus, be given a higher weight in the computation. However, with the approach discussed above, the weight would be equal for all historical observations, and, decreasing in the case of later time periods with a larger number of observations. This study will also investigate a 12-month weighted average, as well as, an exponential moving average as alternative approaches.

Note also that this method assumes a specific stochastic process of dividends and a fixed interest rate. The first assumption can be relaxed with the Campbell and Shiller (1987) approach where they allow for variation in expected dividend growth over time. This method used uses the information based on the difference between the stock price and a multiple of current dividends to forecast future dividend changes. Campbell and Shiller (1988) allowed for variation in interest rates over time to be predicted as well.

4.5. Sectoral and Industrial Index Data

The availability of the official Stock Exchange of Thailand (SET)'s Industry Group indices is quite limited, while the Sectoral indices contain considerable sector-specific noise and comprise too many sectors which make it difficult for interpretation. The Datastream-calculated indices are also inappropriate, as they include extended periods of zero reported dividend yields. Therefore, the K-NI series is a market-capitalisation-weighted index that imitates the SET's eight Industry Group indices but is extended to cover periods of more than 20 years by using information from the Sectoral indices, will be investigated.

The Stock Exchange of Thailand provides two levels of sectoral indices, which are industry group indices and sectoral indices. Similar to the main SET Index, these indices are also market capitalisation-weighted with the base value of 100 points. Adjustments are also made, for instance, when a stock moves from one industry group or sector to another.

The sectoral indices series was launched on 2nd May 1975, based on prices on 30th April 1975, which was the first trading day of the SET. The industry group indices series, however, was only introduced from 5th January 2004 based on 31st December 2003.Several revisions in terms of addition of new sectors or reclassifications were announced since. As of 2013, companies listed on the SET's main board are classified into eight industry groups and 27 sectors[1], based on fundamentals. Table 3 summarises the groupings.

Data utilised in the empirical investigation in this chapter were retrieved from Datastream. Table 4 shows the starting observations of the sectoral indices obtained. There are three main data types required for the analysis with the volume-augmented model. They are price index, dividend yield and trading volume. Datastream only contains the price index from January 2004, dividend yield from June 2005 and trading volume from December 2007 for all the industry groups. This means there is a limited time frame to the study sample ending in December 2012 giving only 49 observations after allowing for 12-month burn-in periods.

As for the sectoral indices, although Datastream includes the price index of many sectors started from the late 1970s or early 1980s, the dividend yield series are only available from September 1988 onwards. Therefore, the longest series available for estimation, after allowing for 12 months burn-in periods, could only begin from August 1989, which includes 280 observations ending December 2012. Other sectoral indices data that become available later will have a shorter sample size.

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[1] As of January 2014, there are eight industry groups and 28 sectors with the addition of Construction Services (CONS) sector under Property & Construction industry group. Property Fund sector was also renamed to Property Fund & REITs (PF&REIT).

An alternative dataset for this investigation of disaggregated indices was the Datastream-calculated indices. For Thailand, 50 stocks were monitored and classified into ten industry groups. This full list is shown in Table 5. The advantages of using these Datastream-calculated indices are that they have reasonably long historical data and are more manageable as compared to working with 27 sectoral indices. However, the drawback is that some of the indices, such as Technology (TECNO) or Telecommunications (TELCM), only include a few stocks, two and three, respectively. Moreover, dividends were not paid by many Thai-listed firms during the period from the late 1990s and thus, dividend yields would be reported as zero. This gives rise to estimation problems in several of the specifications.

Table 3: List of Industry Group and Sectors in the SET

Industry Group		**Sector**	
Symbol	**Description**	**Symbol**	**Description**
AGRO	Agro & Food Industry	AGRI	Agribusiness
		FOOD	Food and Beverage
CONSUMP	Consumer Products	FASHION	Fashion
		HOME	Home & Office Products
		PERSON	Personal Products & Pharmaceuticals
FINCIAL	Financials	BANK	Banking
		FIN	Finance and Securities
		INSUR	Insurance
INDUS	Industrials	AUTO	Automotive
		IMM	Industrial Materials & Machinery
		PAPER	Paper & Printing Materials
		PETRO	Petrochemicals & Chemicals
		PKG	Packaging
		STEEL	Steel
PROPCON	Property & Construction	CONMAT	Construction Materials
		PFUND	Property Fund
		PROP	Property Development
RESOURC	Resources	ENERG	Energy & Utilities
		MINE	Mining
SERVICE	Services	COMM	Commerce
		HELTH	Health Care Services
		MEDIA	Media & Publishing
		PROF	Professional Services
		TOURISM	Tourism & Leisure
		TRANS	Transportation & Logistics
TECH	Technology	ETRON	Electronic Components
		ICT	Information & Communication Technology

Source: Stock Exchange of Thailand

Table 4: Starting Observations of the Sectoral Indices

Sector	Price Index	Dividend Yield	Trading Volume
Banking	Apr 1975	Sep 1988	Apr 1975
Commerce	Apr 1975	Sep 1988	Apr 1975
Construction Materials	Apr 1975	Sep 1988	Apr 1975
Finance & Securities	Apr 1975	Sep 1988	Apr 1975
Petrochemicals & Chemicals	Apr 1975	Sep 1988	Apr 1975
Professional Services	Apr 1975	Sep 1988	Apr 1975
Fashion	Jun 1975	Sep 1988	Jun 1975
Food & Beverage	Jun 1975	Sep 1988	Jun 1975
Automotive	Dec 1975	Sep 1988	Dec 1975
Insurance	Mar 1977	Sep 1988	Mar 1977
Paper & Printing Materials	Dec 1977	Sep 1988	Dec 1977
Mining	Jan 1978	Sep 1988	Jul 1979
Energy & Utilities	Apr 1979	Sep 1988	Apr 1979
Packaging	Nov 1980	Sep 1988	Nov 1980
Media & Publishing	Dec 1982	Feb 1989	Dec 1982
Tourism & Leisure	Jul 1987	Sep 1988	Jul 1987
Property Development	Jun 1988	Oct 1988	Jun 1988
Electronic Components	Aug 1988	Oct 1988	Apr 1987
Personal Products & Pharmaceuticals	Sep 1988	Sep 1988	Sep 1988
Transportation & Logistics	Dec 1988	Dec 1988	Dec 1988
Health Care Services	Sep 1989	Sep 1989	Sep 1989
Home & Office Products	Jun 1990	Mar 1991	Apr 1975
Information & Communication Technology	Mar 1991	Mar 1991	Aug 1990
Agribusiness	Sep 1991	Sep 1988	Dec 1978
Industrial Materials & Machinery	Jul 2006	Jul 2006	Jul 2006
Property Fund	Mar 2009	Mar 2009	Mar 2009
Steel	Dec 2010	Jan 2011	Jan 2011

Table 5: Datastream-calculated Indices

Datastream Group	Company	SET's Industry Group	SET's Sector	Market Value (Dec 2013)	Percentage of Datastream Group
Basic Materials	Indorama Ventures	Industrials	Petrochemicals & Chemicals	115,060.70	41.53%
	Banpu	Resources	Energy & Utilities	87,638.56	31.63%
	IRPC	Resources	Energy & Utilities	74,381.19	26.84%
Consumer Goods	Charoen Pokphand Foods	Agro & Food Industry	Food & Beverage	210,995.10	52.00%
	Sermsuk	Agro & Food Industry	Food & Beverage	24,994.63	6.16%
	Thai Union Frozen Prds.	Agro & Food Industry	Food & Beverage	74,019.75	18.24%
	Land and Houses	Property & Construction	Property Development	95,747.50	23.60%
Consumer Services	Minor International	Agro & Food Industry	Food & Beverage	97,232.81	8.55%
	CP All	Services	Commerce	388,518.90	34.16%
	Home Product Center	Services	Commerce	98,772.31	8.68%
	Siam Makro	Services	Commerce	157,199.90	13.82%
	Robinson Dept.Store	Services	Commerce	57,476.67	5.05%
	Big C Supercenter	Services	Commerce	151,799.90	13.35%
	BEC World	Services	Media & Publishing	105,500.00	9.28%
	Central Plaza Hotel	Services	Tourism & Leisure	46,237.53	4.07%
	Thai Airways Intl.	Services	Transportation & Logistics	34,706.05	3.05%

Source: Datastream

Table 5 (continued)

Datastream Group	Company	SET's Industry Group	SET's Sector	Market Value (Dec 2013)	Percentage of Datastream Group
Financials	Bank of Ayudhya	Financials	Banking	233,854.40	9.41%
	Bangkok Bank	Financials	Banking	353,135.90	14.21%
	Kiatnakin Bank	Financials	Banking	33,972.73	1.37%
	Krung Thai Bank	Financials	Banking	261,352.20	10.51%
	Thanachart Capital	Financials	Banking	41,209.59	1.66%
	Siam Commercial Bank	Financials	Banking	524,374.40	21.10%
	Kasikornbank	Financials	Banking	399,674.60	16.08%
	TMB Bank	Financials	Banking	102,038.70	4.11%
	CIMB Thai Bank	Financials	Banking	41,537.20	1.67%
	Bangkok Life Assurance	Financials	Insurance	80,276.00	3.23%
	SCB Life Assurance	Financials	Insurance	68,894.00	2.77%
	Central Pattana	Property & Construction	Property Development	191,861.90	7.72%
	Pruksa Real Estate	Property & Construction	Property Development	46,234.87	1.86%
	BTS Group Hdg.	Services	Transportation & Logistics	107,228.00	4.31%
Health Care	Bgk.Dusit Med.Svs.	Services	Health Care Services	199,058.60	75.22%
	Bumrungrad Hospital	Services	Health Care Services	65,570.38	24.78%

Table 5 (continued)

Datastream Group	Company	SET's Industry Group	SET's Sector	Market Value (Dec 2013)	Percentage of Datastream Group
Industrials	Siam City Cement	Property & Construction	Construction Materials	91,999.94	9.66%
	Siam Cement	Property & Construction	Construction Materials	482,400.40	50.67%
	Berli Jucker	Services	Commerce	69,184.13	7.27%
	Siam Global House	Services	Commerce	47,037.89	4.94%
	Airports Of Thailand	Services	Transportation & Logistics	261,428.40	27.46%
Oil & Gas	PTT Global Chemical	Industrials	Petrochemicals & Chemicals	355,071.80	17.21%
	Bangchak Petroleum	Resources	Energy & Utilities	45,094.21	2.19%
	PTT	Resources	Energy & Utilities	862,601.20	41.80%
	PTT Exploration & Prdn.	Resources	Energy & Utilities	674,897.30	32.70%
	Thai Oil	Resources	Energy & Utilities	125,971.60	6.10%
Technology	Jasmine International	Technology	Information & Communication Technology	56,028.48	18.85%
	Shin	Technology	Information & Communication Technology	241,283.10	81.15%
Telecommunications	Advanced Info Ser.	Technology	Information & Communication Technology	657,053.80	64.28%
	Total Access Comms.	Technology	Information & Communication Technology	235,005.20	22.99%
	True Corporation	Technology	Information & Communication Technology	130,045.40	12.72%
Utilities	Electricity Generating	Resources	Energy & Utilities	66,861.00	27.45%
	Glow Energy	Resources	Energy & Utilities	102,766.20	42.19%
	Ratchaburi Electricity	Resources	Energy & Utilities	73,950.00	30.36%

Because of the various limitations of available datasets, namely the short sample period of industry group indices, difficulties managing 27 sectoral indices, and the reliability of Datastream-calculated indices, this chapter will therefore also explore the properties of a new index computed to tackle these issues. This index is referred to as the K-NI. The K-NI reproduces the industry indices by using the available sectoral indices. Precisely, the sectoral index is market-capitalisation-weighted, so it is calculated as:

$$SI_{i,t} = \frac{\sum_{j=1}^{k_i} P_{i,j,t} * N_{i,j,t}}{\sum_{j}^{k_i} P_{i,j,0} * N_{i,j,o}} \qquad (40)$$

where $SI_{i,t}$ is the sectoral index of sector i at time t, $P_{i,j,t}$ and $N_{i,j,t}$ are price and number of shares of stock *j* in the sector *i* at time *t*, respectively. The variable k_i is the number of stocks in the sector *i* and the subscript *0* denotes the time at base value. The industry group index is also calculated in a similar manner. For example, if industry group m contains sector 1 and sector 2, the industry group index can be computed as:

$$IGI_{m,t} = \frac{(MV_{1,1,t} + \cdots + MV_{1,k_1,t}) + (MV_{2,1,t} + \cdots + MV_{2,k_2,t})}{\left(MV_{1,1,0} + \cdots + MV_{1,k_1,0}\right) + (MV_{2,1,0} + \cdots + MV_{2,k_2,0})} \qquad (41)$$

where IGI_{mt} is the industry group index of industry group m at time *t*, MV_{ijt} are market capitalisation of stock j in the sector i at time *t*, which is basically $P_{ijt} * N_{ijt}$. It can be rearranged to show that:

$$IGI_{mt} = \frac{SI_{1,t} * SMV_{1,0} + SI_{2t} * SMV_{2,0}}{SMV_{1,0} + SMV_{2,0}} \qquad (42)$$

where $SMV_{i,0}$ is the sector's total market capitalisation on the base day, which is $\sum_{j}^{k_i} MV_{i,j,0}$. This can easily be extended to work with industry groups consisting of more than two sectors. In order to construct the K-NI, the market values of all stocks on 31st December 2003 were, therefore, collected to compute the $SMV_{i,0}$ for each industry group.

The dividend yield series were calculated as:

$$IDY_{m,t} = \frac{\sum_{p=1}^{q_m} SDY_{p,t} * SMV_{p,t}}{\sum_{p=1}^{q_m} SMV_{p,t}} \qquad (43)$$

where $IDY_{m,t}$ is the industry group's dividend yield, $SDY_{p,t}$ and $SMV_{p,t}$ are dividend yield and the market capitalisation of sector p, respectively. The variable q_m is the number of sector in the industry group.

Lastly, the trading volume considered in this chapter is the average daily trading volume in the particular month. The daily trading volume is worked out by summing up the trading volume of each stock in the industry group.

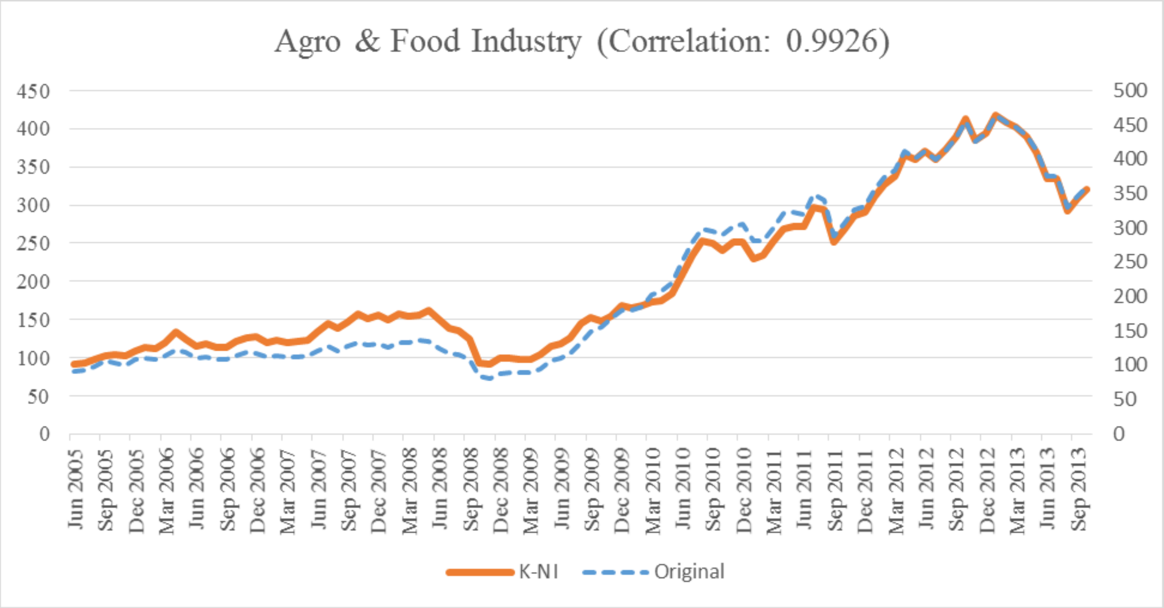
The advantage of the new K-NI is that it extends the industry group indices to start from September 1988, which means 280 observations are available after balancing with available dividend yield and trading volume data and allowing for 12-month burn-in periods. An exception is the Technology industry group where one observation is lost, due to dividend yield data starting from October 1988. Figure 25 shows comparisons of the K-NI and the original series only for the comparable period from June 2005 to December 2012. Overall, the two series tend to move very closely together, with the correlation coefficients, ranging from 0.9424 to 0.99997, supporting this conclusion.

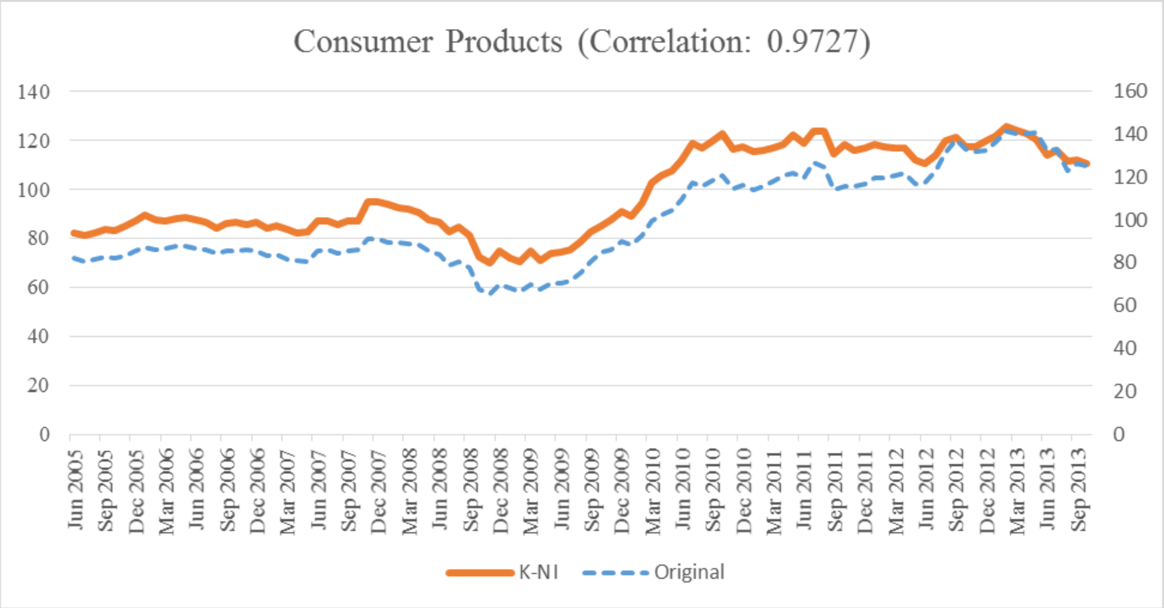
Note also that, as a market-capitalisation-weighted index, there are a couple of limitations with the K-NI. Firstly, it is subject to a concentration bias. It means that the K-NI – as an industry group index – would represent some sub-indices (i.e. the sectoral indices) more heavily, based on their market capitalisation. Alternatively, calculations based on fixed-weight, capped-weight, or equally-weighted methods have been proposed, but the K-NI used a standard market-capitalisation-weighted approach to be in line with most indices observed in practice, including the official Stock Exchange of Thailand's SET index series.

Secondly, the K-NI is also prone to a calculation bias. It refers to the fact that a movement of a sectoral index with a large market capitalisation included in a particular industry group would have a stronger influence on the index – and the same applies for the price change of a stock in a sectoral index. In other words, it mixes up the impact of price and number of shares. Also, this would lead to increased overall volatility when the constituents with high market value fluctuate, as well. The index weighted by actual free-float, instead of the registered number of shares, could partially help reduce the bias. However, in order to be consistent with the SET series and to keep computation more straightforward, this has not been pursued.

Finally, it is also important to note that, the under-priced instruments would bear a lower weight in the market-capitalisation-weighted index, while those with inflated prices – potentially, a bubble – would represent a more significant proportion of the index. This would result in a substantial mispricing, which investors trading based on the index would be at risk.

Figure 25: The K-NI and the Original SET's Industry Group Indices (June 2005 – December 2013)





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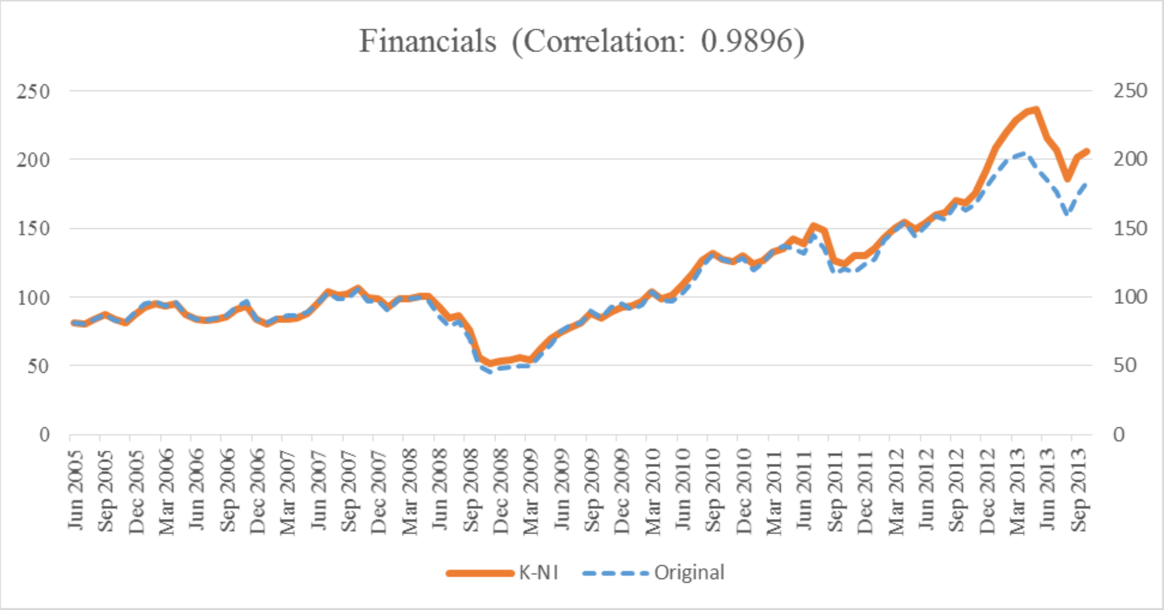

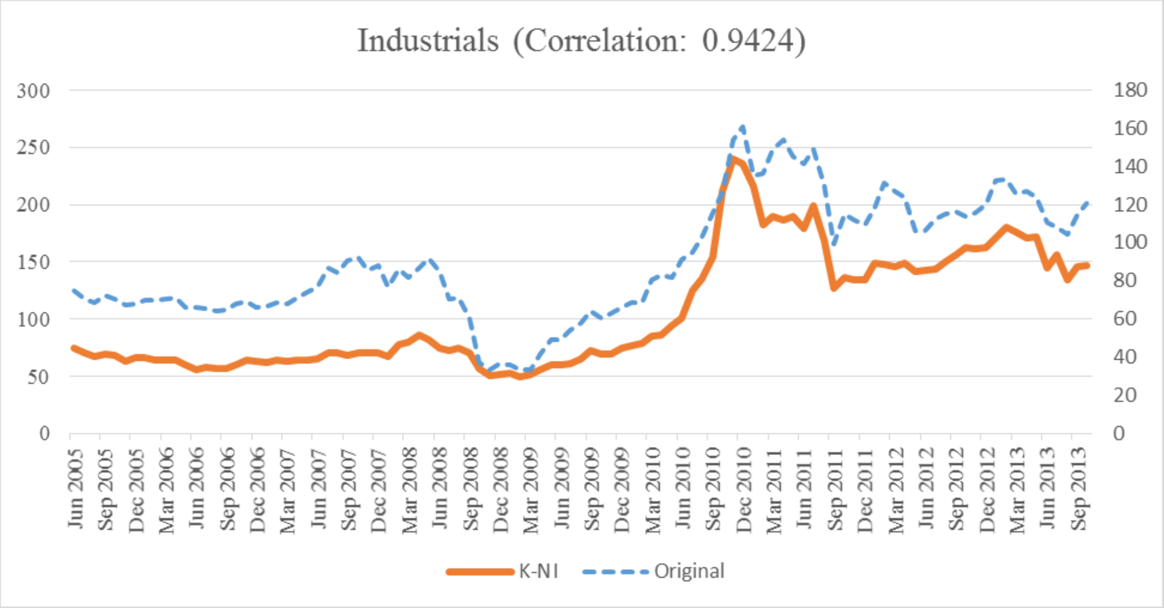

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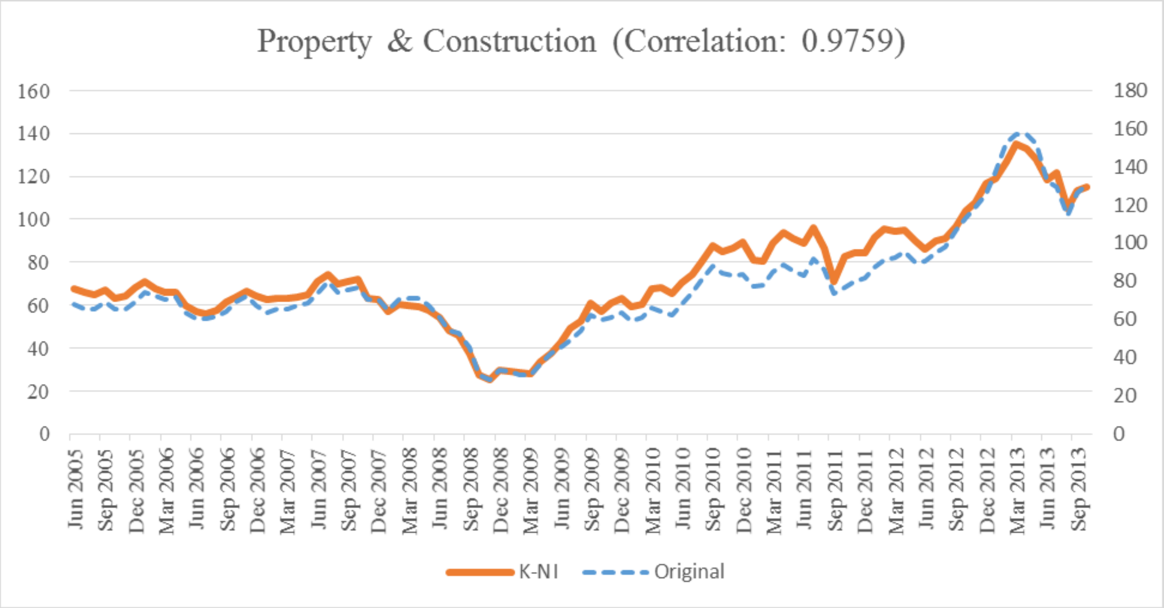

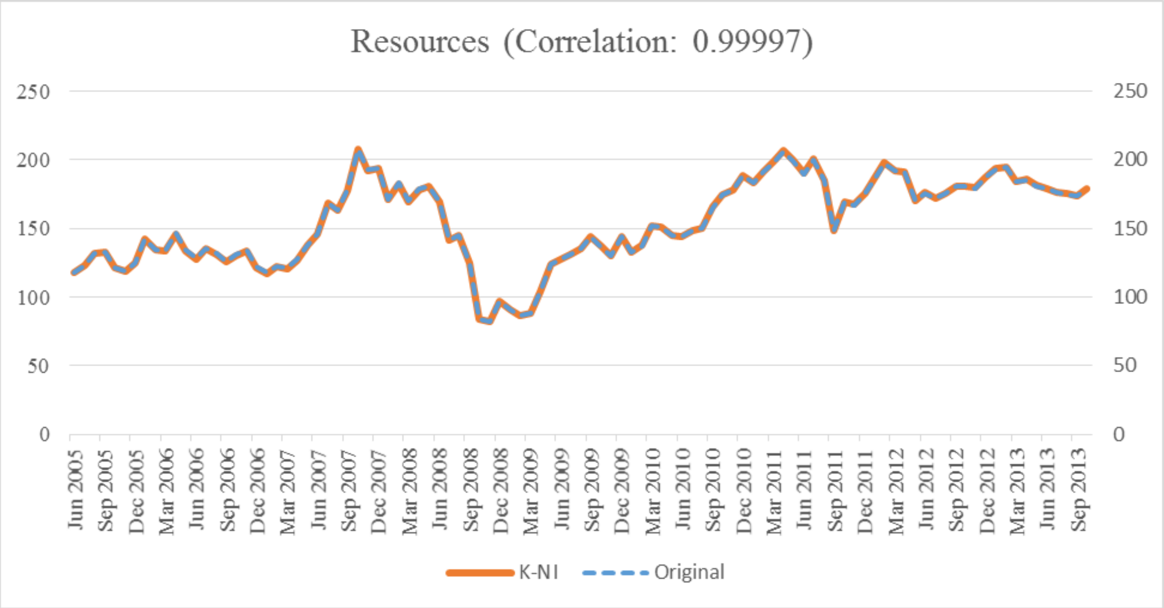

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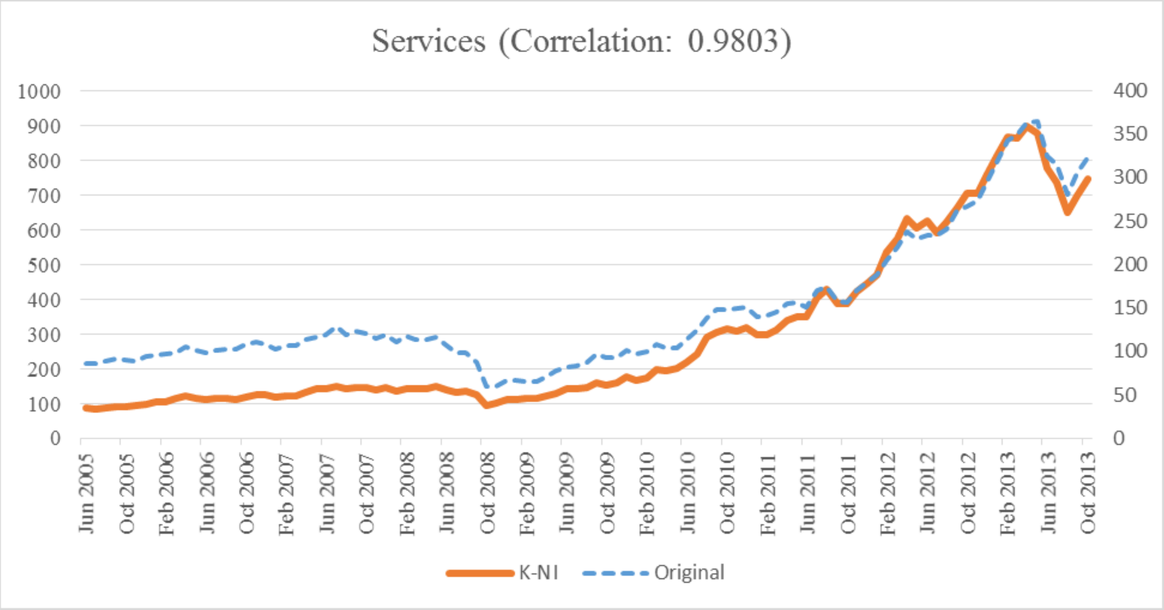
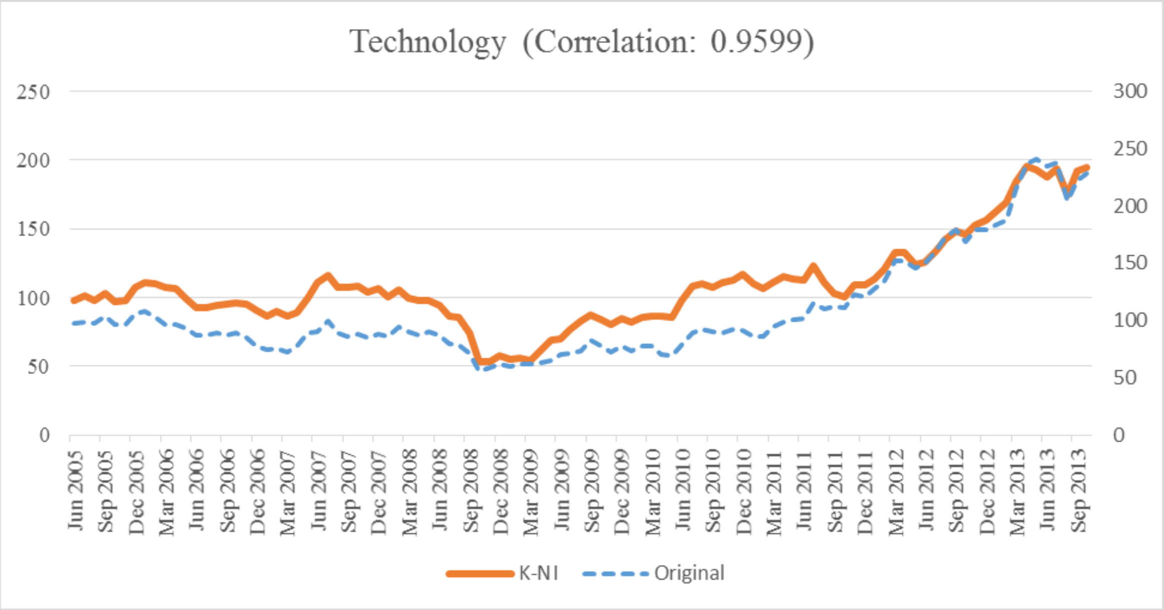




4.6. Contagion Models

Anderson et al. (2010) proposed to extend the original volume-augmented model proposed by Brooks and Katsaris (2005) to study the linkages between sectors or industry groups by also including the lagged bubble size and abnormal trading volume of all other industry groups in the model, and not just lagged bubble size and abnormal trading volume of the particularly industry group whose returns are being considered. The model for g industry groups will then be:

$$r^i_{s,t+1} = \beta^i_{so} + \sum\nolimits_{j=1}^{g} \beta^i_{sbj} B_{jt} + \sum\nolimits_{j=1}^{g} \beta^i_{svj} AV_{jt} + \varepsilon^i_{s,t+1} \tag{44}$$

$$r^i_{c,t+1} = \beta^i_{co} + \sum\nolimits_{j=1}^{g} \beta^i_{cbj} B_{jt} + \varepsilon^i_{c,t+1} \tag{45}$$

$$P\left(r^i_{t+1} \middle| S\right) = q\left(B_{jt}, AV_{jt}\right) = \Omega\left(\beta^i_{qo} + \sum\nolimits_{j=1}^{g} \beta^i_{qbj} \left|B_{jt}\right| + \sum\nolimits_{j=1}^{g} \beta^i_{qvj} AV_{jt}\right) \tag{46}$$

where the superscript *i* and the added subscript *j* refers to the industry groups, while all other variables and parameters have the same definitions as discussed previously. The likelihood function is also modified in a similar manner to be:

$$\begin{aligned} \ell\left(r^i_{t+1} \middle| \xi\right) = \sum_{t=1}^{T} ln \Bigg[& P\left(r^i_{t+1} \middle| S\right) \frac{\omega\left(\frac{r^i_{t+1} - \beta^i_{so} - \sum_{j=1}^{g} \beta^i_{sbj} B_{jt} - \sum_{j=1}^{g} \beta^i_{svj} AV_{jt}}{\sigma^i_s}\right)}{\sigma^i_s} \\ & + P\left(r^i_{t+1} \middle| C\right) \frac{\omega\left(\frac{r^i_{t+1} - \beta^i_{co} - \sum_{j=1}^{g} \beta^i_{cbj} B_{jt}}{\sigma^i_c}\right)}{\sigma^i_c} \Bigg] \end{aligned} \tag{47}$$

This model which includes lagged bubble and volume terms from all industry groups (hereafter Model A) will be estimated g times – one for each industry group as a dependent variable. The number of parameters to be estimated is $5 + 5g$ or 45 in the case of eight industry groups. As this model can be quite large and could be problematic to estimate, Anderson et al. (2010) also suggest several ways to simplify it.

1. Drop the lagged volume terms from the surviving regime equation (and the likelihood function) (hereafter, model type P).
2. Drop the lagged volume terms from the probability equation (hereafter, model type R)
3. Drop the lagged volume terms from both the surviving regime and probability equations (hereafter, model type V)

An alternative approach is to model the return of a particular industry group with its own lagged bubble size and trading volume and the market-wide index's, instead of all other industry groups (Anderson et al., 2010). The bubble contagion model that includes the market data as a proxy (hereafter, Model M) thus become:

$$r^{i}_{s,t+1} = \beta^{i}_{so} + \beta^{i}_{sb}B_{it} + \beta^{i}_{sbM}B_{Mt} + \beta^{i}_{sv}AV_{t} + \beta^{i}_{svM}AV_{Mt} + \varepsilon^{i}_{s,t+1} \tag{48}$$

$$r^{i}_{c,t+1} = \beta^{i}_{co} + \beta^{i}_{cb}B_{it} + \beta^{i}_{cbM}B_{Mt} + \varepsilon^{i}_{c,t+1} \tag{49}$$

$$P\left(r^{i}_{t+1}\middle|S\right) = \Omega\left(\beta^{i}_{qo} + \beta^{i}_{qb}|B_{it}| + \beta^{i}_{qbM}|B_{Mt}| + \beta^{i}_{qv}AV_{it} + \beta^{i}_{qvM}AV_{Mt}\right) \tag{50}$$

where all variables and parameters are as defined earlier and the new subscript M denotes market data.

The results from Model M can show whether an industry group is affected by the bubble in the overall market. However, it does not identify the precise source of transmission. The final model (hereafter Model J) is developed to determine the impact of bubbles from different industry groups on the industry group being considered, but still maintains the efficiency of estimation with a small number of parameters to be estimated. Model J regresses each industry group as a dependent variable on its own lagged bubble size and trading volume as well as lagged bubble size and trading volume from one other industry groups. It is then repeated for all other industry groups. Specifically, the model is:

$$r^{ij}_{s,t+1} = \beta^{ij}_{so} + \beta^{ij}_{sb}B_{it} + \beta^{ij}_{sbj}B_{jt} + \beta^{ij}_{sv}AV_{t} + \beta^{ij}_{svj}AV_{jt} + \varepsilon^{ij}_{s,t+1} \tag{51}$$

$$r^{ij}_{c,t+1} = \beta^{ij}_{co} + \beta^{ij}_{cb}B_{it} + \beta^{ij}_{cbj}B_{jt} + \varepsilon^{ij}_{c,t+1} \tag{52}$$

$$P\left(r^{ij}_{t+1}\middle|S\right) = \Omega\left(\beta^{ij}_{qo} + \beta^{ij}_{qb}|B_{it}| + \beta^{ij}_{qbj}|B_{jt}| + \beta^{ij}_{qv}AV_{it} + \beta^{ij}_{qvj}AV_{jt}\right) \tag{53}$$

where all notation is as above and the subscript *j* refers to a second industry group considered for a potential influence on the dependent variable.

Note that the impact of a particular industry group index or the market index could work through up to five different channels, namely the bubble terms in the two return equations and state-determining equation, and abnormal trading volume terms in the surviving state equation and the probability equation. In order to determine the overall significance, a block exogeneity test will be conducted. The test re-estimates the model without the data from a specific industry group j by assuming $\beta_{sbj}^{ij} = \beta_{svj}^{ij} = \beta_{cbj}^{ij} = \beta_{qbj}^{ij} = \beta_{qvj}^{ij} = 0$. It then performs a nested likelihood ratio (LR) test to compare the restricted model to the unrestricted full model with the null hypothesis that the full model is no better. Therefore, if the test is rejected, it would suggest the industry group *j* is a significant factor in determining return in the dependent industry group. In other words, there is evidence of bubble contagion from industry group *j* to the industry group being investigated.

The results from Model A and Model J will be evaluated using the LR test in a similar fashion. If the test fails to reject the null hypothesis, the results from a more parsimonious Model J will be chosen over those from Model A. The integrated block exogeneity test results from the two models will be presented.

4.7. Granger Causality Test

Lastly, this study will also consider the conventional bivariate Granger Causality test (Granger, 1969) on both returns and relative bubble size from all industry groups. Specifically, the model is:

$$X_1(t) = \sum_{j}^{h} A_{11,j} X_1(t-j) + \sum_{j}^{h} A_{12,j} X_2(t-j) + \varphi_1(t) \qquad (54)$$

$$X_2(t) = \sum_{j}^{h} A_{21,j} X_1(t-j) + \sum_{c}^{h} A_{22,j} X_2(t-j) + \varphi_2(t) \qquad (55)$$

where $X_1(t)$ and $X_2(t)$ are the returns (or relative bubble size) of two selected industry groups in time period t, c is the number of lags with h as the maximum, and φ_i are the residuals.

In this thesis, the pairwise testing will have a maximum number of lags set for 12 months and the optimal lag length is chosen using the Bayesian Information Criterion (BIC). The null hypothesis of the test is that the independent variable does not Granger-cause the dependent variable. Precisely, in checking whether X_2 Granger-causes X_1, the null hypothesis is that all the $A_{12,c}$ coefficients are all zero. If rejected, it means the independent variable X_2 precedes the dependent variable X_1 or there is evidence of possible linkages between two industry groups. The analysis is different from the speculative bubble model approach as it allows for lags of more than one period but it does not permit states of different bubble behaviour.

Chapter 5: Empirical Results for the Aggregate Market Index

5.1. Introduction

This chapter studies the Stock Exchange of Thailand's market-wide SET Index. Data on the monthly price index, corresponding dividend yield, and trading volume since the establishment of the exchange in April 1975 until December 2012 were obtained from Datastream. Implied cash dividends were calculated from the dividend yields. The price index and dividend series were converted into real (constant price) series using Thailand's Consumer Price Index (CPI) retrieved from the same database. Monthly trading volume is calculated as an average daily volume in a certain month. This is done to avoid the impact of events with exceptionally high or low trading volumes. Abnormal trading volume was computed as the percentage deviation of trading volume from the moving average of 3-, 6-, 12-, and 18-month periods.

The structure is organised as followed. The empirical evidence is discussed in the next section. Particularly, it presents estimation results from the main model, various robustness checks and model extensions. It also justifies the use the methodology with the analysis on probability statistics obtained from the models. Finally, the last section offered a conclusion.

5.2. Empirical Evidence on the market-wide SET Index

The following sections present the results of the speculative bubble models for the SET Index. The volume-augmented model was estimated to assess the presence of bubble-like behaviour in the Thai stock market over the sample of April 1975 to December 2012. The tables are separated into panels. The top two panels contain the results from model estimations. They include estimated coefficients with asterisks denoting their significance levels, the maximised log-likelihood function values, and three information criteria statistics. The third panel presents the coefficient restriction tests, which helps evaluate the hypothesis of no-bubble. In order to determine whether this volume-augmented model is better at explaining return variations than simpler models, the log-likelihood tests against four more parsimonious specifications were performed as robustness checks. Their results can be found in the fourth panel. Lastly, the last panel shows the starting observation and number of observations included in estimations. Note that the first 11 observations in the sample were excluded from the estimations to allow for a burn-in period. That is to ensure that the simple average of dividend yield which was used a proxy for the calculation of fundamental values covers at least 12 observations.

5.2.1. The Base Model: Volume-augmented Model

An initial estimation used monthly data with the following definitions. The fundamental value was computed using the dividend multiple approach with simple average as a proxy (see Section 4.4 Measure of Fundamental Values). Abnormal trading volume was defined as a percentage change of the current period's trading volume to the moving average of the latest 12 periods. Precisely, the current trading volume is included in the calculation of the moving average and the monthly trading volume employed in the estimation is the average daily trading volume within the given month. Alternative descriptions of the variables – such as weighted or exponential weighted moving averages of dividend multiple, other numbers of lags included in the trading volume's moving average, exclusion of current period data from the moving average computation, and the ratio of current trading volume to moving average instead of percentage deviation – were also investigated as further robustness checks in Section 5.2.2.

With regard to the base model, the results are shown in Table 6. Overall, they reveal that the volume-augmented model formalised in equations (22) to (24) captures significant additional variations in returns and probability functions when compared to the volatility regimes model [equations (26) to (28)], the mixture of normal distributions model [equations (29) to (31)], the fads model [equations (32) to (34)], and also the VNS model [equations (13) to (17)]. To assess the evidence of a bubble, the number of restriction tests rejected are counted. In this case, only two of the coefficient restrictions are satisfied, but all estimated parameters have the expected signs. Thus, it can be argued that there is some evidence supporting the rejection of the no-bubble hypothesis. Most of the estimated regression coefficients are statistically significant.

Table 6: The Base Model: Volume-augmented

	The Base Model	VNS	Fads	Mixture of Normals	Volatility Regimes
β_{so}	1.0057***	1.0075***	1.0078***	1.0088***	1.0096***
β_{sb}	0.0235	0.0347**	0.0081		
β_{sv}	0.0112*				
β_{co}	1.0263***	1.0185***		1.0134***	
β_{cb}	-0.0374	-0.0257			
β_{qo}	1.5147***	1.4124***	0.4332*	0.4291	0.4464*
β_{qb}	-3.1159***	-3.4989***			
β_{qv}	-0.3121				
σ_s	0.0444***	0.0422***	0.0493***	0.0494***	0.0498***
σ_c	0.1210***	0.1156***	0.1284***	0.1279***	0.1287***
Log-Likelihood	516.7845	513.9311	495.5600	495.3250	495.2720
AIC	-2.2983	-2.2945	-2.2248	-2.2237	-2.2280
SBIC	-2.3437	-2.3308	-2.2474	-2.2464	-2.2461
HQIC	-2.2618	-2.2652	-2.2065	-2.2054	-2.2134
$(R1)\ \beta_{so} \neq \beta_{co}$	1.0433	0.3805			
$(R2)\ \beta_{cb} < 0$	1.1832	0.7229			
$(R3)\ \beta_{sb} > \beta_{cb}$	2.5183	2.9553*			
$(R4)\ \beta_{qb} < 0$	29.8211***	35.5400***			
$(R5)\ \beta_{qv} < 0$	2.1841				
$(R6)\ \beta_{sv} > 0$	3.7030*				
Volatility regimes	43.0251***	37.3181***	0.5760	0.1059	
Mixture of normals	42.9191***	37.2122***			
Fads	42.4490***	36.7421***			
VNS	5.7069*				
Starting observation	Mar 1976	Mar 1976	Mar 1976	Mar 1976	Mar 1976
No. of observations	441	441	441	441	441

Note: The top panel reports estimated parameters from the volume-augmented model as formalised in equations (22) to (24), the VNS model in equations (13) to (17), the fads model in equations (32) to (34), the mixture of normals in equations (29) to (31), and the volatility regimes in equations (26) to (28) with definitions of variables elaborated in the text. The second panel shows maximised log-likelihood statistics and other information criteria. The third and fourth panels present likelihood ratio statistics for tests of coefficient restrictions and robustness checks against simpler specifications. Starting observations and number of observations included in the estimation are contained in the last panel. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Consider the return equations, the coefficient β_{so} and β_{co} are 1.0057 and 1.0263, respectively. This means that the average net monthly return in the surviving and collapsing regime are 0.57% and 2.63% per month or 7.06% and 36.55% per year, respectively. Note that the average return when the bubble survives turns out to be smaller than when it collapses. Although this is rather counter-intuitive, it does not violate any assumption of the model. The theory only postulates that the two regimes should have different average returns. The estimated parameters of the relative bubble term (β_{sb} and β_{cb}) are statistically insignificant in both regimes and the difference between the two regimes is also not statistically significant, as shown by restriction (R3). Specifically, when the $B_t = 0.5$ or when half of the actual price is a deviation from fundamental price, the expected returns with normal trading volume increase to 1.75% (23.07% annualised) in the surviving state and fall to 0.76% (9.51% annualised). Note that this result is consistent with Anderson et al. (2010) who found a positive β_{sb} which suggested investors in the S&P500 were compensated for holding bubbly assets if the bubble survives and continues to grow. Finally, investors are compensated for the additional risk of holding assets with abnormal trading volume, as β_{sv} is positive and statistically significant.

Turning to the probability function, abnormal trading volume was included to proxy for investors offloading bubbly assets. As it increases, the prospect of bubble surviving will diminish. The result shows that β_{qv} is indeed negative but not statistically significant. The average probability, when there is no deviation from fundamental value and the trading volume is normal, can be calculated as the cumulative normal distribution function of β_{qo} which turns out to be 93.51%. Also, as bubble size grows larger, it is less likely to continue. The coefficient β_{qb} is statistically significant and estimated to be -3.1159 which suggest that, assuming normal trading volume, the probability of bubble surviving in next period when $B_t = 0.5$ will fall to only 48.28%. In fact, the average relative bubble size in the sample is 0.2865, which suggests that the probability of being in the bubble surviving state when there is no abnormal trading volume is actually 81.95%, on average.

Finally, returns usually observe very significant fall in the period where the bubble bursts. Thus, the standard deviation in the collapsing state is expected to be greater than in the bubble continues to survive. This view is supported by the evidence where σ_s and σ_c were estimated to be 4.44% and 12.10% on a monthly basis. Thus, the result is consistent with the speculative bubble model.

5.2.2. Further Robustness Checks

As further robustness checks, models with alternative measurements of the variables were estimated, and their results were compared to the base model discussed in the previous section.

5.2.2.1. Measures of Fundamental Value

Table 7 presents the results when the fundamental value is computed using dividend multiple approach with different proxies. As discussed in Section 4.4, the base model utilised a simple average of the all past price/dividend ratios as a proxy for the dividend multiple used in the calculation of the fundamental value. However, it is arguable that the more recent observations should be more relevant in forecasting evolution of prices. Therefore, the exponential moving average and 12-month weighted average were tested. The former model gives a qualitatively and quantitatively comparable result with lower log-likelihood function values at optimum when compared to the base model, although it performs better in terms of restriction test rejection. The latter yields a less satisfactory result with a test against the VNS model cannot be rejected. The last column shows the estimation based on a fundamental value method by Campbell and Shiller (1987). The result is mostly similar to the base model, except for the statistically insignificant negative β_{qo} and positive β_{qb}. It also has a smaller log-likelihood value. Hence, the rest of this study will focus on the simple average dividend multiple approach as a proxy for fundamental value.

Table 7: Measures of Fundamental Values

	The Base Model	Exponential Moving Average	Weighted Moving Average	Campbell and Shiller (1987) Fundamental Value
β_{so}	1.0057***	1.0075***	1.0099***	1.0053***
β_{sb}	0.0235	0.0140	0.0836*	0.0056
β_{sv}	0.0112*	0.0125*	0.0117	0.0120
β_{co}	1.0263***	1.0169***	1.0084***	1.0200***
β_{cb}	-0.0374	-0.0163	-0.0119	-0.0250
β_{qo}	1.5147***	1.5738***	1.4717***	-0.5034
β_{qb}	-3.1159***	-3.3550***	-6.9478***	1.0091
β_{qv}	-0.3121	-0.4874	-0.3128	-0.4593
σ_s	0.0444***	0.0476***	0.0526***	0.0384***
σ_c	0.1210***	0.1249***	0.1313***	0.1097***
Log-Likelihood	516.7845	516.4507	495.3832	504.2660
AIC	-2.2983	-2.2968	-2.2576	-2.2416
SBIC	-2.3437	-2.3422	-2.3041	-2.2869
HQIC	-2.2618	-2.2603	-2.2203	-2.2050
$(R1)\ \beta_{so} \neq \beta_{co}$	1.0433	0.3583	0.0092	1.1819
$(R2)\ \beta_{cb} < 0$	1.1832	0.3372	0.0514	2.4072
$(R3)\ \beta_{sb} > \beta_{cb}$	2.5183	0.7555	1.4771	2.8693*
$(R4)\ \beta_{qb} < 0$	29.8211***	29.7288***	25.3182***	7.8063***
$(R5)\ \beta_{qv} < 0$	2.1841	4.3226**	1.7475	2.3462
$(R6)\ \beta_{sv} > 0$	3.7030*	3.6955*	3.2381*	2.1789
Volatility regimes	43.0251***	42.3573***	37.9953***	17.9880***
Mixture of normals	42.9191***	42.2514***	37.8807***	17.8821***
Fads	42.4490***	41.8379***	35.8551***	17.5411***
VNS	5.7069*	8.4136**	4.4379	4.5323
Starting observation	Mar 1976	Mar 1976	Feb 1977	Mar 1976
No. of observations	441	441	430	441

Note: Results from the volume-augmented model with the data based on a simple average of past price/dividends ratio as a proxy for dividend multiple used in the determination of the fundamental values and subsequently the relative bubble term. The fundamental values of alternative datasets were calculated with exponential weighted or 12-month weighted average as a proxy for dividend multiple or the Campbell-Shiller (1987) approach as discussed in Section 4.4. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

5.2.2.2. Trading Volume's Moving Average

There are three issues about the way abnormal volume is computed. They are about the appropriate number of lags to be included in the calculation of the moving average, whether the current period's trading volume should be included in such calculations and whether the percentage deviation from the moving average or the ratio of current period's trading volume to the moving average is a fitting functional form for abnormal trading volume. All of these matters are more empirical than theoretical and were investigated here.

The results based on 3-, 6-, 12-, and 18-period lags are shown in Table 8. In general, all specifications offer qualitatively similar results. The model with 12-period lag produced the most convincing results, as it yielded the highest log-likelihood statistics. The volume-augmented model with 3- and 6-period lag of trading volume's moving average are not better than the original VNS model, as the test cannot be rejected. While the model with 18-period lag has additional explanatory power from the simple models and the restriction (R5) rejected, it has the lowest log-likelihood value in all four specifications.

The base model measured moving average (MA) by including the current period's trading volume. That is a z-month moving average, $MA(z)_t = (V_t + V_{t-1} + \cdots + V_{t-z+1})/z$, where V_t is the average daily trading volume in month t. The alternative is to include only previous periods and exclude the current data, or is $MA'(z)_t = (V_{t-1} + V_{t-2} + \cdots + V_{t-z})/z$. This mostly had a small impact on all specifications. Only the result of 12-period lag is shown in Table 8. The β_{sv} is no longer statistically significant and the log-likelihood statistics is marginally lower than that of the base model. Also, one extra observation is lost. Thus, moving averages in this research will be calculated with the latest 12 periods, not the previous 12 periods.

Table 8: Measures of Abnormal Trading Volume

	The Base Model	MA(3)	MA(6)	MA(18)	MA’(12) – excluding current period’s	MA(12) – ratio of current period to the moving average
β_{so}	1.0057***	1.0072***	1.0062***	1.0056***	1.0053***	0.9945***
β_{sb}	0.0235	0.0339*	0.0292*	0.0193	0.0210	0.0235
β_{sv}	0.0112*	0.0057	0.0115	0.0121	0.0119	0.0112*
β_{co}	1.0263***	1.0193***	1.0227***	1.0280***	1.0269***	1.0263***
β_{cb}	-0.0374	-0.0272	-0.0331	-0.0397	-0.0375	-0.0374
β_{qo}	1.5147***	1.4222***	1.4765***	1.4937***	1.4990***	1.8268***
β_{qb}	-3.1159***	-3.4561***	-3.2892***	-2.8960***	-3.0017***	-3.1159***
β_{qv}	-0.3121	0.0445	-0.0731	-0.3738	-0.3536	-0.3121
σ_s	0.0444***	0.0426***	0.0441***	0.0453***	0.0445***	0.0444***
σ_c	0.1210***	0.1163***	0.1195***	0.1211***	0.1204***	0.1210***
Log-Likelihood	516.7845	514.0748	515.1138	505.5330	514.8884	516.7845
AIC	-2.2983	-2.2861	-2.2908	-2.2783	-2.2949	-2.2983
SBIC	-2.3437	-2.3314	-2.3361	-2.3243	-2.3404	-2.3437
HQIC	-2.2618	-2.2495	-2.2542	-2.2413	-2.2583	-2.2618
$(R1)\ \beta_{so} \neq \beta_{co}$	1.0433	0.4313	0.7059	1.2161	1.2103	1.0433
$(R2)\ \beta_{cb} < 0$	1.1832	0.7786	1.0029	1.2886	1.2139	1.1832
$(R3)\ \beta_{sb} > \beta_{cb}$	2.5183	2.9451*	2.7820*	2.2371	2.3339	2.5183
$(R4)\ \beta_{qb} < 0$	29.8211***	34.3480***	32.9309***	24.0231***	27.3593***	29.8211***
$(R5)\ \beta_{qv} < 0$	2.1841	0.0090	0.0621	3.4331*	2.3826	2.1841
$(R6)\ \beta_{sv} > 0$	3.7030*	0.2799	2.3579	3.6290*	3.5371*	3.7030*
Volatility regimes	43.0251***	37.6055***	39.6836***	40.9997***	42.0678***	43.0251***
Mixture of normals	42.9191***	37.4996***	39.5776***	40.9077***	41.9357***	42.9191***
Fads	42.4490***	37.0295***	39.1075***	40.4514***	41.4560***	42.4490***
VNS	5.7069*	0.2874	2.3654	6.3678**	4.9370*	5.7069*
Starting observation	Mar 1976	Mar 1976	Mar 1976	Sep 1976	Apr 1976	Mar 1976
No. of observations	441	441	441	435	440	441

Note: Results from the volume-augmented model with different definitions of the abnormal trading volume terms. The base model used abnormal trading volume with moving average of trading volume computed from data in the latest 12 periods. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

The last column in Table 8 shows the result of the data with abnormal trading volume computed as a ratio of current volume to the moving average, instead of percentage deviations. This is done because it is more consistent with other variables in the model. Specifically, the gross return - the dependent variable - is the ratio of next period's price index to the current period and the relative bubble term is the ratio of the bubble deviation to the current price. However, with this definition of the abnormal trading volume, the coefficient β_{so} by itself does not offer any meaningful interpretation. This is because when trading volume is normal or when it is at the same level as the moving average, the abnormal trading volume takes a value of 1. The average gross monthly return in the surviving regime is, therefore, the sum of β_{so} and β_{sv} which is 0.9945+0.0012=1.0057 which is equal to the estimate of β_{so} based on percentage deviation abnormal trading volume with a small rounding error. This also invalidates the restriction (R1). The test was, thus, revised to test whether $\beta_{so} + \beta_{sv} \neq \beta_{co}$ for this case. Similarly, the coefficient β_{qo} by itself does not contain any economic meaning. The average probability, when there is no deviation from fundamental value and the trading volume is normal, can be calculated as the cumulative normal distribution function of the sum of β_{qo} and β_{qv} which also turns out to be 93.51% , which is precisely what was found earlier with the percentage deviation specification. Except for β_{so} and β_{qo}, note that all test statistics, including the final log-likelihood score, with the two measures are alike. Nevertheless, the model with percentage deviation is preferred, as it allows simpler interpretations.

5.2.2.3. Value of Relative Bubble in the Probability Equation

As set out in equation (24), the absolute value – rather than the actual value – of the relative bubble was included in the probability equation. This suggests that the size of the bubble – not the sign –determines the likelihood whether the next period is in the surviving state. It is possible that the kind of the bubble – positive or negative bubble – might have different effects. Therefore, a specification that includes the actual value of relative bubble was estimated. Table 9 showed that the result was very similar to the base model. The main reason is perhaps that only roughly 20% of the sample period had negative bubbles. Moreover, a model with squared relative bubble term instead of the absolute value was also tested. The result is qualitatively similar to the base model as well. The coefficient β_{sb} is now statistically significant but, overall, the model has marginally lower log-likelihood statistics when compared to the base model.

Table 9: Relative Bubble Term in Probability Equation

	The Base Model	B_t	B_t^2
β_{so}	1.0057***	1.0053***	1.0058***
β_{sb}	0.0235	0.0293	0.0260*
β_{sv}	0.0112*	0.0092	0.0118*
β_{co}	1.0263***	1.0304***	1.0261***
β_{cb}	-0.0374	-0.0467	-0.0376
β_{qo}	1.5147***	0.7035***	1.1286***
β_{qb}	-3.1159***	-2.0340***	-4.3575***
β_{qv}	-0.3121	-0.1739	-0.3098
σ_s	0.0444***	0.0397***	0.0449***
σ_c	0.1210***	0.1135***	0.1204***
Log-Likelihood	516.7845	514.6047	516.7831
AIC	-2.2983	-2.2885	-2.2983
SBIC	-2.3437	-2.3338	-2.3437
HQIC	-2.2618	-2.2519	-2.2618
$(R1)\ \beta_{so} \neq \beta_{co}$	1.0433	1.9840	1.0080
$(R2)\ \beta_{cb} < 0$	1.1832	2.1075	1.2239
$(R3)\ \beta_{sb} > \beta_{cb}$	2.5183	2.9514*	2.8272*
$(R4)\ \beta_{qb} < 0$	29.8211***	25.4613***	29.8182***
$(R5)\ \beta_{qv} < 0$	2.1841	0.6410	1.9063
$(R6)\ \beta_{sv} > 0$	3.7030*	2.6765	3.8660**
Volatility regimes	43.0251***	38.6653***	43.0222***
Mixture of normals	42.9191***	38.5594***	42.9162***
Fads	42.4490***	38.0893***	42.4461***
VNS	5.7069*	1.3472	5.7040*
Starting observation	Mar 1976	Mar 1976	Mar 1976
No. of observations	441	441	441

Note: Results from the volume-augmented model with different definitions of the relative bubble terms in the probability equation (24). The absolute value of relative bubble term was used in the base model. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

5.2.2.4. Splitting Sample at July 1997

In July 1997, Thailand switched from a fixed exchange rate regime to a managed floating system. It likely caused a major structural change in the economy. To investigate this issue, the sample was then split into two sub-periods. The results for the sub-samples are presented in Table 10. The sub-sample before July 1997 included 255 observations and the one starting July 1997 only covered 168 observations. With shorter sample periods, the model, understandably, worked slightly less well in terms of expected signs, the statistical significance of parameters and robustness tests against simple models. Still, there seems to appear some evidence of a bubble in the data in both sub-periods. Interestingly, considering the bubble-related parameters $(\beta_{sb}, \beta_{cb}, \beta_{qb})$, the influence of bubble variables on the stock prices seems to have come through the probability function in the first sub-sample and more through the return functions in the latter. Besides, the average probability of bubble surviving into the next period has dropped from 99.12% in the sub-sample before July 1997 to only 20.56% in the sub-sample from July 1997 (based on β_{qo} changing from 2.3741 to -0.8218). In other words, the chance to be in a bubble-collapsing state – which is characterised by higher volatility $(\sigma_c > \sigma_s)$ – was greater in the sub-period starting from 1997. This can possibly be explained with the increased risk coming from exchange rate floatation, as well as, other uncertainties in the global and domestic markets during that point in time. Furthermore, the statistically significant β_{qb} estimated to be -6.8696 implied that the effect from the bubble term on the probability of the bubble surviving in the next period for the first sub-period with fixed exchange rate was negative statistically significant. However, the same effect for the second sub-period with floating exchange rate was statistically insignificant. This issue will be further investigated in the following section.

Table 10: Splitting Sample at July 1997

	The Base Model	Before July 1997	From July 1997
β_{so}	1.0057***	1.0055***	1.1007***
β_{sb}	0.0235	0.0526	0.4175***
β_{sv}	0.0112*	0.0069	0.0243
β_{co}	1.0263***	1.0177***	0.9993***
β_{cb}	-0.0374	-0.0097	-0.0374***
β_{qo}	1.5147***	2.3741***	-0.8218**
β_{qb}	-3.1159***	-6.8696***	-1.1076
β_{qv}	-0.3121	-0.2507	0.1678
σ_s	0.0444***	0.0351***	0.0545***
σ_c	0.1210***	0.0984***	0.0678***
Log-Likelihood	516.7845	328.8238	196.0619
AIC	-2.2983	-2.5006	-2.2150
SBIC	-2.3437	-2.5790	-2.3341
HQIC	-2.2618	-2.4447	-2.1396
$(R1)\ \beta_{so} \neq \beta_{co}$	1.0433	0.2809	7.7905***
$(R2)\ \beta_{cb} < 0$	1.1832	0.0616	56.9467***
$(R3)\ \beta_{sb} > \beta_{cb}$	2.5183	1.3573	7.6331***
$(R4)\ \beta_{qb} < 0$	29.8211***	26.1614***	2.1545
$(R5)\ \beta_{qv} < 0$	2.1841	0.9101	4.0007**
$(R6)\ \beta_{sv} > 0$	3.7030*	2.0660	0.7084
Volatility regimes	43.0251***	42.3958***	14.7227**
Mixture of normals	42.9191***	39.6701***	14.6161**
Fads	42.4490***	39.5945***	13.5701**
VNS	5.7069*	2.6009	0.7817
Starting observation	Mar 1976	Mar 1976	Jun 1998
No. of observations	441	255	168

Note: Results from the volume-augmented model with the full sample in the base model, the sub-samples before 1997 and from 1997. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

5.2.3. Model Extensions

5.2.3.1. *Abnormal Trading Volume in the Collapsing Regime*

The base model assumes that abnormal trading volume signals that bubble is about to burst, and investors should be compensated for this additional risk they take. Therefore, the abnormal trading volume was included in the return equation in the surviving regime. However, it excluded this term in the collapsing regime, which implicitly suggested that the investors will not get the extra return for holding bubbly assets with abnormal trading volume or that the bubble is probably not going to collapse any further, once the return is already in the collapsing regime. To test whether this hypothesis is valid, the abnormal trading volume term with the coefficient β_{cv} is introduced into the collapsing regime return equation as well. Therefore, the revised model is:

$$r_{s,t+1} = \beta_{so} + \beta_{sb}B_t + \beta_{sv}AV_t + u_{s,t+1} \quad , u_{s,t+1} \sim (0, \sigma_s) \tag{56}$$

$$r_{c,t+1} = \beta_{co} + \beta_{cb}B_t + \beta_{cv}AV_t + u_{c,t+1} \quad , u_{c,t+1} \sim (0, \sigma_c) \tag{57}$$

$$P(r_{t+1}|S) = q(B_t, AV_t) = \Omega\big(\beta_{qo} + \beta_{qb}|B_t| + \beta_{qv}AV_t\big) \tag{58}$$

The result is shown in Table 11. Overall, the two estimations have very similar results. The parameter of β_{cv} is positive but not statistically significant. Although, the log-likelihood statistics improved with the abnormal trading volume included in the collapsing regime, the log-likelihood ratio test against the original volume-augmented model and the VNS model were not rejected. Therefore, the base model is deemed appropriate.

Table 11: Abnormal Trading Volume in the Collapsing Regime

	The Base Model	Model with β_{cv}
β_{so}	1.0057***	1.0059***
β_{sb}	0.0235	0.0244
β_{sv}	0.0112*	0.0102
β_{co}	1.0263***	1.0229***
β_{cb}	-0.0374	-0.0369
β_{cv}		0.0085
β_{qo}	1.5147***	1.4932***
β_{qb}	-3.1159***	-3.1496***
β_{qv}	-0.3121	-0.3080
σ_s	0.0444***	0.0439***
σ_c	0.1210***	0.1198***
Log-Likelihood	516.7845	516.9905
AIC	-2.2983	-2.2947
SBIC	-2.3437	-2.3446
HQIC	-2.2618	-2.2545
$(R1)\ \beta_{so} \neq \beta_{co}$	1.0433	1.0433
$(R2)\ \beta_{cb} < 0$	1.1832	1.1832
$(R3)\ \beta_{sb} > \beta_{cb}$	2.5183	2.5183
$(R4)\ \beta_{qb} < 0$	29.8211***	29.8211***
$(R5)\ \beta_{qv} < 0$	2.1841	2.1841
$(R6)\ \beta_{sv} > 0$	3.7030*	3.7030*
Volatility regimes	43.0251***	43.4369***
Mixture of normals	42.9191***	43.3309***
Fads	42.4490***	42.8609***
VNS	5.7069*	6.1188
Volume-augmented		0.4118
Starting observation	Mar 1976	Mar 1976
No. of observations	441	441

Note: Results from the standard volume-augmented model and the model with the addition of abnormal trading volume term in the bubble-collapsing state [equations (56) to (58)]. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

5.2.3.2. *Dummy Variables for Exchange Rate Regime*

The alternative approach to detect the impact of a change in exchange rate regime is to introduce a dummy variable. Dummy variables, $Float_t$, which take a value of 0 before July 1997 and 1 starting from July 1997 were added to all the three equations in the model.

$$r_{s,t+1} = \beta_{so} + \beta_{sb}B_t + \beta_{sv}AV_t + \beta_{sf}Float_t + +u_{s,t+1} \tag{59}$$

$$r_{c,t+1} = \beta_{co} + \beta_{cb}B_t + \beta_{cf}Float_t + u_{c,t+1} \tag{60}$$

$$P(r_{t+1}|S) = \Omega\left(\beta_{qo} + \beta_{qb}|B_t| + \beta_{qv}AV_t + \beta_{qf}Float_t\right) \tag{61}$$

Furthermore, slope dummies, where the dummy variables created earlier were allowed to interact with all other independent variables, were also added. The models with both types of dummy variables then become:

$$\begin{aligned} r_{s,t+1} = \beta_{so} + \beta_{sb}B_t + \beta_{sv}AV_t + \beta_{sf}Float_t + \beta_{sfb}Float_t * B_t \\ + \beta_{sfv}Float_t * AV_t + u_{s,t+1} \end{aligned} \tag{62}$$

$$r_{c,t+1} = \beta_{co} + \beta_{cb}B_t + \beta_{cf}Float_t + \beta_{cfb}Float_t * B_t + u_{c,t+1} \tag{63}$$

$$\begin{aligned} P(r_{t+1}|S) = \Omega\big(\beta_{qo} + \beta_{qb}|B_t| + \beta_{qv}AV_t + \beta_{qf}Float_t + \beta_{qfb}Float_t * |B_t| \\ + \beta_{qfv}Float_t * AV_t\big) \end{aligned} \tag{64}$$

Consider first the results of the extended model in Table 12. The intercept dummy variables in both the surviving and collapsing regimes were statistically significant. Specifically, the fact that β_{sf} is positive and β_{cf} is negative also suggests that investors are compensated for taking this additional risk when the bubble survives and they are penalised further if the bubble bursts with the flexible exchange rate. The specification also yields higher log-likelihood function values at the optimum. The evidence for the second model with additional slope dummy variables is less convincing. Some parameters, particularly the interactive terms, turned statistically insignificant. This may possibly be caused by multicollinearity among the variables, as the correlation coefficients of the pair B_t and $Float_t * B_t$, the pair $Float_t$ and $Float_t * B_t$, and the pair AV_t and $Float_t * AV_t$ are 0.89, 0.67, and 0.65, respectively.

The robustness checks against simpler specifications now include the standard volume-augmented model and the model with intercept dummy variables. Although the test statistics for the model that also includes additional slope dummy variables against the intercept dummy variables was not statistically significant, the hypothesis that the model with intercept dummy variables is equally as good as the standard volume-augmented model was rejected. It indicated that the dummy variables were able to capture additional variations. This could also mean that the collapse of the Thai baht was relevant for stock returns.

As for the evidence of a bubble, the result of the model with only the intercept dummy variables has four restriction tests rejected, compared to just two in the case of the standard volume-augmented model. Using the same assessment criteria, this can be taken to imply a strong evidence of the bubble in the Thai stock market. Besides, while it could be argued that inclusion of dummy variables may have picked up the effects of a bubble behaviour and the evidence would be weakened, allowing for a structural break in the data with the dummy variable has actually strengthened the conclusion.

Table 12: Dummy Variables (DV) for Floating Exchange Rate

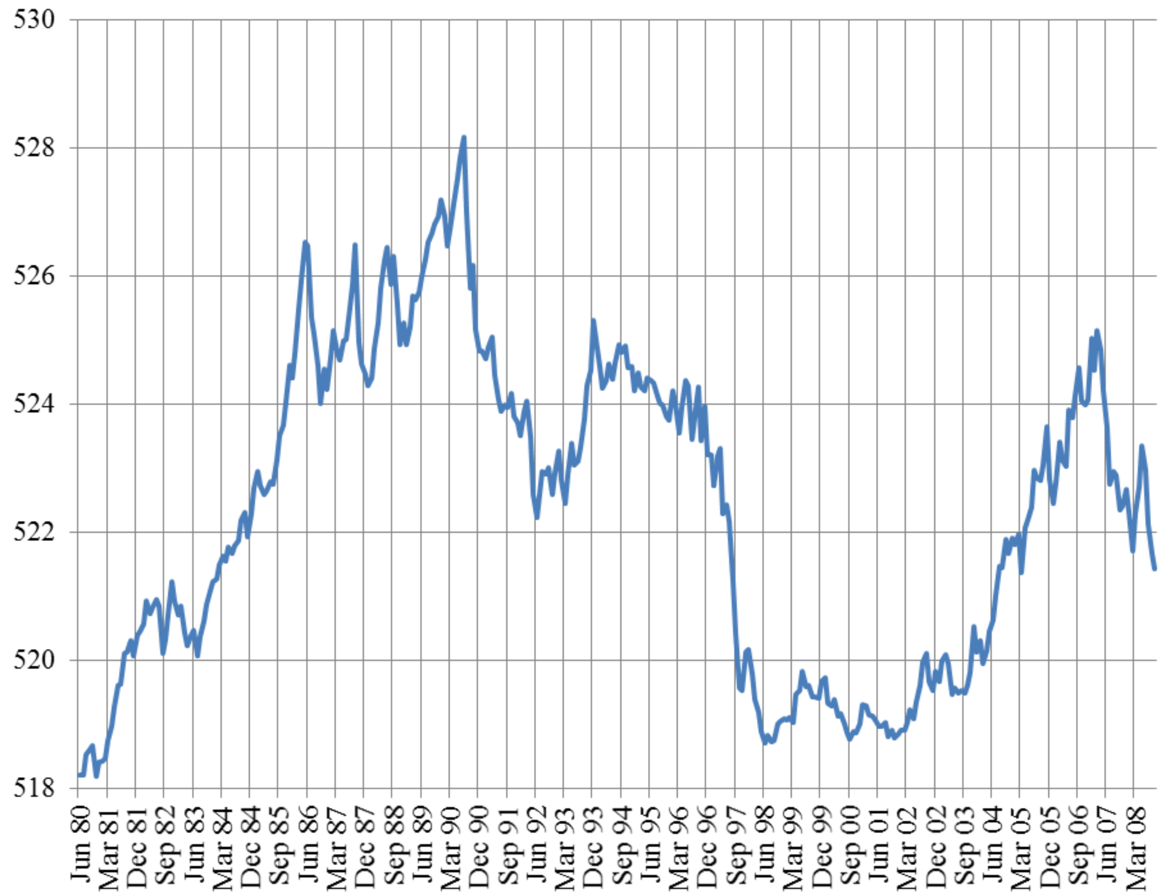
	The Base Model	Intercept DV	Slope DV
β_{so}	1.0057***	0.9995***	1.0004***
β_{sb}	0.0235	0.0054	0.0169
β_{sv}	0.0112*	0.0114*	0.0101*
β_{sf}		0.0230**	0.0225*
β_{sfb}			-0.0298
β_{sfv}			-0.0267
β_{co}	1.0263***	1.0363***	1.0432***
β_{cb}	-0.0374	-0.0238	-0.0451
β_{cf}		-0.0296*	-0.0342
β_{cfb}			0.0206
β_{qo}	1.5147***	1.5512***	1.9238***
β_{qb}	-3.1159***	-3.1404***	-4.2542***
β_{qv}	-0.3121	-0.4100	-0.3835
β_{qf}		-0.5669**	-1.2862**
β_{qfb}			2.3202
β_{qfv}			-0.5120
σ_s	0.0444***	0.0390***	0.0384***
σ_c	0.1210***	0.1141***	0.1136***
Log-Likelihood	516.7845	522.1657	523.8827
AIC	-2.2983	-2.3091	-2.2943
SBIC	-2.3437	-2.3681	-2.3759
HQIC	-2.2618	-2.2616	-2.2284
$(R1)\ \beta_{so} \neq \beta_{co}$	1.0433	3.5710*	2.2145
$(R2)\ \beta_{cb} < 0$	1.1832	0.6241	0.7124
$(R3)\ \beta_{sb} > \beta_{cb}$	2.5183	0.6468	1.1059
$(R4)\ \beta_{qb} < 0$	29.8211***	28.8692***	20.9979***
$(R5)\ \beta_{qv} < 0$	2.1841	3.7175*	2.6505
$(R6)\ \beta_{sv} > 0$	3.7030*	4.5266**	3.7640*
Volatility regimes	43.0251***	53.7874***	57.2213***
Mixture of normals	42.9191***	53.6815***	57.1154***
Fads	42.4490***	53.2114***	56.6453***
VNS	5.7069*	16.4693***	19.9032**
Volume-augmented		10.7624**	14.1963*
Intercept DV			3.4339
Starting observation	Mar 1976	Mar 1976	Mar 1976
No. of observations	441	441	441

Note: Results from the standard volume-augmented model, the model with one set of intercept dummy variables, and the model with one set of intercept and slope dummy variables formalised in equations (59) to (64), assuming the July 1997 breakpoint. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

5.2.3.3. Endogenous Break Model

Motivated by the results in the previous section on dummy variables, it is intriguing to investigate whether there is a structural break in the data. Instead of forcing a break at July 1997, this section allowed the break to be endogenously determined by the model. This is done by re-estimating the model with intercept dummy variables with the $Float$ variable starting to take a value of 1 at different time period. Note that this assumes that there is only one single break in the entire sample. Also, in the same spirit with Gregory and Hansen (1996), the first and last 15% observations will not be considered as possible breakpoints. Figure 26 showed the log-likelihood statistics at different breakpoints. The breakpoint with the highest log-likelihood statistics is from July 1990, which is consistent with the period that Thailand's financial markets were in the process of liberalisation. The results are presented in Table 13. They are essentially comparable to those obtained previously.

Figure 26: Log-likelihood Statistics with Different Breakpoints



Note: Results from the model with one set of intercept dummy variables.

Table 13: Model with One Endogenous Structural Break

	The Base Model	Intercept DV ($Float_t = 1$ from July 1997)	Intercept DV ($Float_t = 1$ from July 1990)
β_{so}	1.0057***	0.9995***	1.0033***
β_{sb}	0.0235	0.0054	0.0332
β_{sv}	0.0112*	0.0114*	0.0085*
β_{sf}		0.0230**	0.0204*
β_{co}	1.0263***	1.0363***	1.0577***
β_{cb}	-0.0374	-0.0238	-0.0178
β_{cf}		-0.0296*	-0.0533***
β_{qo}	1.5147***	1.5512***	1.9160***
β_{qb}	-3.1159***	-3.1404***	-3.6575***
β_{qv}	-0.3121	-0.4100	-0.3813
β_{qf}		-0.5669**	-1.2419***
σ_s	0.0444***	0.0390***	0.0354***
σ_c	0.1210***	0.1141***	0.1043***
Log-Likelihood	516.7845	522.1657	528.1670
AIC	-2.2983	-2.3091	-2.3364
SBIC	-2.3437	-2.3681	-2.3953
HQIC	-2.2618	-2.2616	-2.2888
$(R1)\ \beta_{so} \neq \beta_{co}$	1.0433	3.5710*	6.4879**
$(R2)\ \beta_{cb} < 0$	1.1832	0.6241	0.4260
$(R3)\ \beta_{sb} > \beta_{cb}$	2.5183	0.6468	2.0945
$(R4)\ \beta_{qb} < 0$	29.8211***	28.8692***	22.8229***
$(R5)\ \beta_{qv} < 0$	2.1841	3.7175*	2.9818*
$(R6)\ \beta_{sv} > 0$	3.7030*	4.5266**	3.2068*
Volatility regimes	43.0251***	53.7874***	65.7900***
Mixture of normals	42.9191***	53.6815***	65.6841***
Fads	42.4490***	53.2114***	65.2140***
VNS	5.7069*	16.4693***	28.4719***
Volume-augmented		10.7624**	22.7650***
Starting observation	Mar 1976	Mar 1976	Mar 1976
No. of observations	441	441	441

Note: Results from the standard volume-augmented model, and the model with one set of intercept dummy variables. The intercept dummy variables were included to capture the effects of a structural break. Initially, the break was assumed to be in July 1997 when Thailand switched to a managed-float exchange rate system. However, investigating with endogenously determined break suggested that the most appropriate breakpoint, given the dataset, was actually in July 1990. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Model with Two Endogenous Breaks[2]

The previous model which allows for one endogenous structural break in the sample yields the result that differs from the initial expectation that the break could be at July 1997 where Thailand moved from fixed exchange rate system to a managed floating one. It showed that there is another significant breakpoint in the sample, which was in the early 1990s where the Thai financial market started to be liberalised. This provoked another research attempt to investigate whether there could be more than one structural break in the entire data series that cover almost 40 years. A model with two sets of intercept dummy variables with endogenous breakpoints was developed. It can be formalised as:

$$r_{s,t+1} = \beta_{so} + \beta_{sb}B_t + \beta_{sv}AV_t + \beta_{sl}L_t + \beta_{sf}Float_t + u_{s,t+1} \tag{65}$$

$$r_{c,t+1} = \beta_{co} + \beta_{cb}B_t + \beta_{cl}L_t + \beta_{cf}Float_t + u_{c,t+1} \tag{66}$$

$$P(r_{t+1}|S) = \Omega\big(\beta_{qo} + \beta_{qb}|B_t| + \beta_{qv}AV_t + \beta_{ql}L_t + \beta_{qf}Float_t\big) \tag{67}$$

where L_t and $Float_t$ are intercept dummy variables taking a value of 1 starting from date t_L and t_F – which t_L precedes t_F – respectively, and 0 otherwise.

Based on this extended model, a procedure similar to the previously section on one endogenous break were conducted. Figure 27 shows the combination of breakpoints that gives the highest log-likelihood statistics were September 1996 and August 1998. This is to say, there appear to be three sub-periods in the sample: before the crisis, during the crisis, and after the crisis. Detailed results of the model based on imposing two sets of intercept dummy variables as suggested by the iteration exercise can be found in Table 14.

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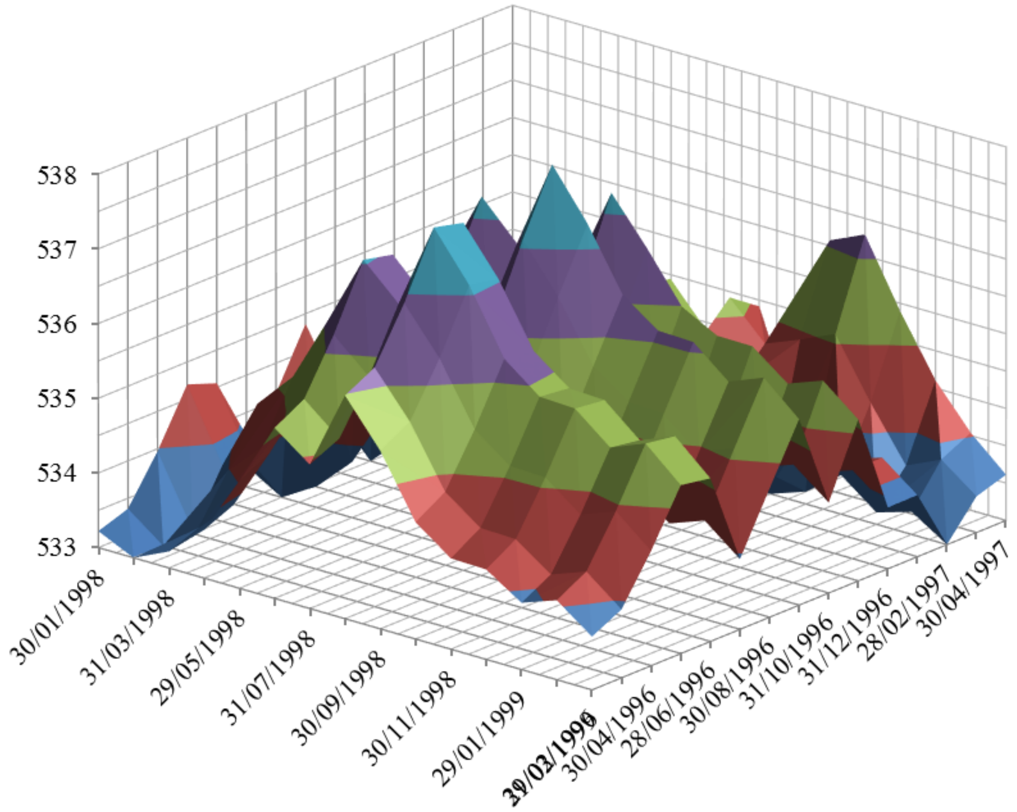
[2] Note that the models with more than two breakpoints were not explored due to computation difficulties.

Figure 27: Selected Log-likelihood Statistics of Model with Two Breakpoints



The model with two structural breaks at September 1996 and August 1998 results in higher log-likelihood statistics at optimum. In fact, it performs very well, such the robustness check against simple specifications – including the standard volume-augmented model and the model with one structural break – are all rejected. This indicates that this model provides the best fit with the given dataset.

Moreover, recall that the standard volume-augmented model and the model with one structural break had two and four restriction tests rejected, respectively. This model with two structural breaks has five out of the whole six restriction tests refuted, implying an even stronger evidence of bubble-like behaviour in the Thai stock market.

With regard to the estimated parameters, not only that allowing for two breakpoints – especially, around the period of the 1997 Asian Financial Crisis – is more consistent with the facts than crudely splitting the entire sample period into just two sub-periods before and after a particular event, the extended model also offers some other interesting insights.

Table 14: Model with Two Endogenous Structural Breaks

	The Base Model	One IDV (at Sep 1996)	One IDV (at Aug 1998)	Two IDVs
β_{so}	1.0057***	1.0025***	0.9995***	1.0025***
β_{sb}	0.0235	0.0212	0.0054	0.0161
β_{sv}	0.0112*	0.0105*	0.0114*	0.0113**
β_{sl}				-0.0910**
β_{sf}		0.0211**	0.0230**	0.1045**
β_{co}	1.0263***	1.0369***	1.0363***	1.0522***
β_{cb}	-0.0374	-0.0267	-0.0238	-0.0526
β_{cl}				-0.0947***
β_{cf}		-0.0305*	-0.0296*	0.0760**
β_{qo}	1.5147***	1.8990***	1.5512***	1.8597***
β_{qb}	-3.1159***	-4.0792***	-3.1404***	-3.4703***
β_{qv}	-0.3121	-0.4110	-0.4100	-0.3487
β_{ql}				-2.2452*
β_{qf}		-1.0588**	-0.5669**	1.8298*
σ_s	0.0444***	0.0369***	0.0390***	0.0408***
σ_c	0.1210***	0.1083***	0.1141***	0.1161***
Log-Likelihood	516.7845	524.2757	522.1657	537.9468
AIC	-2.2983	-2.3187	-2.3091	-2.3671
SBIC	-2.3437	-2.3777	-2.3681	-2.4397
HQIC	-2.2618	-2.2712	-2.2616	-2.3086
$(R1)\ \beta_{so} \neq \beta_{co}$	1.0433	2.6175	3.5710*	4.7163**
$(R2)\ \beta_{cb} < 0$	1.1832	0.9397	0.6241	2.2833
$(R3)\ \beta_{sb} > \beta_{cb}$	2.5183	1.7529	0.6468	2.9342*
$(R4)\ \beta_{qb} < 0$	29.8211***	30.4802***	28.8692***	31.2501***
$(R5)\ \beta_{qv} < 0$	2.1841	2.8004*	3.7175*	2.7968*
$(R6)\ \beta_{sv} > 0$	3.7030*	3.6949*	4.5266**	4.8264**
Volatility regimes	43.0251***	58.0073***	53.7874***	85.3495***
Mixture of normals	42.9191***	57.9014***	53.6815***	85.2435***
Fads	42.4490***	57.4313***	53.2114***	84.7734***
VNS	5.7069*	20.6892***	16.4693***	48.0313***
Volume-augmented		14.9823***	10.7624**	42.3244***
Intercept DV				27.3421***
Starting observation	Mar 1976	Mar 1976	Mar 1976	Mar 1976
No. of observations	441	441	441	441

Note: Results from the standard volume-augmented model, the model with one and two sets of intercept dummy variables (IDV) [equations (59) to (61) and (65) to (67)] to allow for structural breaks at September 1996 and August 1998. The model with one break assumes the breakpoint at either September 1996 or August 1998 for comparability with the model with two breaks. The robustness check for the model with two breaks was tested against the model with one break in September 1996, due to higher log-likelihood statistics at maximum. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Given the setup of the dummy variables, it is important to clarify that the period before the crisis will have the average returns in the two regimes and the average surviving probability of $\beta_{so}, \beta_{co},$ and $\beta_{qo},$ respectively. The intercept terms for the period around the crisis – from September 1996 to July 1998 – would include the effect of the first dummy variable, $L_t,$ so that they are $\beta_{so} + \beta_{sl}, \beta_{co} + \beta_{cl},$ and $\beta_{qo} + \beta_{ql},$ respectively. Finally, the period after the crisis will also contain in the impact of the second dummy variable, $Float_t,$ as well. The average returns if the bubble survives would be $\beta_{so} + \beta_{sl} + \beta_{sf},$ and $\beta_{so} + \beta_{sl} + \beta_{sf}, \beta_{co} + \beta_{cl} + \beta_{cf}$ if it bursts, while the average probability that the next-period return is in the bubble-surviving regime would be $\beta_{qo} + \beta_{ql} + \beta_{qf}.$

Consider the estimated intercept coefficients for the bubble-surviving regime, the gross return denoted by β_{so} is 1.0025, which means a net return of 0.25%. This number fell significantly during the crisis period as $\beta_{sl} = -0.0910$, resulting in the average gross return of 0.9116 or a net return of -8.8%. After the crisis, the average gross return rebounded strongly to $\beta_{so} + \beta_{sl} + \beta_{sf} = 1.0161$, implying a net return 1.6%. In other words, this suggests that, provided there is no bubble and trading volume is normal, investors would earn an even higher return in the Thai stock market after the 1997 crisis. The returns in the bubble-collapsing regime, however, do not have the same effects. The average return declined quite drastically during the crisis. Although it did recover afterwards, the improvement was not sufficient to offset the drop. As for the probability equation, a similar pattern to the bubble-collapsing state was found. Precisely, the coefficients of average bubble-surviving probability computed from intercept terms applicable in the periods before, during, and after the crisis are 1.8597, -0.3856, and 1.4442. These estimates indicate that the average probability of bubble living on in the next period is 96.9% in the period before September 1996, while it nosedives to only 35% around the time of the Asian Financial Crisis, and it bounces back to 92.6% from August 1998 onwards. Therefore, it could be concluded that, after the crisis, it is slightly less likely that a bubble would survive in Thai stock market, but investors are compensated with higher returns if they successful ride the bubbles.

5.2.3.4. Relative Bubble Term in the Probability Equation Revisited

To further investigate the asymmetric impact of positive and negative bubbles on the likelihood of the bubble surviving in next period, a dummy variable for a positive bubble is added to the probability equation. Specifically, a dummy variable, D_t, which takes a value of 1 if the relative bubble is positive and 0 otherwise was added into the probability function:

$$P(r_{t+1}|S) = q(B_t, AV_t, D_t) = \Omega\left(\beta_{qo} + \beta_{qb}|B_t| + \beta_{qbd}D_t * |B_t| + \beta_{qv}AV_t\right) \tag{68}$$

Table 15 presented the evidence of this specification. All estimated parameters in the return equations are very similar to the base model. The parameter β_{qbd} is negative but statistically insignificant. The log-likelihood test against the standard volume-augmented model is also not rejected, suggesting that this specification is not capturing the extra variability of the returns. In other words, the type of bubble is actually not a crucial factor determining the probability whether the next period’s return will be in the surviving or collapsing state.

Table 15: Nonlinearity in Relative Bubble and Abnormal Trading Volume

	The Base Model	Model with D_t	Model with AV_t^2
β_{so}	1.0057***	1.0062***	1.0051***
β_{sb}	0.0235	0.0307	0.0206
β_{sv}	0.0112*	0.0090	0.0062
β_{co}	1.0263***	1.0258***	1.0299***
β_{cb}	-0.0374	-0.0376	-0.0399
β_{qo}	1.5147***	1.6332***	1.3999***
β_{qb}	-3.1159***	-2.9021***	-3.0707***
β_{qbd}		-0.5233	
β_{qvv}			0.4449
β_{qv}	-0.3121	-0.2162	-1.0244**
σ_s	0.0444***	0.0405***	0.0437***
σ_c	0.1210***	0.1147***	0.1199***
Log-Likelihood	516.7845	517.6047	519.2908
AIC	-2.2983	-2.2975	-2.3052
SBIC	-2.3437	-2.3474	-2.3551
HQIC	-2.2618	-2.2573	-2.2649
Volatility regimes	43.0251***	44.6653***	48.0376***
Mixture of normals	42.9191***	44.5593***	47.9317***
Fads	42.4490***	44.0892***	47.4616***
VNS	5.7069*	7.3471*	10.7195**
Volume-augmented		1.6402	5.0126**
Starting observation	Mar 1976	Mar 1976	Mar 1976
No. of observations	441	441	441

Note: Results from the standard volume-augmented model, the model with the addition of dummy variable, D_t, classifying between positive and negative bubbles [equation (68)], and the model with the squared abnormal trading volume term [equation (69)] to examine the non-linear impact of trading volume on probability. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

5.2.3.5. *Nonlinearity of Abnormal Trading Volume in the Probability Function*

In order to test for nonlinearity effects of abnormal trading volume in the probability function, the squared abnormal trading volume term, AV_t^2, was introduced. The probability function is then:

$$P(r_{t+1}|S) = q(B_t, AV_t) = \Omega\big(\beta_{qo} + \beta_{qb}|B_t| + \beta_{qvv}AV_t^2 + \beta_{qv}AV_t\big) \tag{69}$$

Table 15 presents the results from this new probability function. The evidence was very interesting in several aspects. The robustness test is rejected, implying that additional variation was captured. Estimated coefficients have expected signs with reasonable magnitudes and are statistically significant. Specifically, the coefficients β_{qvv} and β_{qv} were estimated to be 0.4449 and -1.0244, respectively. This suggested a convex parabolic relationship between abnormal trading volume and the probability of bubble surviving. Precisely, the level of abnormal trading volume that gives the lowest probability of surviving is when $AV_t = 1.1513$. This means that when the observed trading volume deviates from the moving average less than 115.13% (which is when trading volume is below 2.15 times of the moving average), the increase in trading volume will result in lower probability of bubble surviving. In other words, investors may be offloading the bubbly assets. However, as the trading volume increases above the threshold of 2.15 times of the moving average, any further increase in volume will suggest a higher chance of bubble continue to grow in the next period. Investors are rushing to buy the bubbly assets, as they believe the price will continue to rise. This is consistent with a concept in behavioural finance known as herding.

5.2.4. Probabilities

Both the volume-augmented and the extended model with intercept dummy variables allow for computations of several probability values, and they can be obtained in two ways.

With the regard to the types of probability the models yield, the most straightforward ones are the likelihood that the return will be in either the bubble surviving, $P(r_{t+1}|S)$, or collapsing regime, $P(r_{t+1}|C)$, in the next period. They can be calculated as $P(r_{t+1}|S) = q(B_t, AV_t) = \Omega(\beta_{qo} + \beta_{qb}|B_t| + \beta_{qv}AV_t)$ for the volume-augmented model and $P(r_{t+1}|S) = \Omega\left(\beta_{qo} + \beta_{qb}|B_t| + \beta_{qv}AV_t + \beta_{qf}Float_t\right)$ for the extended model with intercept dummy variables, while the bubble-bursting probabilities, $P(r_{t+1}|C)$, are simply, $1 - P(r_{t+1}|S)$. The probability of extreme cases where the stock index would crash, which is to be at least two standard deviations below the mean of past gross returns, given the probabilities of being in a surviving and collapsing regimes, can be computed with the following equation:

$$P(r_{t+1} < K)_t = q(r_{t+1}|S)_t \Omega\left(\frac{K - \beta_{so,t} - \beta_{sb,t}B_t - \beta_{sv,t}AV_t}{\sigma_{s,t}}\right) + q(r_{t+1}|C)_t \Omega\left(\frac{K - \beta_{co,t} - \beta_{cb,t}B_t}{\sigma_{c,t}}\right) \quad (70)$$

or

$$P(r_{t+1} < K)_t = q(r_{t+1}|S)_t \Omega\left(\frac{K - \beta_{so,t} - \beta_{sb,t}B_t - \beta_{sv,t}AV_t - \beta_{sf}Float_t}{\sigma_{s,t}}\right) + q(r_{t+1}|C)_t \Omega\left(\frac{K - \beta_{co,t} - \beta_{cb,t}B_t - \beta_{cf}Float_t}{\sigma_{c,t}}\right) \quad (71)$$

where $q(r_{t+1}|S)_t = \Omega(\beta_{qo} + \beta_{qb}|B_t| + \beta_{qv}AV_t)$ or $q(r_{t+1}|S)_t = \Omega(\beta_{qo} + \beta_{qb}|B_t| + \beta_{qv}AV_t + \beta_{qf}Float_t)$ and K is the threshold for a crash and it is defined as $K = \mu_t - 2(\sigma_{r,t})$, where μ_t is the mean of past gross returns and $\sigma_{r,t}$ is the standard deviation of gross returns. Likewise, the probability of a rally, where the return could be at least two standard deviations above the mean of past gross returns, can be computed in a similar fashion.

Finally, these probability values can be derived from the point estimates of the base model regression using all the samples, or they could be obtained from a sequential or recursive estimation, where only the data up to and including the current period are included. To ensure a sufficient number of observations with the latter methodology, only approximately half of the sample was assessed. That is, only the estimates starting from August 1994 were available.

Figure 28 and Figure 29 show examples of probabilities obtained from the estimation. The former displays the natural logarithms of real-series SET index on the primary axis and the probabilities of being in a bubble collapsing regime calculated from the point estimates from the volume-augmented model on the secondary axis, while the latter was based on probability estimates from sequential estimations. Both figures reveal very similar patterns, especially as the number of observations increases and approach a full sample. This is confirmed by the correlation coefficient between the two series from August 1994 onwards which turns out to be 0.9611. It can be seen that the model correctly forecasted several of the episodes of corrections after periods of bubble building ups, such as September-October 1987, May-June 1990, or the all-time peak at December 1993-January 1994, by showing high probabilities of a collapse. Interestingly, the period roughly between August 1998 and June 1999 saw the index picked up from the all-time low, but the likelihood of a collapse stayed relatively high. As the model also allows for a negative bubble or a price-decreasing bubble, this is consistent with the investors overselling Thai stocks as the crisis hit the market and thus the index fell too low beyond the fundamental values. A similar situation may have taken place again after the bankruptcy of Lehman Brothers in September 2008.

Figure 28: Probability of a Collapse with the Volume-augmented Model (Point Estimates)

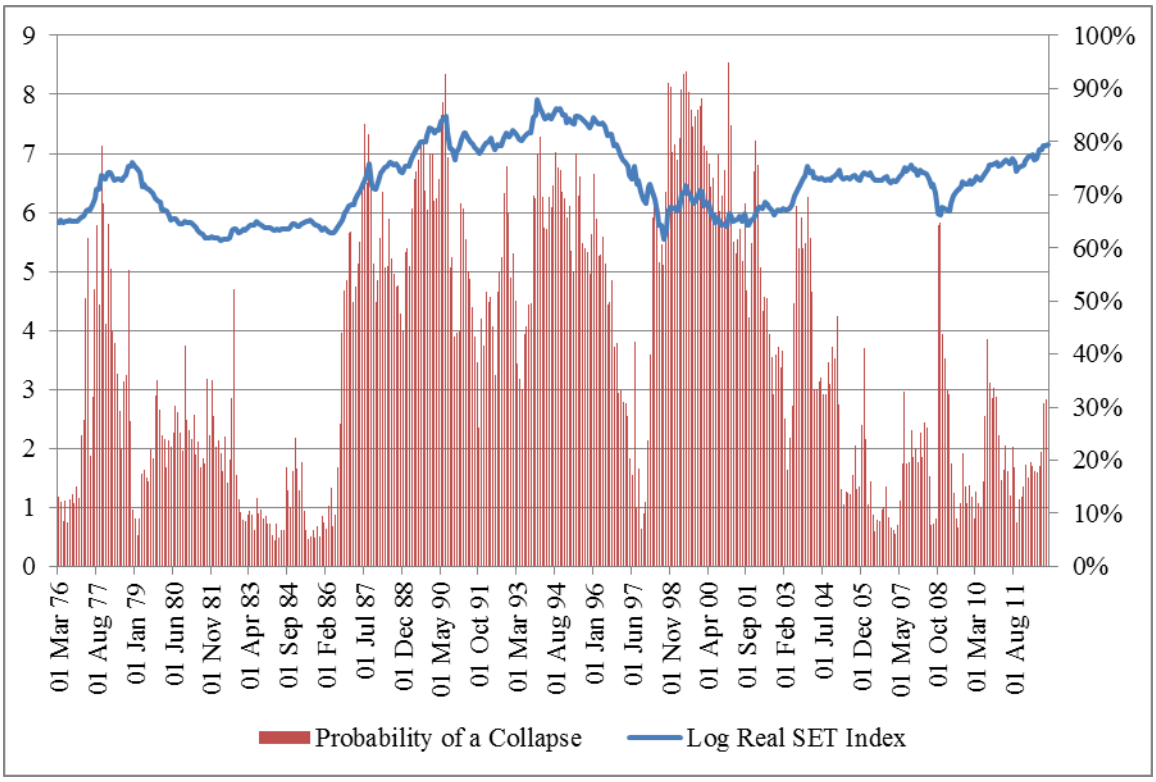
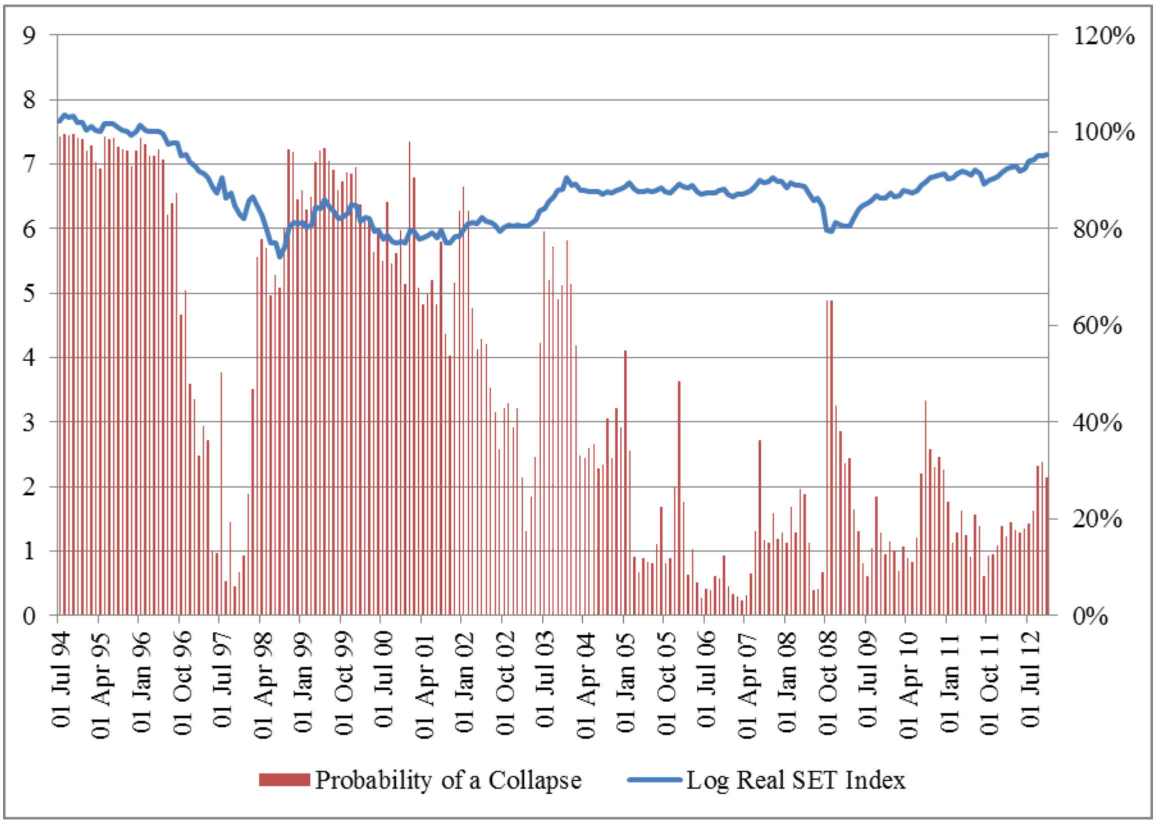


Figure 29: Probability of a Collapse with the Volume-augmented Model (Sequential Estimates)



Note: Based on equation (70)

Investors would be keen to make abnormal profits and avoid significant losses. As discussed earlier, the probabilities of a crash and a rally can also be found from the model. The previous figure only considered the level of the index, but it is probably more appropriate to look at the total return to investors, meaning to include pro-rata dividends. As for the likelihood of a crash and/or a rally, it is quite informative also to monitor the change of the probabilities from the previous period. Figure 30 and Figure 31 present the total net one-month return on the primary axis and the percentage change of crash and rally probabilities, respectively. As both types of probabilities focus on extreme events, they tend to rise at the same time when volatility in the market is high.

Consider the two figures, there are two major events of highly fluctuating probabilities, namely, the period around the financial crisis in 1997 and the period around the collapse of the Lehman Brothers in 2008. Table 16 provides a closer look at the numbers. Specifically, at the end of June 1997, the probability of a next-period crash decreased by 15%, the likelihood of a next-period rally increased by 42% and the net return based on a real-series SET index with a pro-rata dividend when invested then and held until the end of July 1997 was indeed 25.80%. Then, at the end of July 1997, the probability of a crash skyrocketed by 381% and the net return nose-dived to -26.19%. In the following period, the same probability dropped by 87%, and the return was a positive 8.41%. The likelihood of a rally was a better indicator in several other periods, for instance, October-November 1997 and December 1997- January 2008. Over the entire sub-sample from August 1994, the changes in the probability of a crash and a rally were correct by approximately 57% and 52%, respectively. Both of them provided good signals in about 30% of the time. The event around the collapse of Lehman Brothers revealed a somewhat less convincing result. The bankruptcy was announced on 15 September 2008 in the US, and the probability of a crash at the end of September 2008 rose by 98% with the net next-month return plummeted to -28.90%. The following period saw an increase of 557% in the crash probability, but investors incurred only a small loss of 1.74%.

Figure 30: Probability of a Crash with the Volume-augmented Model (Sequential Estimate)

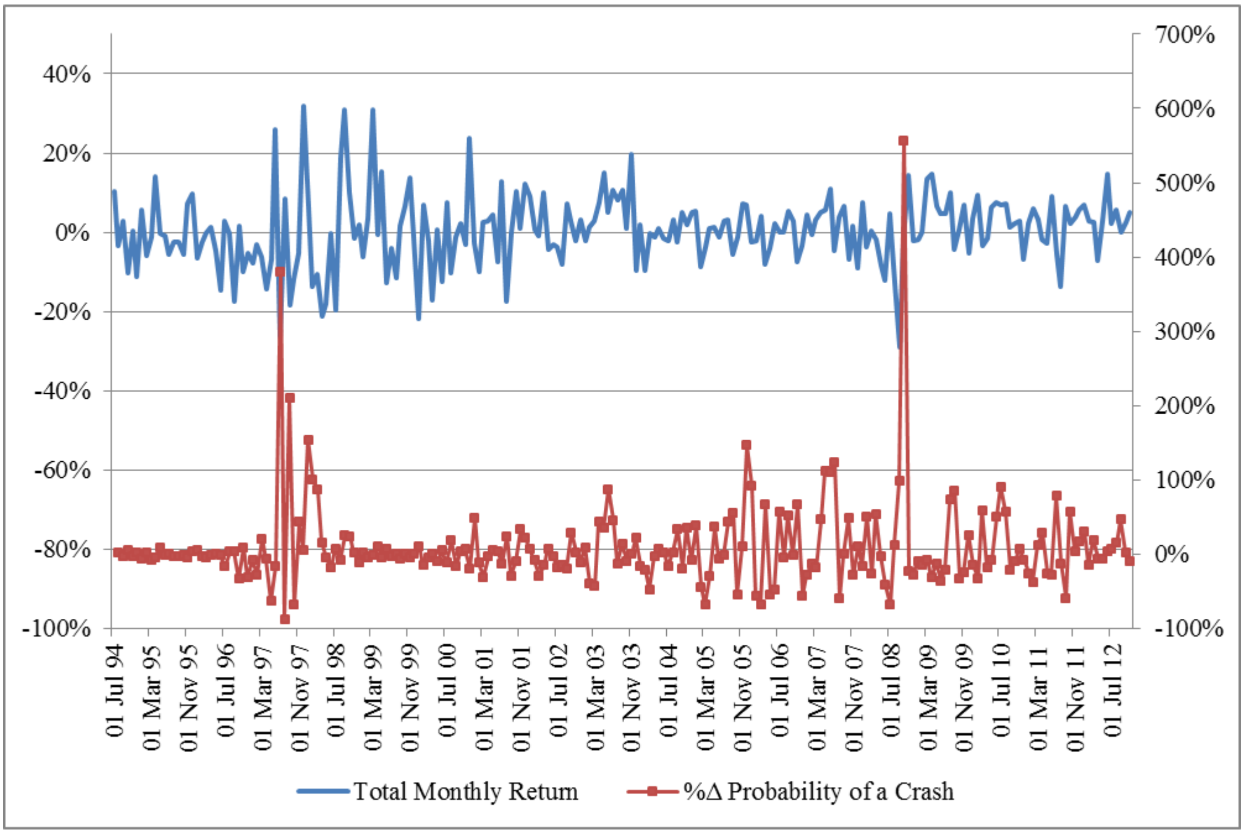
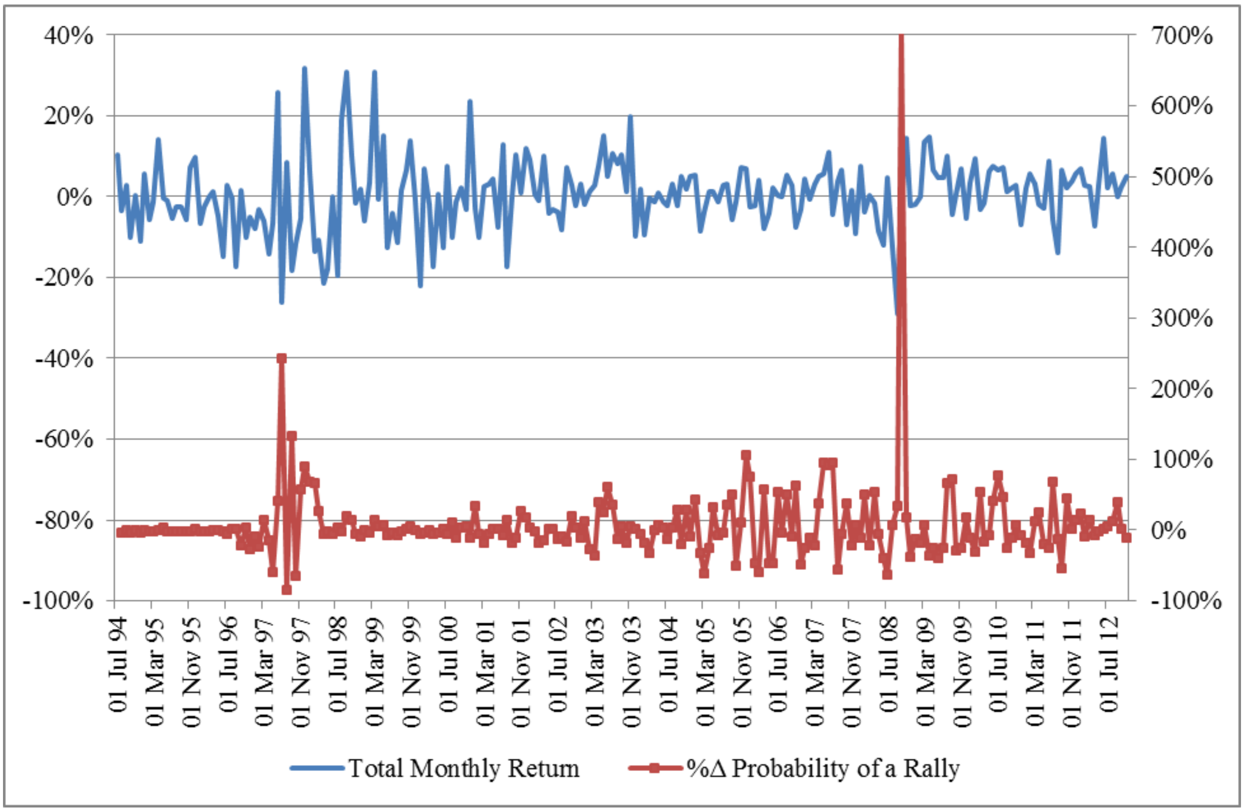


Figure 31: Probability of a Rally with the Volume-augmented Model (Sequential Estimate)



Note: Based on equation (70)

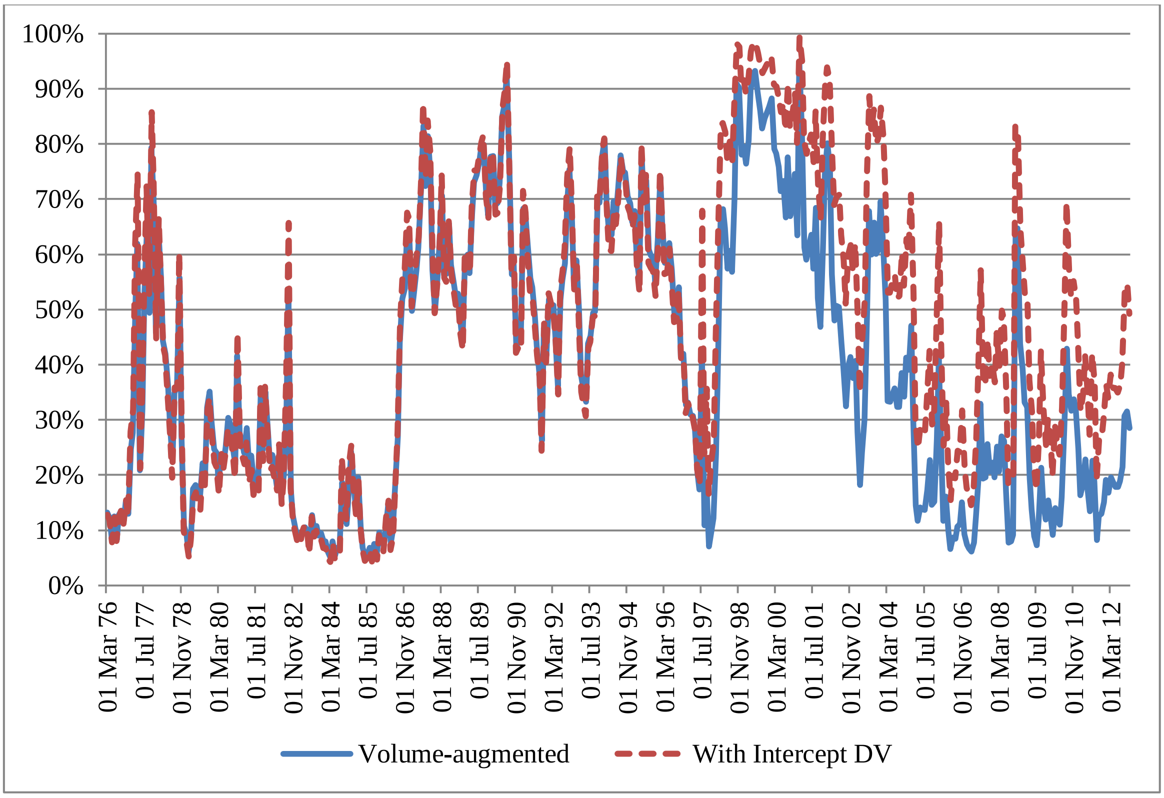
Table 16: Selected Results of Net One-month Total Return and Percentage Change in Probabilities of a Crash and a Rally

Period	Net Total Return	%Δ Probability of a Crash	%Δ Probability of a Rally
Jun 97	25.80%	-15%	42%
Jul 97	-26.19%	381%	242%
Aug 97	8.41%	-87%	-85%
Sep 97	-18.25%	210%	133%
Oct 97	-11.81%	-68%	-65%
Nov 97	-5.28%	44%	58%
Dec 97	31.88%	7%	90%
Jan 98	6.26%	154%	68%
Feb 98	-13.66%	101%	66%
Mar 98	-10.71%	87%	28%
Apr 98	-21.33%	16%	-5%
May 98	-18.12%	-5%	-2%
Jun 98	-0.14%	-17%	-5%
Jul 98	-19.65%	8%	3%
Aug 98	18.81%	-8%	-3%
Sep 98	30.85%	25%	19%
Aug 08	-12.65%	13%	7%
Sep 08	-28.90%	98%	33%
Oct 08	-1.74%	557%	710%
Nov 08	14.44%	-22%	18%

Note: The shaded cells denote when the increase (decrease) in the probability of a crash or a decrease (positive) in the probability of a rally coincides with a negative (positive) net one-month total return.

Figure 32 compares the likelihood of a collapse with point estimates from the volume-augmented model those from the model with intercept dummy variables, $Float_t = 1$, from July 1997 onwards. The two lines were almost identical before July 1997. However, they seem to have diverged thereafter although they, in general, were still moving in the same direction. This is supported by the descriptive statistics shown in Table 17. The correlation coefficients between the probabilities obtained from the two models showed a drop from 99.57% to 98.46% moving from the first sub-sample before July 1997 to the one after. In fact, the model with intercept dummy variables yielded a higher probability of a collapse on average at 46.65% as compared to 39.66% from the volume-augmented model. The basic volume-augmented model assumes no structural change over the sample and produced roughly the same average probability over the sub-samples, while the model with intercept dummy variables returned two distinct average probabilities before and after July 1997 at 40.60% and 55.02%, respectively. This is consistent with the intuition that the second sub-sample after July 1997 should be more volatile and more likely that the bubble will burst as the exchange rate was allowed to move more freely.

Figure 32: Comparison of Probabilities of a Collapse with Point Estimates from the Volume-augmented Model and the Model with Intercept Dummy Variables



Note: Based on equations (70) and (71)

Table 17: Descriptive Statistics of Probabilities of a Collapse with Point Estimates from the Volume-augmented Model and the Model with Intercept Dummy Variables

		Volume-augmented Model	Model with Intercept DV
Mean	**Overall**	39.66%	46.65%
	Before July 1997	40.58%	40.60%
	From July 1997	38.39%	55.02%
Standard Deviation	**Overall**	24.66%	25.98%
	Before July 1997	23.80%	24.62%
	From July 1997	25.83%	25.56%
Correlation Coefficient	**Overall**	93.96%	
	Before July 1997	99.57%	
	From July 1997	98.46%	

Unfortunately, the same analysis with the percentage change of probabilities of a crash and/or a rally with sequential estimations cannot be done. This is because when attempting to estimate the first few probabilities after July 1997, the estimations did not include sufficient observations with dummy variables equal to one. Thus, they gave unreliable probability figures. Nonetheless, the analysis based on point estimates instead was conducted. It suggested that percentage change in the likelihood of a next-period crash and rally have a similar level of predictability on net one-month total return. Precisely, they gave proper signals for 54% and 48% of the time, and, they were both correct at the same time at a slightly lower level at 27%.

Overall, the evidence implied the probabilities produced from the models were reasonably helpful in forecasting the state of the returns and to time the market before a crash or a rally. Brooks and Katsaris (2005a and 2005b) offer a more formal approach for determining the predictability and usefulness for investors in terms of profitability by comparing the results to other trading strategies.

5.3. Conclusions

This chapter analyses asset price bubbles in the Stock Exchange of Thailand (SET) from the establishment of the exchange in April 1975 until December 2012. The results from the volume-augmented regime-switching speculative bubble model show some evidence in support of the bubble-like behaviour in the SET. The results are robust to specifications and various extensions applied.

One particular significant extension in this chapter was the investigation of the possible structural break. This is pursued because the period studied covers about 25 years of data and Thailand also adopted a new exchange rate regime in 1997 after being severely affected by the Asian financial crisis. The evidence suggests that returns differ significantly before and after the floatation of Thai baht. However, once the breakpoint was allowed to be determined endogenously by the data, the most appropriate split is in July 1990, which coincides with the period where Thailand was implementing policies of financial liberalisation. Then again, when two breakpoints were allowed instead, the breaks fall on to September 1996 and August 1998, separating the series into three sub-periods, namely pre-crisis, the crisis, and post-crisis periods. Overall, the inclusion of dummy variables in the model to allow for structural breaks in the series has improved the fit with the data. Moreover, it has strengthened the evidence of a bubble in the Thai stock market.

The result section also presents the probabilities statistics obtained from the model estimations. They help justify the use of this periodically collapsing regime-switching model, even though they do not forecast all the crashes and rallies perfectly. This is because if they do, that would mean the investors would be able to predict asset prices with certainty and would have violated the notion of speculative bubbles that were caused by investors taking the risk of not knowing the timing of a collapse.

At this point, it would be interesting to examine the bubbles further with more disaggregated data to see whether the bubbles were caused by one or few particular popular sectors like technology, real estate or finance, and do not represent the whole market or it is actually a widespread phenomenon. The next chapter will investigate bubble-like behaviour in industry group and sectoral indices in the Stock Exchange of Thailand.

Chapter 6: Disaggregated Indices: Analysis and Results

6.1. Introduction

The previous chapter examined the Stock Exchange of Thailand (SET)'s market-wide SET Index and concluded that there is some evidence of bubble-like behaviour. This chapter extends the discussion by looking at more disaggregated indices.

There are several benefits from investigating disaggregated indices. Firstly, the results would shed light on whether the bubble behaviour observed in the aggregated index was a pervasive phenomenon, or it was limited to some segments. The particular groups of stocks with bubbly assets could also be discovered and analysed. More precisely, the nature of business could be a major factor determining the bubble formation. This has important implications for both regulators and investors, as they monitor price movements. In addition, the evidence based on aggregated and disaggregated indices can be compared. Jung and Shiller (2005) postulated that bubbles could be detected more clearly with more disaggregated indices. This is because the changes on an individual stock were averaged out as more assets are included in the aggregated index. Finally, the analysis in this chapter also serves as a preliminary examination of bubble transmission within the Thai stock market, which will be discussed in the next chapter.

Initially, three datasets were investigated. There were eight SET's industry group indices, 27 SET's sectoral indices, and the ten Datastream-calculated indices. However, each of them suffered various limitations. For example, the industry group indices were only available for an extremely short span, such that reliable estimates for the empirical models cannot be obtained. The results are, therefore, reported in Appendix 1. On the other hand, the analyses of the sectoral indices were complicated and less manageable, as there were 27 indices to be considered. This is particularly critical for the bubble contagion analysis to be pursued in the next chapter. The Datastream-calculated indices also encountered some issues. It has a classification system that differs from the SET's official series and it only tracked a few stocks for each index. More importantly, there were a couple of indices with extended periods of zero reported dividend yields, which weakened the reliabilities of fundamental value calculation, and the subsequent bubble computations as well.

Consequently, this chapter also considered a newly computed index series called the K-NI. It was constructed based on the same methodology as the SET's industry group indices but employed the data from SET' sectoral indices to extend the K-NI to include almost 300 observations, which allow the bubble detection tests with different specifications to be applied, while remaining tractable with eight indices. The detailed construction of the K-NI can be found in Chapter 4.

The next section discusses the empirical evidence based on the different datasets. Then, the last section offered a summary.

6.2. Empirical Evidence

This section presents the results of the speculative bubble model by Van Norden and Schaller (2002) (hereafter VNS) [equations (13) to (17)], the volume-augmented model by Brooks and Katsaris (2005) [equations (22) to (24)] and, when applicable, the models with intercept dummy variables [equations (59) to (61) and (65) to (67)] as reviewed in Chapter 4 and Chapter 5 with different data sets as discussed in the previous section. Abnormal trading volumes are computed as percentage deviation of the current month's (average daily) trading volume from the moving average. Moving average is based on the mean of the last 12 months' trading volume, up to and including the current month. Price indices are converted to real series using the Thailand's Consumer Price Index (CPI).

The previous chapter concluded that there is some evidence for bubble-like behaviour in the market-wide SET index. This chapter will further explore the Thai market in more details. Analyses on the disaggregated indices will reveal which industry groups or sectors contain bubbles. Precisely, this is done by formulating different types of bubbles and imposing restrictions implied by the specifications. If the model fits the data satisfactorily, i.e. having at least two restriction tests rejects and preferably more, it would suggest that there is a bubble in the industry group or sector. However, if the model does not work very well, it does not imply that there is no bubble at all, rather, there is no identifiable bubble of the kind postulated by the model.

Meanwhile, given an extremely limited number of observations of the SET's official industry group indices available, the results from estimations are rather unreliable. Therefore, they are reported in Appendix 1. The remainder of this section will investigate results based on other datasets.

6.2.1. Results based on the SET's Sectoral Indices

This section elaborates on results from the SET's 27 sectoral indices. It will analyse the disaggregated indices in each industry group to determine whether which sector is driving the bubble-like behaviour if any.

The results with the VNS model were presented in Table 18. It implies that there is evidence of a bubble in Mining (Resources industry group), Information & Communication Technology (Technology), and some evidence in Tourism & Leisure (Services), although the specification may not always capture more variability of returns than simpler models. With two sectors without results, that means there are 22 other sectors with no bubble-like behaviour as estimated with the VNS model.

Table 18: SET's Sectoral Indices: VNS model

Industry Group	Agro & Food Industry		Consumer Products			Financials		
Sector	Agribusiness	Food & Beverage	Fashion	Home & Office Products	Personal Products & Pharmaceuticals	Banking	Finance & Securities	Insurance
β_{so}	0.9840***	1.0099***	0.9981***	0.9846***	0.9980***	1.0112***	0.9962***	1.0131***
β_{sb}	-0.0195	0.0098	-0.0052	-0.0436***	0.0106	-0.0232	-0.0075	0.0306***
β_{co}	1.0255***	1.0171***	1.0076***	0.9962***	1.0792***	1.0200***	1.0576***	1.0150***
β_{cb}	-0.0049	-0.0482	-0.1118	-0.1426**	-0.0051	0.0019	-0.0332	-0.0384
β_{qo}	-0.2813	0.7377**	1.1757***	1.2643***	0.9602***	0.9529***	0.9988***	1.2754***
β_{qb}	0.3791	0.0687	-0.8641	-0.4934	0.1203	-1.1712***	-0.4561*	-0.5393
σ_s	0.0412***	0.0482***	0.0469***	0.0546***	0.0602***	0.0625***	0.0912***	0.0427***
σ_c	0.0956***	0.1175***	0.1301***	0.1819***	0.2349***	0.1989***	0.3072***	0.1395***
Log-Likelihood	295.6041	360.9656	377.7722	293.6140	278.5711	227.9404	143.6333	393.1143
AIC	-2.2557	-2.5212	-2.6412	-2.2849	-1.9327	-1.5710	-0.9688	-2.7508
SBIC	-2.3185	-2.5783	-2.6984	-2.3489	-1.9898	-1.6281	-1.0260	-2.8080
HQIC	-2.2110	-2.4795	-2.5996	-2.2396	-1.8910	-1.5293	-0.9272	-2.7092
$(R1)\ \beta_{so} \neq \beta_{co}$	6.7169***	0.1269	0.1371	0.0769	4.0174**	0.0984	1.8648	0.0041
$(R2)\ \beta_{cb} < 0$	2.3546	1.6534	2.5079	3.8233*	0.0050	0.0000	0.5174	0.8132
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000	2.1889	1.9840	1.8930	0.0461	0.0000	0.2413	2.4932
$(R4)\ \beta_{qb} < 0$	0.0000	0.0000	1.2748	1.3212	0.0000	9.2078***	2.9787*	1.6326
Volatility regimes	8.2308*	3.7948	6.5760	25.1094***	6.8635	10.8283**	6.9452	20.1728***
Mixture of normals	2.6964	2.9033	5.3908	23.5827***	2.6260	10.0995**	4.4643	17.7106***
Fads	7.2896*	3.0887	5.1740	6.1306	4.6225	10.0557**	6.1061	5.7002
Starting observation	Sep 1991	Aug 1989	Aug 1989	Feb 1992	Aug 1989	Aug 1989	Aug 1989	Aug 1989
No. of observations	255	280	280	250	280	280	280	280

Note: Results from the VNS model [equations (13) to (17)]. The top panel presents estimated parameters from the relevant models, while the second panel reports maximised log-likelihood statistics and other information criteria. The third and fourth panels show likelihood ratio statistics for tests of coefficient restrictions and robustness checks against simpler specifications. Starting observations and number of observations included in the estimation are contained in the last panel. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 18 (continued)

Industry Group	Industrials					
Sector	Automotive	Industrial Materials & Machinery	Paper & Printing Materials	Petrochemicals & Chemicals	Packaging	Steel
β_{so}	0.9940***		0.9929***	1.0030***	0.9986***	
β_{sb}	-0.0182*		-0.0131**	0.0038	-0.0210	
β_{co}	1.0848***		1.0588***	1.0258***	1.0480***	
β_{cb}	0.1796*		0.0582	0.0051	0.0361	
β_{qo}	1.0538***		0.8500**	0.1576	1.5083***	
β_{qb}	0.2092		0.1387	-0.0437	-1.6700**	
σ_s	0.0649***		0.0561***	0.0610***	0.0635***	
σ_c	0.1360***		0.1434***	0.1965***	0.1467***	
Log-Likelihood	311.0180		323.5164	180.5813	297.9651	
AIC	-2.1644		-2.2537	-1.2327	-2.0712	
SBIC	-2.2216		-2.3108	-1.2899	-2.1283	
HQIC	-2.1228		-2.2120	-1.1911	-2.0295	
$(R1)\ \beta_{so} \neq \beta_{co}$	7.1099***		5.0560**	1.0333	3.4253*	
$(R2)\ \beta_{cb} < 0$	0.0000		0.0000	0.0000	0.0000	
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000		0.0000	0.0000	0.0000	
$(R4)\ \beta_{qb} < 0$	0.0000		0.0000	0.0389	2.1915	
Volatility regimes	9.5125**		12.3875**	1.5594	12.8096**	
Mixture of normals	4.4333		5.9167	0.3237	10.6372**	
Fads	8.9973**		9.9838**	1.1478	10.4189**	
Starting observation	Aug 1989	Jun 2007	Aug 1989	Aug 1989	Aug 1989	Dec 2011
No. of observations	280	66	280	280	280	12

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 18 (continued)

Industry Group	Property & Construction			Resources	
Sector	Construction Materials	Property Development	Property Fund	Energy & Utilities	Mining
β_{so}	1.0086***	0.9906***	1.0034***	1.0105***	1.0058***
β_{sb}	0.0099	-0.0047	0.0618*	-0.0143**	-0.0206
β_{co}	1.0169***	1.0699***	0.4378	1.0235***	1.0011***
β_{cb}	-0.0101	0.0377	3.4832	0.0072	-0.0019
β_{qo}	1.3055***	0.7697***	2.1488**	1.1716**	0.1750
β_{qb}	-0.5367*	-0.1938	-2.1784	0.2492	-3.0014**
σ_s	0.0813***	0.0871***	0.0173***	0.0799***	0.0345***
σ_c	0.2031***	0.2389***	0.0000	0.2149***	0.1506***
Log-Likelihood	232.6004	170.2642	113.8756	261.9049	178.5734
AIC	-1.6043	-1.1632	-6.2280	-1.8136	-1.2184
SBIC	-1.6614	-1.2205	-6.6986	-1.8707	-1.2755
HQIC	-1.5626	-1.1214	-6.1055	-1.7720	-1.1767
$(R1)\ \beta_{so} \neq \beta_{co}$	0.0486	4.2079**	41.5779***	0.0617	3.3864*
$(R2)\ \beta_{cb} < 0$	0.1210	0.0000	0.0000	0.0000	8.7897***
$(R3)\ \beta_{sb} > \beta_{cb}$	0.3726	0.0000	0.0000	0.0000	0.0000
$(R4)\ \beta_{qb} < 0$	3.9974**	0.5565	0.5970	0.0000	11.9337***
Volatility regimes	5.8794	4.8382	60.7540***	4.1249	2.7769
Mixture of normals	5.5561	1.2676	60.5042***	4.1236	0.0000
Fads	5.1342	4.7715	59.2950***	0.4095	0.9180
Starting observation	Aug 1989	Sep 1989	Feb 2010	Aug 1989	Aug 1989
No. of observations	280	279	34	280	280

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 18 (continued)

Industry Group	Services						Technology	
Sector	Commerce	Health Care Services	Media & Publishing	Professional Services	Tourism & Leisure	Transportation & Logistics	Electronic Components	Information & Communication Technology
β_{so}	1.0072***	1.0055***	0.9866***	0.9905***	0.9911***	0.9961***	1.0025***	0.9859***
β_{sb}	-0.0162	0.0177	-0.0246**	-0.0051	-0.0034	-0.0114	0.0054	-0.0172***
β_{co}	0.9990***	1.0139***	1.0628***	1.0405***	1.0354***	1.0223***	1.0203***	1.5528***
β_{cb}	-0.0070	0.0108	0.0424	-0.0180	-0.0068	-0.0347	-0.0085	-0.2339***
β_{qo}	1.9544***	1.2038*	0.5655	1.0093**	1.0448***	0.2990	0.5226*	1.3647***
β_{qb}	-1.2082*	-0.7678	0.2734	-0.0012	-0.9898*	0.1920	-0.3662	0.3957
σ_s	0.0658***	0.0647***	0.0645***	0.0645***	0.0426***	0.0635***	0.0603***	0.0959***
σ_c	0.1787***	0.1328***	0.1797***	0.1914***	0.1266***	0.1794***	0.1768***	0.1276***
Log-Likelihood	324.9943	300.9897	245.0605	285.5802	366.6491	224.4793	222.6315	192.5427
AIC	-2.2642	-2.1308	-1.7691	-1.9827	-2.5618	-1.5630	-1.5386	-1.4763
SBIC	-2.3214	-2.1890	-1.8288	-2.0399	-2.6189	-1.6208	-1.5959	-1.5403
HQIC	-2.2226	-2.0886	-1.7261	-1.9411	-2.5201	-1.5210	-1.4968	-1.4310
$(R1)\ \beta_{so} \neq \beta_{co}$	0.0186	0.0960	4.8753**	1.6339	4.8941**	1.2697	0.5716	16.2674***
$(R2)\ \beta_{cb} < 0$	0.0077	0.0000	0.0000	0.2080	0.0378	1.2503	0.1341	21.4788***
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000	0.0468	0.0000	0.0995	0.0076	0.4813	0.2348	21.3998***
$(R4)\ \beta_{qb} < 0$	52.6443***	10.9898***	0.0000	0.0000	2.7638*	0.0000	1.6284	0.0000
Volatility regimes	5.9937	4.2594	8.1329*	3.3612	7.9586*	5.9187	2.7392	17.9693***
Mixture of normals	5.9917	3.9347	5.6797	1.4043	3.7125	4.6279	1.8290	13.4565***
Fads	3.5238	1.7740	6.0676	1.9939	6.2396	2.3521	2.7356	7.9198**
Starting observation	Aug 1989	Jan 1990	Aug 1990	Aug 1989	Aug 1989	Nov 1989	Sep 1989	Feb 1992
No. of observations	280	275	268	280	280	277	279	250

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 19 reports results with the volume-augmented model, which suggests bubbles in five sectors, namely, Banking (Financials), Industrial Materials & Machinery (Industrials) – although the magnitudes of standard deviations in the two regimes are quite unrealistic, Packaging (Industrials), Tourism & Leisure (Services), Information & Communication Technology (Technology), and some evidence in four other sectors including Agribusiness (Agro & Food Industry), Property Development (Property & Construction), Property Fund (Property & Construction), and Health Care Services (Services). No result was obtained for one sector, so that leaves 17 other sectors with no evidence of bubbles.

To sum up, the basic VNS and volume-augmented models appear to have picked up evidence of bubbles in Financials industry group via Banking sector, Industrials industry via Packing and perhaps Industrial Materials & Machinery, and Technology industry via Information & Communication Technology. There was also some evidence in Agro & Food Industry via Agribusiness sector, Property & Construction industry via Property Development and Property Fund sectors, and Services industry via Tourism & Leisure and possibly Health Care Services. This means both Consumer Products and Resources industries are free of bubble-like behaviour.

Table 19: SET's Sectoral Indices: Volume-augmented model

Industry Group	Agro & Food Industry		Consumer Products			Financials		
Sector	Agribusiness	Food & Beverage	Fashion	Home & Office Products	Personal Products & Pharmaceuticals	Banking	Finance & Securities	Insurance
β_{so}	0.9843***	1.0088***	0.9975***	0.9825***	0.9980***	1.0097***	0.9956***	1.0123***
β_{sb}	-0.0155	0.0082	-0.0011	-0.0491***	0.0104	-0.0156	-0.0104	0.0287***
β_{sv}	-0.0048	0.0080	-0.0029	0.0050	0.0004	0.0008	0.0138	0.0031
β_{co}	1.0278***	1.0166***	1.0100***	1.0052***	1.0794***	1.0214***	1.0537***	1.0155***
β_{cb}	-0.0081	-0.0475	-0.1168	-0.1369*	-0.0052	-0.0051	-0.0330	-0.0376
β_{qo}	-0.1735	0.7857**	1.0819***	1.4486***	0.9562***	1.1797***	0.9846***	1.2920***
β_{qb}	0.4431	0.0354	-0.6263	-0.6350	0.1315	-1.4709***	-0.4608*	-0.5510
β_{qv}	-0.8314**	-0.2190	-0.2483*	-0.0342	0.0150	-0.6337**	-0.2714	-0.0372
σ_s	0.0427***	0.0479***	0.0457***	0.0567***	0.0603***	0.0640***	0.0881***	0.0427***
σ_c	0.0975***	0.1156***	0.1245***	0.1933***	0.2352***	0.1986***	0.3011***	0.1402***
Log-Likelihood	300.9068	362.8955	379.0067	294.3857	278.5836	232.9138	145.7608	393.6402
AIC	-2.2816	-2.5207	-2.6358	-2.2751	-1.9185	-1.5922	-0.9697	-2.7403
SBIC	-2.3601	-2.5921	-2.7072	-2.3551	-1.9899	-1.6637	-1.0411	-2.8117
HQIC	-2.2258	-2.4686	-2.5837	-2.2184	-1.8664	-1.5402	-0.9177	-2.6882
$(R1)\ \beta_{so} \neq \beta_{co}$	6.8671***	0.1533	0.3067	0.2073	4.0232**	32.8933***	1.9189	0.0109
$(R2)\ \beta_{cb} < 0$	0.1515	1.6110	3.0335*	2.7569*	0.0049	0.0169	0.5477	0.7708
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000	1.9881	2.5305	1.1750	0.0434	0.0000	0.1932	2.2722
$(R4)\ \beta_{qb} < 0$	0.0000	0.0000	0.6322	1.8263	0.0000	11.9792***	3.0015*	1.7012
$(R5)\ \beta_{qv} < 0$	9.5122***	1.5723	2.3829	0.0492	0.0000	9.9192***	2.3111	0.0437
$(R6)\ \beta_{sv} > 0$	0.0000	2.9278*	0.0000	1.4917	0.0152	0.0043	1.8651	0.9599
Volatility regimes	18.8361***	7.6545	9.0450	26.6529***	6.8884	20.7751***	11.2002*	21.2247***
Mixture of normals	13.3017**	6.7630	7.8598	25.1262***	2.6509	20.0463***	8.7193	18.7625***
Fads	17.8950***	6.9484	7.6431	7.6741	4.6475	20.0025***	10.3611*	6.7520
VNS	10.6053***	3.8597	2.4690	1.5435	0.0250	9.9468***	4.2550	1.0518
Starting observation	Sep 1991	Aug 1989	Aug 1989	Feb 1992	Aug 1989	Aug 1989	Aug 1989	Aug 1989
No. of observations	255	280	280	250	280	280	280	280

Note: Results from the volume-augmented model [equations (22) to (24)]. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 19 (continued)

Industry Group	Industrials					
Sector	Automotive	Industrial Materials & Machinery	Paper & Printing Materials	Petrochemicals & Chemicals	Packaging	Steel
β_{so}	0.9924***	1.0254***	0.9932***	1.0030***	0.9959***	1.0046***
β_{sb}	-0.0158	0.0064	-0.0135**	0.0042	-0.0213	-0.1011
β_{sv}	-0.0084*	-0.0199*	0.0030	-0.0099	-0.0095	-0.0002
β_{co}	1.0667***	0.5789***	1.0510***	1.0247***	1.0376***	1.0983
β_{cb}	0.0740	-0.3658***	0.0583	0.0047	0.0231	0.5109
β_{qo}	0.9980***	2.2497**	0.7896*	0.1484	2.0766**	2.6796***
β_{qb}	-0.3296	1.1569	0.1455	-0.0626	-2.4721	1.1435
β_{qv}	-0.0904	2.0821	-0.1490	-0.2785	-1.2478	6.7339
σ_s	0.0598***	0.0826***	0.0547***	0.0580***	0.0627***	0.0284**
σ_c	0.1347***	0.0522**	0.1395***	0.1934***	0.1372***	0.0000
Log-Likelihood	312.7630	64.2172	323.8436	182.8099	307.6298	48.9932
AIC	-2.1626	-1.6429	-2.2417	-1.2344	-2.1259	-6.4989
SBIC	-2.2340	-1.9460	-2.3132	-1.3058	-2.1974	-8.1655
HQIC	-2.1105	-1.5119	-2.1897	-1.1823	-2.0739	-6.6485
$(R1)\ \beta_{so} \neq \beta_{co}$	2.8318*	6.2689**	5.0274**	1.0161	4.1821**	37.4830***
$(R2)\ \beta_{cb} < 0$	0.0000	4.8040**	0.0000	0.0000	0.0000	0.0000
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000	20.0343***	0.0000	0.0000	0.0000	0.0000
$(R4)\ \beta_{qb} < 0$	0.2502	0.0000	0.0000	0.0802	4.6375**	0.0000
$(R5)\ \beta_{qv} < 0$	0.4207	0.0000	0.6361	2.7864*	19.1648***	0.0000
$(R6)\ \beta_{sv} > 0$	0.0000	0.0000	0.1982	0.0000	0.0000	0.0000
Volatility regimes	13.0025**	11.9030*	13.0418**	6.0166	32.1390***	59.2768***
Mixture of normals	7.9233	0.0000	6.5711	4.7808	29.9666***	28.1034***
Fads	12.4873**	11.7591**	10.6382*	5.6050	29.7484***	58.1689***
VNS	3.4900	0.0000	0.6544	4.4572	19.3294***	0.0000
Starting observation	Aug 1989	Jun 2007	Aug 1989	Aug 1989	Aug 1989	Dec 2011
No. of observations	280	66	280	280	280	12

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 19 (continued)

Industry Group	Property & Construction			Resources	
Sector	Construction Materials	Property Development	Property Fund	Energy & Utilities	Mining
β_{so}	1.0066***	0.9882***	1.0112***	1.0108***	0.9841***
β_{sb}	0.0056	-0.0104	0.0258	-0.0142*	-0.0161**
β_{sv}	0.0006	0.0079	0.0051	-0.0022	-0.0078
β_{co}	1.0259***	1.0817***	0.7736***	1.0225***	1.1714***
β_{cb}	-0.0008	0.0476	1.7352**	0.0031	0.2647**
β_{qo}	1.4750***	0.9382***	1.3790*	1.1326**	1.3068**
β_{qb}	-0.6342*	-0.2529	-0.5876	0.2564	0.1548
β_{qv}	-0.3176	-0.2931	0.1221	-0.1344	-0.0725
σ_s	0.0818***	0.0903***	0.0129***	0.0789***	0.1063***
σ_c	0.2050***	0.2439***	0.0566**	0.2080***	0.1575***
Log-Likelihood	233.9446	171.8654	86.8530	262.2004	185.5944
AIC	-1.5996	-1.1603	-4.5208	-1.8014	-1.2542
SBIC	-1.6710	-1.2320	-5.1090	-1.8729	-1.3257
HQIC	-1.5475	-1.1081	-4.3677	-1.7494	-1.2022
$(R1)\ \beta_{so} \neq \beta_{co}$	0.2513	4.9903**	13.4439***	0.0569	7.4694***
$(R2)\ \beta_{cb} < 0$	0.0007	0.0000	0.0000	0.0000	0.0000
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0374	0.0000	0.0000	0.0000	0.0000
$(R4)\ \beta_{qb} < 0$	4.7147**	0.3416	0.0213	0.0000	0.0000
$(R5)\ \beta_{qv} < 0$	2.2348	3.5421*	0.0000	0.2239	0.3622
$(R6)\ \beta_{sv} > 0$	0.0034	1.0667	57.7959***	0.0000	0.0000
Volatility regimes	8.5678	8.0406	6.7089	4.7159	16.8188***
Mixture of normals	8.2446	4.4700	6.4591	4.7147	13.8616**
Fads	7.8226	7.9739	5.2500	1.0005	14.9599**
VNS	2.6884	3.2024	0.0000	0.5910	14.0419***
Starting observation	Aug 1989	Sep 1989	Feb 2010	Aug 1989	Aug 1989
No. of observations	280	279	34	280	280

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 19 (continued)

Industry Group	Services						Technology	
Sector	Commerce	Health Care Services	Media & Publishing	Professional Services	Tourism & Leisure	Transportation & Logistics	Electronic Components	Information & Communication Technology
β_{so}	1.0061***	1.0060***	0.9889***		0.9911***	0.9954***	1.0029***	0.9867***
β_{sb}	-0.0209	0.0188	-0.0225**		-0.0035	-0.0119	0.0054	-0.0168***
β_{sv}	0.0095	-0.0053	-0.0046		0.0015	0.0048	-0.0039	-0.0042
β_{co}	1.0067***	1.0110***	1.0583***		1.0351***	1.0230***	1.0202***	1.5543***
β_{cb}	0.0072	0.0086	0.0395		-0.0075	-0.0344	-0.0088	-0.2337***
β_{qo}	1.6749**	1.6417***	0.4892		1.0940***	0.3152	0.5525**	1.3746***
β_{qb}	-0.9914	-1.1721	0.3276		-1.0259*	0.2171	-0.3648	0.3923
β_{qv}	-0.2884	-0.4617	0.0797		-0.2452	-0.0808	-0.1568	-0.0166
σ_s	0.0629***	0.0663***	0.0633***		0.0426***	0.0640***	0.0603***	0.0959***
σ_c	0.1596***	0.1351***	0.1786***		0.1261***	0.1802***	0.1775***	0.1266***
Log-Likelihood	326.6385	303.3122	246.0198		368.2126	224.7945	223.3337	192.6848
AIC	-2.2617	-2.1332	-1.7613		-2.5587	-1.5509	-1.5293	-1.4615
SBIC	-2.3331	-2.2059	-1.8360		-2.6301	-1.6231	-1.6010	-1.5415
HQIC	-2.2096	-2.0804	-1.7075		-2.5066	-1.4984	-1.4771	-1.4048
$(R1)\ \beta_{so} \neq \beta_{co}$	0.0001	0.0320	3.9018**		4.9345**	1.3620	0.5361	19.6456***
$(R2)\ \beta_{cb} < 0$	0.0000	0.0000	0.0000		0.0480	1.1602	0.1371	24.6457***
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000	1.0099	0.0000		0.0112	0.4305	0.2384	24.5447***
$(R4)\ \beta_{qb} < 0$	1.9291	20.3772***	0.0000		2.8265*	0.0000	1.6593	0.0000
$(R5)\ \beta_{qv} < 0$	1.1425	4.0117**	0.0000		2.7341*	0.2066	0.8883	23.7626***
$(R6)\ \beta_{sv} > 0$	2.0917	0.0000	0.0000		0.1168	0.5094	0.0000	0.0000
Volatility regimes	9.2822	8.9045	10.0514		11.0856*	6.5490	4.1435	18.2537***
Mixture of normals	9.2801*	8.5798	7.5982		6.8395	5.2582	3.2334	13.7409**
Fads	6.8123	6.4190	7.9861		9.3666*	2.9824	4.1399	8.2042
VNS	3.2885	4.6450*	1.9185		3.1270	0.6303	1.4043	0.2844
Starting observation	Aug 1989	Jan 1990	Aug 1990	Aug 1989	Aug 1989	Nov 1989	Sep 1989	Feb 1992
No. of observations	280	275	268	280	280	277	279	250

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Given the length of the sample period and the various development of the Thai capital market, it is possible for industry structure to have changed. This can be investigated by extending the core models with dummy variables. The first model includes one set of dummy variables, $Float_t$ or the coefficients with subscript f, in all three equations. The break is set at July 1997 when Thailand started adopting a managed floating exchange rate regime. The new model now includes parameters β_{sf}, β_{cf}, β_{qf}, which reveal the impact of the structural break on the return equations in both regimes and the probability equation. For instance, the results from the Agribusiness sector had $\beta_{sf} = 0.0250$, $\beta_{cf} = -0.0154$, and $\beta_{qf} = -0.8827$. This implied that investors are additionally compensated when the bubble survives since Thailand adopted the floating exchange rate system in July 1997, which essentially means more risks. However, they are also punished more severely when the bubble collapses. Finally, the probability of the bubble surviving in the next period has also reduced after the structural break.

The results from all the sectors suggest four sectors with evidence of bubbles. They include Food and Beverage (Agro & Food Industry), Home & Office Products (Consumer Products), Media & Publishing (Services), and Information & Communication Technology (Technology), although three of them yield standard deviations that are contrary to expectations. Eight other sectors exhibit some evidence of bubbles. They are Agribusiness (Agro & Food Industry), Fashion (Consumer Products), Banking (Financials), Packaging (Industrials), Construction Materials (Property & Construction), Property Development (Property & Construction), Mining (Resources), and Commerce (Services). Ten sectors reveal no evidence of bubbles and five sectors that no results were obtained from the estimation. These are shown in Table 20.

Table 20: SET's Sectoral Indices: Model with one set of intercept dummy variables at July 1997

Industry Group	Agro & Food Industry		Consumer Products			Financials		
Sector	Agribusiness	Food & Beverage	Fashion	Home & Office Products	Personal Products & Pharmaceuticals	Banking	Finance & Securities	Insurance
β_{so}	0.9688***	0.9888***	0.9697***	0.9824***	0.9697***	0.9992***	0.9949***	0.9991***
β_{sb}	-0.0124	0.0110	-0.0131	-0.0505***	-0.0019	-0.0260	-0.0188	0.0249***
β_{sv}	-0.0113	0.0096	-0.0023	0.0078*	-0.0004	0.0045	0.0133	0.0028
β_{sf}	0.0250**	0.0295***	0.0346***	0.0026	0.0396***	0.0201	-0.0008	0.0178**
β_{co}	1.0425***	1.0335***	1.0138***	0.8032***	1.0564***	1.0623***	1.0544***	1.0276***
β_{cb}	-0.0123	-0.0551	-0.0647	-0.2188***	0.0166	0.0112	-0.0205	-0.0390
β_{cf}	-0.0154	-0.0344	-0.0128	0.5024***	0.0463	-0.0698	-0.0186	-0.0292
β_{qo}	0.5909	0.4100	0.1109	2.0722***	0.6587**	0.8879***	0.4813	0.9972***
β_{qb}	0.3702	0.0378	-0.9575	-1.4790***	0.1026	-1.4477***	-0.8878**	-0.6086
β_{qv}	-0.9521***	-0.3330	-0.2787*	-0.0502	0.0404	-0.4767*	-0.2488	-0.0957
β_{qf}	-0.8827*	0.4161	1.0690***	1.0138**	0.4753*	0.2730	0.9280***	0.5491*
σ_s	0.0437***	0.0449***	0.0373***	0.0726***	0.0573***	0.0595***	0.0810***	0.0420***
σ_c	0.0980***	0.1075***	0.1088***	0.0015***	0.2324***	0.1920***	0.2836***	0.1392***
Log-Likelihood	306.6460	368.6703	390.5242	303.8706	287.9298	235.2338	150.2705	398.1049
$(R1)\ \beta_{so} \neq \beta_{co}$	4.5162**	3.0147*	3.3954*	15.6779***	2.2443	2.4390	1.1983	0.5877
$(R2)\ \beta_{cb} < 0$	0.3585	2.3377	1.8197	18.5427***	0.0000	0.0000	0.3032	0.7251
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000	2.9413*	0.7069	17.1702***	0.0000	0.0000	0.0017	1.8510
$(R4)\ \beta_{qb} < 0$	0.0000	0.0000	1.5167	16.4324***	0.0000	10.5208***	7.6252***	1.9667
$(R5)\ \beta_{qv} < 0$	8.2210***	2.9197*	2.8996*	15.6783***	0.0000	6.4558**	1.8747	0.3297
$(R6)\ \beta_{sv} > 0$	0.0000	2.4515	0.0000	16.7366***	0.0000	0.1660	2.0002	0.7544
Volatility regimes	30.3147***	19.2041**	32.0799***	45.6227***	25.5809***	25.4149***	20.2197**	30.1542***
Mixture of normals	24.7802***	18.3126**	30.8947***	44.0960***	21.3434***	24.6861***	17.7388**	27.6919***
Fads	29.3735***	18.4980**	30.6780***	26.6439***	23.3400***	24.6423***	19.3806**	15.6815**
VNS	22.0838***	15.4093***	25.5039***	20.5133***	18.7175***	14.5866**	13.2745**	9.9813*
Volume-augmented	11.4785***	11.5496***	23.0349***	10.2483**	18.6925***	4.6398	9.0195**	8.9295**
Starting observation	Sep 1991	Aug 1989	Aug 1989	Feb 1992	Aug 1989	Aug 1989	Aug 1989	Aug 1989
No. of observations	255	280	280	250	280	280	280	280

Note: Results from the model with one set of intercept dummy variables [equations (59) to (61)]. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 20 (continued)

Industry Group	Industrials					
Sector	Automotive	Industrial Materials & Machinery	Paper & Printing Materials	Petrochemicals & Chemicals	Packaging	Steel
β_{so}	0.9730***		0.9727***	0.9842***	0.9882***	
β_{sb}	-0.0289***		-0.0184***	0.0069	-0.0139	
β_{sv}	-0.0076*		0.0027	-0.0027	-0.0086	
β_{sf}	0.0299***		0.0259**	0.0291	0.0126	
β_{co}	1.1574***		1.0330***	1.0183***	1.0252***	
β_{cb}	0.1862**		0.0385	0.0012	0.0109	
β_{cf}	-0.0962		0.0053	0.0079	0.0091	
β_{qo}	1.1860***		0.2526	0.1349	2.6331*	
β_{qb}	0.3032		-0.1158	0.0115	-3.1258	
β_{qv}	-0.0318		-0.1366	-0.3172	-1.4732	
β_{qf}	-0.2217		0.5432	-0.1571	-0.4726	
σ_s	0.0628***		0.0462***	0.0540***	0.0620***	
σ_c	0.1301***		0.1260***	0.1890***	0.1339***	
Log-Likelihood	317.2490		327.2005	184.6377	308.8037	
$(R1)\ \beta_{so} \neq \beta_{co}$	8.0160***		4.9130**	0.8273	0.9580	
$(R2)\ \beta_{cb} < 0$	0.0000		0.0000	0.0000	0.0000	
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000		0.0000	0.0529	0.0000	
$(R4)\ \beta_{qb} < 0$	0.0000		0.0732	0.0000	5.2634**	
$(R5)\ \beta_{qv} < 0$	0.0543		0.8298	3.1340*	17.4821***	
$(R6)\ \beta_{sv} > 0$	0.0000		0.2429	0.0000	0.0000	
Volatility regimes	21.9744***		19.7556**	9.6722	34.4868***	
Mixture of normals	16.8951**		13.2848	8.4365	32.3145***	
Fads	21.4592***		17.3519**	9.2606	32.0962***	
VNS	12.4619**		7.3681	8.1128	21.6773***	
Volume-augmented	10.8565**		6.7137*	3.6556	2.3478	
Starting observation	Aug 1989	Jun 2007	Aug 1989	Aug 1989	Aug 1989	Dec 2011
No. of observations	280	66	280	280	280	12

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 20 (continued)

Industry Group	Property & Construction			Resources	
Sector	Construction Materials	Property Development	Property Fund	Energy & Utilities	Mining
β_{so}	0.9817***	0.9613***		1.0365***	0.9371***
β_{sb}	0.0141	0.0052		-0.0283***	-0.0215***
β_{sv}	0.0090	0.0066		-0.0048	-0.0016
β_{sf}	0.0463***	0.0480***		-0.0433***	0.0681***
β_{co}	1.0992***	1.1310***		0.8048***	0.9878***
β_{cb}	-0.0058	0.0170		0.1427	0.0296*
β_{cf}	-0.1031	-0.1023		0.3580	0.0210
β_{qo}	1.7853**	0.8201***		1.7508***	-1.3089***
β_{qb}	-0.7806*	-0.4034		0.0726	0.3623**
β_{qv}	-0.4469*	-0.3328*		0.2640	-0.7057**
β_{qf}	-0.5089	0.2797		-0.1594	0.3961
σ_s	0.0775***	0.0864***		0.0834***	0.0320***
σ_c	0.1826***	0.2405***		0.2186***	0.1508***
Log-Likelihood	239.5184	177.1705		266.7489	188.6629
$(R1)\ \beta_{so} \neq \beta_{co}$	2.0337	7.3646***		1.8513	3.5396*
$(R2)\ \beta_{cb} < 0$	0.0683	0.0000		0.0000	0.0000
$(R3)\ \beta_{sb} > \beta_{cb}$	0.4868	0.0000		0.0000	0.0000
$(R4)\ \beta_{qb} < 0$	5.0712**	2.1420		0.0000	0.0000
$(R5)\ \beta_{qv} < 0$	3.5144*	3.6085*		0.0000	2.7538*
$(R6)\ \beta_{sv} > 0$	0.6106	0.2867		0.0000	0.0000
Volatility regimes	19.7154**	18.6507**		13.8131	22.9559***
Mixture of normals	19.3921**	15.0801*		13.8118*	19.9987**
Fads	18.9702**	18.5839**		10.0976	21.0970***
VNS	13.8360**	13.8125**		9.6881*	20.1790***
Volume-augmented	11.1476**	10.6101**		9.0971**	17.2449***
Starting observation	Aug 1989	Sep 1989	Feb 2010	Aug 1989	Aug 1989
No. of observations	280	279	34	280	280

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 20 (continued)

Industry Group	Services						Technology	
Sector	Commerce	Health Care Services	Media & Publishing	Professional Services	Tourism & Leisure	Transportation & Logistics	Electronic Components	Info. & Comm. Tech.
β_{so}	0.9867***		1.0232***		0.9661***	0.9820***	0.9921***	1.1173***
β_{sb}	-0.0147		0.0436		-0.0071	-0.0066	0.0147	0.0215
β_{sv}	0.0045		0.0632*		0.0033	0.0043	-0.0044	0.1318
β_{sf}	0.0270**		0.0663		0.0374***	0.0201	0.0204	-0.0511
β_{co}	1.0104***		1.0181***		1.0333***	1.0330***	1.0275***	0.9913***
β_{cb}	0.0123		-0.0596***		-0.0045	-0.0380	-0.0142	-0.0209***
β_{cf}	0.0156		-0.0579***		0.0036	-0.0172	-0.0143	-0.0128
β_{qo}	0.9173**		0.4146		0.8448***	0.3120	0.5205*	-0.0188
β_{qb}	-1.4033*		-0.5581		-1.0930*	0.2000	-0.4044	-1.5010***
β_{qv}	-0.5206*		-0.2678*		-0.1962	-0.0221	-0.1478	-0.3709
β_{qf}	1.0076**		-1.0381***		0.5420*	-0.0842	0.0803	0.8995**
σ_s	0.0577***		0.1585***		0.0399***	0.0613***	0.0598***	0.2389***
σ_c	0.1370***		0.0610***		0.1314***	0.1765***	0.1771***	0.0710***
Log-Likelihood	331.6283		253.9513		383.7148	225.7518	224.2528	207.8020
$(R1)\ \beta_{so} \neq \beta_{co}$	0.4538		0.0172		5.2441**	1.6872	0.9288	2.8629*
$(R2)\ \beta_{cb} < 0$	0.0000		16.6179***		0.0132	1.5866	0.2924	13.2352***
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000		4.4379**		0.0000	0.8743	0.7854	0.7236
$(R4)\ \beta_{qb} < 0$	3.4804*		1.2526		2.5374	0.0000	2.0073	26.3905***
$(R5)\ \beta_{qv} < 0$	3.9720**		4.5654**		1.9967	0.0192	0.7723	2.6334
$(R6)\ \beta_{sv} > 0$	0.3987		3.4792*		0.8277	0.6175	0.0000	3.1693*
Volatility regimes	19.2617**		25.9146***		42.0899***	8.4637	5.9818	48.4880***
Mixture of normals	19.2596**		23.4614***		37.8439***	7.1729	5.0716	43.9752***
Fads	16.7918**		23.8492***		40.3709***	4.8971	5.9781	38.4385***
VNS	13.2680**		17.7816***		34.1314***	2.5450	3.2426	30.5187***
Volume-augmented	9.9795**		14.6534***		31.0044***	1.9147	1.8382	5.2060
Starting observation	Aug 1989	Jan 1990	Aug 1990	Aug 1989	Aug 1989	Nov 1989	Sep 1989	Feb 1992
No. of observations	280	275	268	280	280	277	279	250

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Finally, Table 21 presents the results with two sets of dummy variables at September 1996 and August 1998 as determined by the results of the market-wide SET index discussed in the previous chapter. Note that the breaks coincide with the 1997 Asian Financial Crisis and practically separate the total sample into three sub-periods: the pre-crisis, the crisis where *l* dummy variables = 1, and the post-crisis where both *l* and *f* dummy variables are 1. In other words, the results are to be interpreted in the same manner as the volume-augmented model with the all the parameters with *o*, *b*, *v* subscripts and in the period before September 1996, to also consider the impact of parameters with the *l* subscript during September 1996 to August 1998, and to include the effects of both the *l* and *f* parameters after August 1998. Consider, for instance, the Food & Beverage sector, $\beta_{sl} = -0.0543$ suggests that the average return in the surviving regime during the crisis period of September 1996 to August 1998 is lower than the pre-crisis period by 5.43% per month, and $\beta_{sf} = 0.0756$ implies that the average return when the bubble continues to grow in the post-crisis period of August 1998 onwards is 7.56% per month higher than the crisis period. In other words, the return has rebounded and could be expected to be 2.13% per month higher than during the pre-crisis period, on average.

Regarding the evidence from all sectors, the bubble-like behaviour is found in two sectors, namely, Banking (Financials), and Information & Communication Technology (Technology) – though it was not proved to be more fitting that the model with only one set of dummy variables. Some evidence of a bubble is detected in nine sectors. They are Agribusiness (Agro & Food Industry), Fashion (Consumer Products), Home & Office Products (Consumer Products), Finance and Securities (Financials), Petrochemicals & Chemicals (Industrials), Packaging (Industrials), Property Development (Property & Construction), Mining (Resources), and Media & Publishing (Services) sectors. Results were not obtained for four sectors which leave 12 sectors with no evidence of bubbles.

Table 21: SET's Sectoral Indices: Model with two sets of intercept dummy variables at September 1996 and August 1998

Sector	Agribusiness	Food & Beverage	Fashion	Home & Office Products	Personal Products & Pharmaceuticals	Banking	Finance & Securities	Insurance
β_{so}	0.9721***	0.9978***	0.9766***	0.9785***	0.9612***	1.0190***	1.0008***	0.9941***
β_{sb}	-0.0145	-0.0001	0.0044	-0.0408***	-0.0156	-0.0377**	-0.0305***	0.0116
β_{sv}	-0.0107	0.0042	-0.0054	0.0042	0.0003	0.0102	0.0199**	0.0028
β_{sl}	-0.0279	-0.0543***	-0.0610	-0.0608**	-0.0032	-0.1836***	-0.2518***	-0.0303
β_{sf}	0.0512***	0.0756***	0.0893	0.0722***	0.0554**	0.1851***	0.2426***	0.0553**
β_{co}	1.0454***	1.0310***	1.0163***	1.1103***	1.0370***	1.2283***	1.1125***	1.0303***
β_{cb}	-0.0116	-0.0315	-0.1813***	-0.2392***	-0.0641	-0.5572***	-0.0693	-0.0771
β_{cl}	-0.0469	0.1499	-0.1073***	-0.1847	-0.2189	-0.6876***	-0.0080	-0.1003
β_{cf}	0.0343	-0.2309	0.1590***	0.0764	0.3548**	0.9623***	0.0141	0.0720
β_{qo}	0.6099	0.7631*	0.2376	1.7037***	0.3049	2.0805***	0.5777**	0.6410
β_{qb}	0.2761	-0.6218	-1.8573	0.3374	0.5329	-3.7372***	-0.3350	0.0568
β_{qv}	-0.9129**	-0.1834	-0.5009	0.0144	0.0466	-0.9403***	-0.2516	-0.0889
β_{ql}	-0.5762	0.8054	-0.8932	-1.7457**	-0.1835	1.8853*	0.2484	0.1202
β_{qf}	-0.1928	0.5687	3.2024	0.9226*	1.0436	-0.4884	0.4923	0.8481
σ_s	0.0430***	0.0511***	0.0424***	0.0527***	0.0571***	0.0743***	0.0823***	0.0425***
σ_c	0.0981***	0.1194***	0.0975***	0.1528***	0.2155***	0.1781***	0.2869***	0.1450***
Log-Likelihood	309.5890	380.3547	404.5261	304.0023	295.2487	263.9480	172.9176	407.9945
$(R1)\ \beta_{so} \neq \beta_{co}$	4.4545**	1.1525	2.6285	0.9782	2.2285	8.4511***	2.9402*	0.8012
$(R2)\ \beta_{cb} < 0$	0.2631	0.3418	4.4822**	8.0375***	0.7099	10.5181***	1.1127	1.5389
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000	0.3209	2.5800	6.0845**	0.3920	8.5358***	0.3038	1.8497
$(R4)\ \beta_{qb} < 0$	0.0000	1.0858	1.7212	0.0000	0.0000	13.3854***	1.0917	0.0000
$(R5)\ \beta_{qv} < 0$	10.0679***	1.2989	4.4394**	0.0000	0.0000	18.0606***	1.7323	0.2246
$(R6)\ \beta_{sv} > 0$	0.0000	1.4436	0.0000	1.1396	0.0083	1.1024	4.0081**	0.8335
Volatility regimes	36.2006***	42.5728***	60.0837***	45.8861***	40.2186***	82.8433***	65.5139***	49.9334***
Mixture of normals	30.6661***	41.6814***	58.8986***	44.3594***	35.9811***	82.1145***	63.0330***	47.4712***
Fads	35.2594***	41.8668***	58.6818***	26.9073***	37.9777***	82.0707***	64.6747***	35.4607***
VNS	27.9697***	38.7781***	53.5078***	20.7767***	33.3552***	72.0151***	58.5687***	29.7605***
Volume-augmented	17.3644***	34.9183***	51.0387***	19.2332***	33.3302***	62.0682***	54.3137***	28.7087***
One Intercept DV	4.1103	11.9375***	9.9846**	12.8814***	2.6832	45.8902***	33.4380***	6.9346*
Starting observation	Sep 1991	Aug 1989	Aug 1989	Feb 1992	Aug 1989	Aug 1989	Aug 1989	Aug 1989
No. of observations	255	280	280	250	280	280	280	280

Note: Results from the model with two sets of intercept dummy variables [equations (62) to (64)]. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 21 (continued)

Sector	Automotive	Industrial Materials & Machinery	Paper & Printing Materials	Petrochemicals & Chemicals	Packaging	Steel
β_{so}	0.9757***		0.9733***	0.9735***	1.0012***	
β_{sb}	-0.0433***		-0.0158***	0.0106	-0.0335**	
β_{sv}	-0.0069		0.0000	-0.0005	-0.0005	
β_{sl}	-0.0631***		-0.0093	0.3900***	-0.0669***	
β_{sf}	0.0943***		0.0330	-0.3464***	0.0723***	
β_{co}	1.1299***		1.0428***	1.0226***	1.0170***	
β_{cb}	0.1420		0.0653**	-0.0088	0.0201	
β_{cl}	-0.1783		-0.0956	-0.1283***	0.0884	
β_{cf}	0.1230		0.1765**	0.1430***	-0.0639	
β_{qo}	1.0546**		0.4167	-0.3381	2.3326***	
β_{qb}	0.3774		-0.4901	0.3471	-1.8716*	
β_{qv}	-0.0825		-0.0874	-0.2422	-1.0789***	
β_{ql}	-0.0614		-0.0346	-1.6037***	0.4417	
β_{qf}	-0.0273		1.1578	1.6124***	-1.0666	
σ_s	0.0589***		0.0514***	0.0450***	0.0609***	
σ_c	0.1295***		0.1130***	0.1675***	0.1411***	
Log-Likelihood	331.1702		331.8773	190.7145	316.9688	
$(R1)\ \beta_{so} \neq \beta_{co}$	3.2848*		4.2090**	6.9425***	0.0865	
$(R2)\ \beta_{cb} < 0$	0.0000		0.0000	1.1462	0.0000	
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000		0.0000	1.6341	0.0000	
$(R4)\ \beta_{qb} < 0$	0.0000		0.7133	0.0000	5.5572**	
$(R5)\ \beta_{qv} < 0$	0.3473		0.4536	7.7142***	18.4963***	
$(R6)\ \beta_{sv} > 0$	0.0000		0.7724	0.0000	0.0000	
Volatility regimes	49.8169***		29.1092***	21.8258**	50.8170***	
Mixture of normals	44.7376***		22.6385**	20.5901**	48.6446***	
Fads	49.3017***		26.7056***	21.4142**	48.4263***	
VNS	40.3044***		16.7218**	20.2664***	38.0074***	
Volume-augmented	36.8144***		16.0674**	15.8092**	18.6780***	
One Intercept DV	17.6621***		2.9219	8.1194**	12.1831***	
Starting observation	Jun 2007	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Dec 2011
No. of observations	66	280	280	280	280	12

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 21 (continued)

Sector	Construction Materials	Property Development	Property Fund	Energy & Utilities	Mining
β_{so}	0.9898***	0.9707***		1.0391***	0.9848***
β_{sb}	0.0083	-0.0079		-0.0195**	0.0355*
β_{sv}	0.0075	0.0078		-0.0049	-0.0034
β_{sl}	-0.0842*	-0.1305***		-0.0986***	-0.0142
β_{sf}	0.1178**	0.1668***		0.0630**	0.0470
β_{co}	1.1426***	1.1556***		0.8696***	0.9549***
β_{cb}	0.0016	-0.0193		0.0498	-0.0201***
β_{cl}	-0.1770	-0.2514*		0.2529	-0.0449
β_{cf}	0.0666	0.2266*		-0.0626	0.0979***
β_{qo}	2.1808***	0.8371***		1.4677**	1.0699***
β_{qb}	-0.9294**	-0.0878		0.1803	-0.2987*
β_{qv}	-0.4865*	-0.3259*		0.2941	0.5123*
β_{ql}	-1.9731**	-0.4959		-0.8295	0.1154
β_{qf}	1.8859***	1.0329		0.8058	-0.5261
σ_s	0.0799***	0.0883***		0.0792***	0.1530***
σ_c	0.2049***	0.2468***		0.2069***	0.0329***
Log-Likelihood	250.7672	193.7047		271.4455	192.6394
$(R1)\ \beta_{so} \neq \beta_{co}$	1.9338	7.0632***		1.4307	0.5942
$(R2)\ \beta_{cb} < 0$	0.0000	0.1232		0.0000	4.4992**
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0401	0.0381		0.0000	12.4039***
$(R4)\ \beta_{qb} < 0$	6.2658**	0.0529		0.0000	0.7278
$(R5)\ \beta_{qv} < 0$	1.3876	3.5137*		0.0000	0.0000
$(R6)\ \beta_{sv} > 0$	0.5591	0.5420		0.0000	0.0000
Volatility regimes	42.2129***	51.7192***		23.2062**	30.9089***
Mixture of normals	41.8896***	48.1486***		23.2049**	27.9518***
Fads	41.4677***	51.6525***		19.4907*	29.0501***
VNS	36.3335***	46.8810***		19.0812**	28.1320***
Volume-augmented	33.6451***	43.6786***		18.4902***	13.6649**
One Intercept DV	16.2983***	20.4559***		12.0642***	2.0316
Starting observation	Aug 1989	Sep 1989	Feb 2010	Aug 1989	Aug 1989
No. of observations	280	279	34	280	280

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 21 (continued)

Sector	Commerce	Health Care Services	Media & Publishing	Professional Services	Tourism & Leisure	Transportation & Logistics	Electronic Components	Information & Communication Technology
β_{so}	0.9890***	0.9689***	1.0319***		0.9660***	0.9825***	0.9925***	1.0136***
β_{sb}	-0.0137	-0.0599***	0.0196		-0.0049	-0.0042	0.0115	-0.0192***
β_{sv}	0.0046	-0.0029	0.0579*		0.0045	0.0032	-0.0019	-0.0077
β_{sl}	-0.0660**	-0.0963***	-0.0754		0.0004	-0.1057***	0.4688***	-0.2228***
β_{sf}	0.0949***	0.1709***	0.1222*		0.0383**	0.1272***	-0.4554***	0.1949***
β_{co}	1.0465***	0.9859***	1.0016***		1.0220***	1.0247***	1.0121***	1.8357***
β_{cb}	-0.0750	0.0069	-0.0376**		-0.0059	-0.0346	0.0002	-0.4899***
β_{cl}	-0.1394	-0.0313	-0.0490		0.0287	0.0257	-0.0537	-0.8936***
β_{cf}	0.1072	0.1380	0.0259		-0.0042	-0.0268	0.0758*	0.7743***
β_{qo}	0.9822**	1.6697	0.8414		0.7405**	0.3157	0.3871	1.3839***
β_{qb}	-0.9016	-0.3303	-0.7500		-1.0013	-0.1067	-0.7050*	0.9887***
β_{qv}	-0.3497	-0.2687	-0.3143*		-0.1605	0.0272	-0.1948	-0.0335
β_{ql}	-0.0246	-0.3150	-0.4313		-0.1095	-0.5824	-1.4922***	-2.1099***
β_{qf}	1.0307	0.2004	-0.9597		0.8821	0.8209	1.8754***	1.2863***
σ_s	0.0571***	0.0636***	0.1577***		0.0397***	0.0576***	0.0564***	0.0822***
σ_c	0.1435***	0.1422***	0.0578***		0.1313***	0.1731***	0.1518***	0.0984***
Log-Likelihood	344.6066	327.3794	257.2330		387.0620	233.4061	230.7823	224.0134
$(R1)\ \beta_{so} \neq \beta_{co}$	1.3060	0.0284	0.5035		3.5848*	1.2082	0.3452	19.8517***
$(R2)\ \beta_{cb} < 0$	1.1765	0.0000	7.7375***		0.0201	1.7167	0.0000	15.7783***
$(R3)\ \beta_{sb} > \beta_{cb}$	0.7717	0.0000	1.9177		0.0005	1.0403	0.1235	15.4638***
$(R4)\ \beta_{qb} < 0$	1.1228	0.1984	1.5137		1.8191	0.1365	4.3825**	0.0000
$(R5)\ \beta_{qv} < 0$	1.0928	2.3473	4.6939**		1.2462	0.0000	1.1982	0.0282
$(R6)\ \beta_{sv} > 0$	16.3495***	0.0000	3.4211*		1.5703	0.4250	0.0000	0.0000
Volatility regimes	45.2182***	57.0388***	32.4780***		48.7844***	23.7722**	19.0406*	80.9108***
Mixture of normals	45.2162***	56.7141***	30.0248***		44.5383***	22.4814**	18.1305*	76.3980***
Fads	42.7483***	54.5533***	30.4127***		47.0654***	20.2056**	19.0370*	70.8613***
VNS	39.2245***	52.7794***	24.3451***		40.8258***	17.8535**	16.3015**	62.9415***
Volume-augmented	35.9360***	48.1343***	0.0000		37.6988***	17.2232***	12.0502*	37.6288***
One Intercept DV	11.7014***	15.5688***	4.7709		0.4248	10.1959**	0.0000	1.8854
Starting observation	Aug 1989	Jan 1990	Aug 1990	Aug 1989	Aug 1989	Nov 1989	Sep 1989	Feb 1992
No. of observations	280	275	268	280	280	277	279	250

Although the two models with structural breaks did not always obtain results in all sectors, from what is available, they have identified additional evidence of bubbles that were not picked up by the simpler models. For example, it detected some evidence in Fashion (Consumer Products), Home & Office Products (Consumer Products), Finance & Securities (Financials), Petrochemicals & Chemicals (Industrials), Mining (Resources), and Media & Publishing (Services). Nevertheless, the evidence for Packaging (Industrials) seems to have weakened. Lastly, they reaffirmed evidence suggested by either the VNS or the volume-augmented models in many sectors, such as Agribusiness (Agro & Food), Banking (Financials), Property Development (Property & Construction), and Information & Communication Technology (Technology). Therefore, allowing for structural breaks appears to have improved the ability for the models to explain the variability of the returns in different sectors and industry groups. Specifically, when the results are available, the model with one structural break mostly performed better than the basic VNS and volume-augmented models and the model with two sets of structural breaks were better than the model with one set of structural breaks. Although the model with two sets of dummy variables which is supposedly more demanding on the data and is perhaps less likely to obtain results, it surprisingly only failed to converge in four sectors, while the results from the model with one set of dummy variables were not available in five sectors. However, the effect of including the structural breaks on the strengths of bubble evidence is rather mixed. For most of the industry groups, the extended model does not lead to a change in the number of restriction tests rejected. Nonetheless, the evidence of a bubble has strengthened substantially in some cases – for instance, when one structural break is added to the model for the Home & Office Products. In several other cases, such as the Industrial Materials & Machinery and the Tourism & Leisure industry groups, the evidence turns out to be weaker when a structural break is allowed for.

Overall, the results from all the different specifications indicated evidence of bubbles in two industry groups, namely, Financials (via Banking, and some evidence in Finance and Securities) and Technology (via Information & Communication Technology) and some evidence in Agro & Food (via Agribusiness), Consumer Products (via Fashion and Home & Office Products), Industrials (via Petrochemicals & Chemicals and Packaging), Property & Construction (via Property Development), Resources (via Mining), and Services (via Media & Publishing). In other words, there appears to be at least some evidence from all industry groups in the Thai stock market.

The most appropriate specification for each sector can be determined by considering the robustness checks with simpler models. The results revealed that 14 sectors were most suited to the model with two sets of structural breaks, and six sectors worked best with the model with one set of structural breaks. No sector fitted most with the volume-augmented model, and the basic VNS model would have been sufficient for estimating three sectors. Finally, there were four sectors where none of the four models performed optimally. This is summarised in Table 22.

6.2.2. Results based on the Datastream-calculated Indices

Table 5 listed the Datastream groups, elaborate on the companies included in each of them and the industry groups and sectors they are in under the classifications of the Stock Exchange of Thailand. Four groups are directly related. They are Health Care (100% SET's Services – Health Care Services), Technology and Telecommunications groups (both 100% SET's Technology – Information & Communication Technology), and Utilities (100% SET's Resources – Energy & Utilities). Four groups that are mostly weighted with companies in a particular SET's Industry groups are Consumer Goods (76% SET's Agro & Food – Food & Beverage), Consumer Services (75% SET's Services – Commerce), Financials (80% SET's Financials – Banking), and Oil & Gas (83% SET's Resources – Energy & Utilities). Datastream's Industrials group is heavily weighted by 60% SET's Property & Construction –Construction Materials and 27% SET's Services – Transportation & Logistics, while the Basic Materials is split between 42% SET's Industrials – Petrochemicals & Chemicals and 58% SET's Resources – Energy & Utilities). It should be noted that, although companies with real estate business are quite significant in the Thai economy, they were not given a separate group and were either included in Financials or Consumer Goods.

The results with the VNS model and the volume-augmented models are shown in Table 23 and Table 24, respectively. They indicated some evidence in Health Care although the specifications were not better than simpler ones, Financials, Industrials, Oil & Gas, and Utilities groups. Table 25 reports the results from the model with one set of intercept dummy variables at July 1997. It picked up evidence of bubble-like behaviour in Technology and

Financials groups. While, it also supports some evidence of bubbles in Utilities, Health Care and Industrials, the results from these three groups did not perform better than the two basic models. Finally, the results with two structural breaks during the Asian Financial Crisis in the model are presented in Table 26. It implies evidence of bubbles in Consumer Goods, Consumer Services, Financials, and Health Care. Some evidence in Industrials and Utilities groups were also detected.

Table 22: SET's Sectoral Indices: Summary

Industry Group	Sector	VNS model	Volume-augmented model	Model with one set of structural breaks	Model with two sets of structural breaks	Evidence of bubbles	Some evidence of bubbles
Agro & Food Industry	Agribusiness			X			X
	Food and Beverage				X		
Consumer Products	Fashion				X		X
	Home & Office Products				X		X
	Personal Products & Pharmaceuticals			X			
Financials	Banking				X	X	
	Finance and Securities				X		X
	Insurance				X		
	Automotive				X		
Industrials	Industrial Materials & Machinery					X	
	Paper & Printing Materials	X					
	Petrochemicals & Chemicals				X		X
	Packaging				X		X
	Steel						
Property & Construction	Construction Materials				X		
	Property Fund	X					
	Property Development			X			X
Resources	Energy & Utilities				X		
	Mining			X			X
Services	Commerce				X		
	Health Care Services				X		
	Media & Publishing			X			X
	Professional Services						
	Tourism & Leisure			X			
	Transportation & Logistics				X		
Technology	Electronic Components						
	Information & Communication Technology	X				X	

Note: X's denote the most fitting model and its result

Table 23: Datastream-calculated Indices: VNS model

	Basic Materials	Consumer Goods	Consumer Services	Financials	Health Care
β_{so}	1.0125***	1.0089***	0.9922***	1.0166***	1.0092***
β_{sb}	0.0205	0.0016	-0.0334***	-0.0237	0.0064
β_{co}	1.0024***	1.0356***	1.0607***	1.0268***	1.0272***
β_{cb}	-0.0184	-0.0128	0.0385	-0.0384	-0.1462
β_{qo}	2.3969***	0.4689	0.7072*	0.9554***	0.7459
β_{qb}	-2.4136***	0.0351	0.2860	-1.6302***	0.8756
σ_s	0.0882***	0.0706***	0.0649***	0.0571***	0.0657***
σ_c	0.2236***	0.1861***	0.1645***	0.1783***	0.1481***
Log-Likelihood	237.1912	223.4947	297.2474	246.9664	320.5967
AIC	-1.5279	-1.4913	-1.9283	-1.5931	-2.1633
SBIC	-1.5813	-1.5467	-1.9816	-1.6464	-2.2187
HQIC	-1.4884	-1.4506	-1.8888	-1.5536	-2.1226
$(R1)\ \beta_{so} \neq \beta_{co}$	0.0598	1.0190	5.1403**	0.1927	0.2901
$(R2)\ \beta_{cb} < 0$	0.5908	0.1265	0.0000	1.2960	4.0566**
$(R3)\ \beta_{sb} > \beta_{cb}$	1.5393	0.1351	0.0000	0.0979	4.2174**
$(R4)\ \beta_{qb} < 0$	24.2366***	0.0000	0.0000	16.2985***	0.0000
Volatility regimes	29.6317***	1.5970	14.3286***	17.8805***	6.1088
Mixture of normals	28.8154***	0.1394	17.5456***	17.5737***	5.2002
Fads	29.1940***	1.5934	5.5373	13.5628***	5.9947
Starting observation	Dec 1987	Nov 1988	Dec 1987	Dec 1987	Nov 1988
No. of observations	300	289	300	300	289

Note: Results from the VNS model. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 23 (continued)

	Industrials	Oil & Gas	Technology	Telecommunications	Utilities
β_{so}	0.9898***	1.0002***	0.9988***	0.9698***	1.0123***
β_{sb}	-0.0303**	-0.0151**	-0.0018	-0.0135***	0.0007
β_{co}	1.1620***	1.0957***	1.6643***	1.0402***	1.0072***
β_{cb}	0.0739**	0.0260	0.0584***	-0.0201	0.0001
β_{qo}	2.3580***	1.0687**	1.9472***	1.0039***	1.7483***
β_{qb}	-1.7248**	-0.0377	-0.0491	-0.0620	-0.2176***
σ_s	0.0969***	0.0848***	0.1244***	0.0746***	0.0493***
σ_c	0.1865***	0.1930***	0.1014***	0.2355***	0.1552***
Log-Likelihood	161.4218	223.8945	140.2155	190.4388	232.4276
AIC	-1.3517	-1.5933	-1.0289	-1.5078	-2.2221
SBIC	-1.4222	-1.6524	-1.0912	-1.5739	-2.3013
HQIC	-1.3030	-1.5506	-0.9845	-1.4613	-2.1690
$(R1)\ \beta_{so} \neq \beta_{co}$	6.9729***	3.7900*	6.2693**	1.3746	0.0307
$(R2)\ \beta_{cb} < 0$	0.0000	0.0000	0.0000	0.9343	0.0000
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000	0.0000	0.0000	0.0977	0.0260
$(R4)\ \beta_{qb} < 0$	1.1349	0.0177	0.5171	0.4284	23.4920***
Volatility regimes	11.0251**	7.8069*	7.6377	23.2932***	32.4082***
Mixture of normals	10.8503**	5.4261	1.9552	19.0579***	32.1017***
Fads	10.4137**	3.8301	7.3639*	4.8515	27.7616***
Starting observation	Jan 1994	May 1990	Jul 1991	Oct 1992	Feb 1996
No. of observations	227	271	257	242	202

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 24: Datastream-calculated Indices: Volume-augmented model

	Basic Materials	Consumer Goods	Consumer Services	Financials	Health Care
β_{so}	1.0115***	1.0066***	0.9894***	1.0165***	1.0087***
β_{sb}	0.0178	-0.0020	-0.0360***	-0.0237	0.0082
β_{sv}	0.0079	0.0130	0.0002	-0.0029	0.0150**
β_{co}	1.0023***	1.0416***	1.1737***	1.0272***	1.0206***
β_{cb}	-0.0178	-0.0056	0.1649***	-0.0385	-0.1132
β_{qo}	2.4777***	0.6207	1.3619***	1.1332***	0.5491
β_{qb}	-2.5049***	0.0249	-0.1187	-1.7232***	0.8661
β_{qv}	-0.0910	-0.1727	0.5222*	-0.6421***	-0.1582
σ_s	0.0884***	0.0740***	0.0735***	0.0585***	0.0617***
σ_c	0.2232***	0.1937***	0.1239***	0.1802***	0.1377***
Log-Likelihood	237.5733	224.6975	300.1667	251.4424	322.5398
AIC	-1.5172	-1.4858	-1.9344	-1.6096	-2.1629
SBIC	-1.5838	-1.5550	-2.0011	-1.6763	-2.2321
HQIC	-1.4677	-1.4350	-1.8850	-1.5602	-2.1121
$(R1)\ \beta_{so} \neq \beta_{co}$	0.0491	1.3724	7.7653***	0.2129	0.2140
$(R2)\ \beta_{cb} < 0$	0.5570	0.0179	0.0000	1.3319	4.2091**
$(R3)\ \beta_{sb} > \beta_{cb}$	1.2516	0.0061	0.0000	0.1126	4.5419**
$(R4)\ \beta_{qb} < 0$	24.4005***	0.0000	0.0446	13.6630***	0.0000
$(R5)\ \beta_{qv} < 0$	0.0884	0.6297	0.0000	8.5593***	0.4502
$(R6)\ \beta_{sv} > 0$	0.6502	0.9727	0.0054	0.0000	3.8530**
Volatility regimes	30.3959***	4.0025	20.1672***	26.8325***	9.9950
Mixture of normals	29.5795***	2.5449	23.3842***	26.5257***	9.0864
Fads	29.9581***	3.9989	11.3759**	22.5149***	9.8809*
VNS	0.7641	2.4055	5.8386*	8.9520**	3.8862
Starting observation	Dec 1987	Nov 1988	Dec 1987	Dec 1987	Nov 1988
No. of observations	300	289	300	300	289

Note: Results from the volume-augmented model. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 24 (continued)

	Industrials	Oil & Gas	Technology	Telecommunications	Utilities
β_{so}	0.9902***	0.9964***	0.9716***	0.9753***	1.0123***
β_{sb}	-0.0330**	-0.0171**	-0.0175*	-0.0132***	0.0014
β_{sv}	-0.0146*	-0.0202*	0.0020	-0.0157***	-0.0121
β_{co}	1.1550***	1.0603***	1.1265***	1.0212***	1.0095***
β_{cb}	0.0677**	0.0086	0.0179*	-0.0199	0.0002
β_{qo}	2.3612***	0.6793*	0.9356***	0.8424***	2.6790***
β_{qb}	-1.8245**	-0.1222	-0.1710**	-0.0833	-0.3615**
β_{qv}	0.4790*	-0.2468*	0.0864	0.2281	-1.8155**
σ_s	0.0950***	0.0707***	0.0906***	0.0667***	0.0484***
σ_c	0.1899***	0.1655***	0.2519***	0.2205***	0.1503***
Log-Likelihood	164.7350	226.3256	139.2672	196.0055	240.4114
AIC	-1.3633	-1.5965	-1.0060	-1.5372	-2.2813
SBIC	-1.4514	-1.6703	-1.0838	-1.6199	-2.3803
HQIC	-1.3024	-1.5431	-0.9504	-1.4792	-2.2150
$(R1)\ \beta_{so} \neq \beta_{co}$	6.2119**	4.2773**	4.2531**	0.8107	0.0114
$(R2)\ \beta_{cb} < 0$	0.0000	0.0000	0.0000	1.2608	0.0000
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000	0.0000	0.0000	0.1394	0.1130
$(R4)\ \beta_{qb} < 0$	45.6318***	0.2408	2.0484	0.8021	25.3992***
$(R5)\ \beta_{qv} < 0$	0.0000	4.8565**	0.0000	0.0000	14.9783***
$(R6)\ \beta_{sv} > 0$	0.0000	0.0000	1.6288	0.0000	0.0000
Volatility regimes	17.6516***	12.6690**	5.7410	34.4265***	48.3758***
Mixture of normals	17.4767***	10.2882*	0.0585	30.1913***	48.0693***
Fads	17.0402***	8.6922	5.4672	15.9848***	43.7292***
VNS	6.6265**	4.8621*	0.0000	11.1333***	15.9676***
Starting observation	Jan 1994	May 1990	Jul 1991	Oct 1992	Feb 1996
No. of observations	227	271	257	242	202

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 25: Datastream-calculated Indices: Model with one set of intercept dummy variables at July 1997

	Basic Materials	Consumer Goods	Consumer Services	Financials	Health Care
β_{so}	1.0055***	1.0012***	0.9825***	1.0065***	0.9933***
β_{sb}	0.0212	0.0005	-0.0300***	-0.0495**	0.0071
β_{sv}	0.0087	0.0146	0.0011	0.0028	0.0137*
β_{sf}	0.0094	0.0095	0.0157	0.0294**	0.0224**
β_{co}	1.0974***	1.0470***	1.2038***	1.0622***	1.0370***
β_{cb}	-0.0225	-0.0149	0.0121	-0.0302	-0.1100
β_{cf}	-0.1099	-0.0197	-0.1866**	-0.0589	-0.0358
β_{qo}	2.6469***	0.3011	0.9202**	0.9708***	0.4095
β_{qb}	-2.2627***	-0.1318	0.5252	-1.7942***	0.7702
β_{qv}	-0.1474	-0.2501	0.3912*	-0.5252**	-0.1661
β_{qf}	-0.4118	0.6888**	-0.4892	0.2712	0.2991
σ_s	0.0882***	0.0745***	0.0657***	0.0553***	0.0610***
σ_c	0.2216***	0.1936***	0.1365***	0.1783***	0.1336***
Log-Likelihood	238.2708	227.2010	302.9809	255.6100	325.0491
$(R1)\ \beta_{so} \neq \beta_{co}$	0.5900	1.2298	19.1235***	2.7467*	1.1788
$(R2)\ \beta_{cb} < 0$	0.8770	0.1217	0.0000	0.8257	2.6522
$(R3)\ \beta_{sb} > \beta_{cb}$	1.8706	0.1109	0.0000	0.0000	2.7120*
$(R4)\ \beta_{qb} < 0$	18.7527***	0.1589	0.0000	12.0203***	0.0000
$(R5)\ \beta_{qv} < 0$	0.2446	0.9685	0.0000	6.3358**	0.4048
$(R6)\ \beta_{sv} > 0$	0.7922	1.0305	0.1286	0.0472	3.6569*
Volatility regimes	31.7908***	9.0095	25.7956***	35.1678***	15.0136*
Mixture of normals	30.9744***	7.5519	29.0126***	34.8610***	14.1050*
Fads	31.3531***	9.0059	17.0043**	30.8501***	14.8995*
VNS	2.1591	7.4125	11.4670**	17.2873***	8.9048
Volume-augmented	1.3949	5.0070	5.6284	8.3353**	5.0187
Starting observation	Dec 1987	Nov 1988	Dec 1987	Dec 1987	Nov 1988
No. of observations	300	289	300	300	289

Note: Results from the model with one set of intercept dummy variables. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 25 (continued)

	Industrials	Oil & Gas	Technology	Telecommunications	Utilities
β_{so}	0.9710***	1.0058***	0.9820***	0.9736***	0.9389***
β_{sb}	-0.0304**	-0.0267***	-0.0027	-0.0135***	-0.0009
β_{sv}	-0.0141*	-0.0156	0.0006	-0.0155***	-0.0123
β_{sf}	0.0258	-0.0203	0.0214	0.0010	0.0688**
β_{co}	1.2258***	1.0752***	1.7623***	1.0869***	1.0202***
β_{cb}	0.0663**	0.0372*	0.0683***	-0.0189	0.0003
β_{cf}	-0.0771	0.0620	-0.1488***	-0.0728	-0.0082
β_{qo}	2.5237***	0.4205	1.6954***	0.9672*	5.4219**
β_{qb}	-3.6744**	-0.2780	-0.0665	-0.0890	-0.5189*
β_{qv}	0.6186*	-0.2291	-0.0908	0.2306	-2.6628*
β_{qf}	1.7250	1.0017**	0.4911	-0.0785	-1.8971
σ_s	0.0942***	0.0777***	0.1246***	0.0685***	0.0492***
σ_c	0.1882***	0.1567***	0.0606***	0.2228***	0.1492***
Log-Likelihood	167.8363	229.7663	144.9461	196.2844	241.9207
$(R1)\ \beta_{so} \neq \beta_{co}$	3.4467*	2.9760*	10.6010***	1.0610	1.2367
$(R2)\ \beta_{cb} < 0$	0.0000	0.0000	0.0000	0.9791	0.0000
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000	0.0000	0.0000	0.0778	0.0000
$(R4)\ \beta_{qb} < 0$	10.4727***	1.0691	5.5342**	0.8067	23.2525***
$(R5)\ \beta_{qv} < 0$	0.0000	1.3614	5.5337**	0.0000	14.6765***
$(R6)\ \beta_{sv} > 0$	0.0000	0.0000	5.5455**	0.0000	0.0000
Volatility regimes	23.8542***	19.5504**	17.0989**	34.9844***	51.3944***
Mixture of normals	23.6794***	17.1696**	11.4163	30.7492***	51.0879***
Fads	23.2428***	15.5736**	16.8250**	16.5427**	46.7479***
VNS	12.8291**	11.7435**	9.4611*	11.6912**	18.9862***
Volume-augmented	6.2026	6.8814*	11.3579***	0.5579	3.0186
Starting observation	Jan 1994	May 1990	Jul 1991	Oct 1992	Feb 1996
No. of observations	227	271	257	242	202

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 26: Datastream-calculated Indices: Model with two sets of intercept dummy variables at September 1996 and August 1998

	Basic Materials	Consumer Goods	Consumer Services	Financials	Health Care
β_{so}	1.0121***	1.0114***	0.9838***	1.0092***	0.9972***
β_{sb}	-0.0024	-0.0272	-0.0274***	-0.0370*	0.0025
β_{sv}	0.0138	0.0224*	0.0003	0.0032	0.0066
β_{sl}	-0.1468***	-0.1559***	-0.0869**	-0.2100***	-0.1299*
β_{sf}	0.1507***	0.1718***	0.1073***	0.2288***	0.1507**
β_{co}	1.1410***	1.4324***	1.2148***	1.1440***	1.2197***
β_{cb}	-0.0204	-0.0020	0.0083	-0.1988***	-0.1103***
β_{cl}	-0.1037	-0.1249**	-0.1416	-0.1949*	-0.2209***
β_{cf}	-0.0115	-0.3120***	-0.0513	0.1870*	-0.2575***
β_{qo}	3.1587***	1.9934***	1.2438***	1.1115***	2.3995***
β_{qb}	-3.8692**	-1.1469**	-0.0017	-1.4984***	-1.3852*
β_{qv}	0.1304	0.2038	0.5465*	-0.5043**	0.5561
β_{ql}	2.4530	-0.0700	-1.1366	0.1381	-3.0650***
β_{qf}	-1.6385	-1.1183**	0.9839	0.2066	3.9565***
σ_s	0.0926***	0.1053***	0.0669***	0.0605***	0.0718***
σ_c	0.2267***	0.0524***	0.1376***	0.1654***	0.0676***
Log-Likelihood	245.8402	253.6041	310.9395	281.1562	328.1050
AIC	-1.5323	-1.6443	-1.9663	-1.7677	-2.1599
SBIC	-1.6389	-1.7550	-2.0729	-1.8744	-2.2706
HQIC	-1.4532	-1.5630	-1.8872	-1.6887	-2.0786
$(R1)\ \beta_{so} \neq \beta_{co}$	0.7250	20.7960***	8.2948***	10.6782***	14.0171***
$(R2)\ \beta_{cb} < 0$	0.4399	0.0288	0.0000	14.0752***	5.4723**
$(R3)\ \beta_{sb} > \beta_{cb}$	0.2358	0.0000	0.0000	7.8049***	6.3177**
$(R4)\ \beta_{qb} < 0$	46.9563***	14.5454***	8.6404***	14.4306***	2.8191*
$(R5)\ \beta_{qv} < 0$	0.0000	0.0000	0.0000	6.5785**	0.0000
$(R6)\ \beta_{sv} > 0$	2.0620	3.8614**	10.0721***	0.0855	11.0164***
Volatility regimes	46.9297***	61.8158***	41.7126***	86.2602***	21.1254**
Mixture of normals	46.1133***	60.3582***	44.9297***	85.9534***	20.2169**
Fads	46.4920***	61.8122***	32.9214***	81.9425***	21.0114**
VNS	17.2980**	60.2188***	27.3841***	68.3797***	15.0166*
Volume-augmented	16.5339**	57.8133***	17.8391***	59.4277***	11.1305*
One intercept DV	13.8282***	27.7761***	7.3337*	42.5254***	2.0901
Starting observation	Dec 1987	Nov 1988	Dec 1987	Dec 1987	Nov 1988
No. of observations	300	289	300	300	289

Table 26 (continued)

	Industrials	Oil & Gas	Technology	Telecommunications	Utilities
β_{so}	0.9584***	1.0050***	0.9940***	0.9819***	0.9949***
β_{sb}	0.0052	-0.0188**	-0.0025	-0.0140***	0.0019
β_{sv}	-0.0155**	-0.0212**	-0.0026	-0.0145***	-0.0191*
β_{sl}	-0.0288	-0.0616**	-0.1373***	-0.2320***	0.0217
β_{sf}	0.0914**	0.0535*	0.1428***	0.2243***	-0.0044
β_{co}	1.0611***	1.0734***	1.7837***	1.2360***	1.1197***
β_{cb}	-0.2707***	0.0282	0.0853***	-0.0369	0.0007
β_{cl}	-0.0087	0.0747	-0.1040	-0.2738	-0.1407
β_{cf}	0.9945***	-0.0343	-0.3466***	0.1136	0.0572
β_{qo}	0.8372	0.3019	1.7367***	1.3967***	15.2894*
β_{qb}	-0.4213	-0.2372	-0.0495	0.0083	-0.4050*
β_{qv}	-0.2191	-0.2410	-0.0193	-0.0143	-2.0297**
β_{ql}	-0.8169	0.6119	-0.6997	-1.7960***	-12.5808
β_{qf}	3.1376***	0.4825	0.3497	1.5394***	0.2007
σ_s	0.1046***	0.0755***	0.1084***	0.0705***	0.0484***
σ_c	0.0979***	0.1594***	0.1380***	0.2046***	0.1478***
Log-Likelihood	174.6105	233.1050	159.6704	214.4116	244.8007
AIC	-1.3974	-1.6023	-1.1181	-1.6398	-2.2654
SBIC	-1.5384	-1.7203	-1.2426	-1.7720	-2.4238
HQIC	-1.3000	-1.5169	-1.0292	-1.5468	-2.1593
$(R1)\ \beta_{so} \neq \beta_{co}$	1.3263	2.5792	12.5793***	1.7470	0.3769
$(R2)\ \beta_{cb} < 0$	13.0237***	0.0000	0.0000	2.3719	0.0000
$(R3)\ \beta_{sb} > \beta_{cb}$	13.0345***	0.0000	0.0000	0.9058	0.0703
$(R4)\ \beta_{qb} < 0$	0.6527	0.7490	0.3750	0.0000	30.5770***
$(R5)\ \beta_{qv} < 0$	0.9328	1.3887	0.0181	0.0101	36.2668***
$(R6)\ \beta_{sv} > 0$	0.0000	0.0000	0.0000	0.0000	0.0000
Volatility regimes	37.4027***	26.2279***	46.5474***	71.2388***	57.1545***
Mixture of normals	37.2278***	23.8471**	40.8649***	67.0035***	56.8479***
Fads	36.7912***	22.2511**	46.2736***	52.7971***	52.5079***
VNS	26.3775***	18.4210**	38.9097***	47.9456***	24.7462***
Volume-augmented	0.0000	13.5589**	40.8065***	36.8123***	8.7786
One intercept DV	1.4350	4.2504	19.0825***	23.1934***	5.9822
Starting observation	Jan 1994	May 1990	Jul 1991	Oct 1992	Feb 1996
No. of observations	227	271	257	242	202

All results based on Datastream-calculated indices are summarised in Table 27. They appear to suggest evidence of bubbles in bubbles in Consumer Goods, Consumer Services, and Financials, and some evidence in Health Care, Industrials and Utilities groups. These results are largely consistent with those obtained from SET's Sectoral indices discussed in the previous section. Precisely, at least some evidence of bubbles were identified in Food & Beverages, Banking, Property Development and Commerce sectors, while evidence was detected here in Consumer Goods, Consumer Services and Financials groups. Some evidence was also found Petrochemicals & Chemicals sector, but no evidence was picked up here in the Basic Materials group. The most striking discrepancies would be in the technology-related groups. No evidence of bubble was observed in either the Technology or Telecommunications groups, even though there was relatively strong evidence of a bubble in the SET's Information & Communication Technology sector. This may partly be caused by issues with dividend yield data collected by Datastream. As Datastream only tracked a few stocks in each group and there were parts of the sample that contain an extended period of zero dividend yields, which were used in the calculation of fundamental values and, subsequently, relative bubble terms. Specifically, during April 1998 to March 2001, there were 24, 13, 25, 24 and 7 consecutive months of dividend yields reported in Industrials, Oil & Gas, Technology, Telecommunications, and Utilities groups, respectively. Therefore, these results are also to be interpreted with caution.

Table 27: Datastream-calculated Indices: Summary

Datastream Group	VNS model	Volume-augmented model	Model with one set of structural breaks	Model with two sets of structural breaks	Evidence of bubbles	Some evidence of bubbles
Basic Materials				X		
Consumer Goods				X	X	
Consumer Services				X	X	
Financials				X	X	
Health Care						X
Industrials		X				X
Oil & Gas			X			
Technology				X		
Telecommunications				X		
Utilities		X				X

Note: X's denote the most fitting model and its result

6.2.3. Results based on the K-NI

Noting the issues with the length of data of SET's Industry Group indices available, the difficulty managing 27 SET's Sectoral indices, and limitations of using Datastream-calculated indices, the K-NI series are computed as elaborated in the previous section.

First of all, in order to further check for consistency with the official SET's industry group indices, the results based on only the replicating observations of the K-NI have been estimated. However, as they cover a limited number of observations, the estimates are also less reliable, similar to what was found with the SET's industry group indices. They also differ significantly from results based on the full K-NI series, which reinforces the unfavourable effect of having small sample size. Therefore, the results on based on just the first 49 observations of the K-NI are reported in Appendix 2.

The following analyses, thus, focus on the full K-NI series. The results with the VNS showed some evidence of bubbles in only the Consumer Products industry group in Table 28, while the results with the volume-augmented in Table 29 picked up evidence in Technology, and Services, and some evidence in Agro & Food, in addition. The next model extension is to include one set of a structural break in July 1997 and the results were shown in Table 30. New evidence of some bubble-like behaviour was found in the Property & Construction industry group.

Finally, Table 31 presents the results of the model with two sets of dummy variables with the K-NI series. The robustness checks against all simpler models including the model with one set of dummy variables indicated that all industry groups performed best with this model with two structural breaks at September 1996 and August 1998, except for Technology industry group, which was better than most models, but the original volume-augmented. Also, the results for Technology industry group yielded higher standard deviations in the bubbles will be in the surviving state than the collapsing state. As for detection of bubbles, the conclusion is drawn based on the number of restriction tests rejected, given the model with two structural breaks that has been established as the most fitting specification. There was an evidence of bubble-like behaviour in Consumer Products, Property & Construction, and Technology industry groups. Some evidence of bubbles was also found in Agro & Food, Financials, Industrials, and Services industry groups. In other words, Resources is the only industry group that does not contain evidence of a bubble in the Thai stock market, which contradicts with the evidence from the SET's Sectoral indices discussed earlier that found some evidence of bubbles in Mining sector under the Resources industry groups. It is to be noted that including structural breaks not only improve the performance of the model, but also picked up additional evidence in three industry groups – Financials, Industrials, and Property & Construction – that were not detected by either the VNS or the volume-augmented models.

Table 28: The K-NI: VNS model

	Agro & Food Industry	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	1.0098***	0.9977***	1.0132***	1.0057***	1.0077***	1.0072***	1.0122***	0.9934***
β_{sb}	0.0094	-0.0145	-0.0268	-0.0549**	0.0080	-0.0501**	-0.0031	-0.0161***
β_{co}	1.0170***	0.9975***	1.0117***	1.0216***	1.0135***	1.0273***	0.9850***	1.0607***
β_{cb}	-0.0555	-0.1125	-0.0036	0.0199	-0.0226	0.0057	-0.0053	0.0912
β_{qo}	0.6823*	1.2344***	0.8152***	1.3189**	1.6105***	0.9272**	1.9181***	0.2035
β_{qb}	0.1592	-1.8298*	-1.5688***	-1.8840*	-1.0118**	-1.4972**	-1.8225**	1.2130***
σ_s	0.0478***	0.0446***	0.0572***	0.0570***	0.0837***	0.0580***	0.0606***	0.0687***
σ_c	0.1161***	0.1218***	0.1843***	0.1251***	0.2044***	0.1361***	0.1426***	0.3460***
Log-Likelihood	361.2944	383.3613	224.6584	319.3996	231.4582	263.5970	338.2726	234.7421
AIC	-2.5235	-2.6812	-1.5476	-2.2243	-1.5961	-1.8257	-2.3591	-1.6254
SBIC	-2.5807	-2.7383	-1.6047	-2.2814	-1.6533	-1.8828	-2.4162	-1.6827
HQIC	-2.4819	-2.6395	-1.5059	-2.1826	-1.5545	-1.7840	-2.3174	-1.5836
$(R1)\ \beta_{so} \neq \beta_{co}$	0.1314	0.0001	0.0045	0.5021	0.0207	1.3378	0.5134	1.2519
$(R2)\ \beta_{cb} < 0$	1.8562	3.2669*	0.0107	0.0000	0.4291	0.0000	0.0190	0.0000
$(R3)\ \beta_{sb} > \beta_{cb}$	2.3183	2.0902	0.0000	0.0000	0.5923	0.0000	0.0025	0.0000
$(R4)\ \beta_{qb} < 0$	0.0000	4.7059**	13.5026***	1.4351	17.0915***	3.1649*	8.5412***	0.0000
Volatility regimes	3.6117	12.8147**	14.7805***	11.4530**	8.9619*	7.4831	9.8557**	23.8725***
Mixture of normals	2.7413	11.6372***	14.5404***	9.4207**	8.6606**	7.4818*	9.7262**	20.9833***
Fads	3.1379	9.0964**	14.6903***	5.9044	8.9288**	4.0165	9.3628**	17.2299***
Starting observation	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Sep 1989
No. of observations	280	280	280	280	280	280	280	279

Note: Results from the VNS model. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 29: The K-NI: Volume-augmented model

	Agro & Food Industry	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	1.0105***	0.9979***	1.0132***	1.0220***	1.0060***	1.0078***	1.0105***	1.0927***
β_{sb}	0.0061	-0.0108	-0.0292	0.0382	0.0066	-0.0524**	-0.0008	0.0669
β_{sv}	0.0177**	-0.0059	0.0137	0.0128	0.0057	-0.0170	0.0243***	0.1992
β_{co}	1.0157***	0.9972***	1.0119***	1.0015***	1.0205***	1.0273***	0.9734***	0.9925***
β_{cb}	-0.0329	-0.1197*	-0.0020	-0.0308**	-0.0216	0.0029	-0.0147	-0.0167***
β_{qo}	0.7823**	1.2199***	0.8427***	-1.2352***	1.7474***	0.9224**	2.3226***	-0.1551
β_{qb}	0.0113	-1.7164*	-1.5324***	0.5806	-1.0767**	-1.6416**	-1.8150***	-1.2750***
β_{qv}	-0.6311**	-0.1684	-0.2999	0.5104	-0.2235	0.0080	-0.6782*	-0.4026*
σ_s	0.0468***	0.0441***	0.0572***	0.1386***	0.0848***	0.0564***	0.0610***	0.3285***
σ_c	0.1149***	0.1211***	0.1844***	0.0595***	0.2082***	0.1335***	0.1568***	0.0686***
Log-Likelihood	366.4002	384.4292	226.8595	322.3473	232.0534	264.5318	344.8655	237.6609
AIC	-2.5457	-2.6745	-1.5490	-2.2311	-1.5861	-1.8181	-2.3919	-1.6320
SBIC	-2.6171	-2.7459	-1.6204	-2.3025	-1.6575	-1.8895	-2.4633	-1.7037
HQIC	-2.4936	-2.6224	-1.4969	-2.1790	-1.5340	-1.7660	-2.3398	-1.5798
$(R1)\ \beta_{so} \neq \beta_{co}$	0.0753	0.0010	0.0033	0.4511	0.1105	1.3204	0.6150	2.5097
$(R2)\ \beta_{cb} < 0$	0.8789	3.6441*	0.0034	4.9593**	0.3600	0.0000	0.0998	10.2180***
$(R3)\ \beta_{sb} > \beta_{cb}$	1.0726	2.5503	0.0000	1.5753	0.4708	0.0000	0.0772	0.6616
$(R4)\ \beta_{qb} < 0$	0.0000	4.1446**	14.3221***	0.0000	8.0637***	3.9772**	9.7171***	15.8768***
$(R5)\ \beta_{qv} < 0$	8.5126***	0.9323	2.0470	0.0000	0.3738	0.0000	3.4109*	4.5748**
$(R6)\ \beta_{sv} > 0$	4.4085**	0.0000	2.1186	0.2117	0.2040	0.0000	7.8955***	3.1040*
Volatility regimes	13.8232**	14.9507**	19.1829***	17.3484***	10.1523	9.3528	23.0414***	29.7101***
Mixture of normals	12.9528**	13.7732**	18.9428***	15.3160***	9.8510*	9.3515*	22.9118***	26.8210***
Fads	13.3494**	11.2324**	19.0927***	11.7998**	10.1192*	5.8863	22.5484***	23.0675***
VNS	10.2115***	2.1360	4.4024	5.8953*	1.1904	1.8697	13.1856***	5.8376*
Starting observation	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Sep 1989
No. of observations	280	280	280	280	280	280	280	279

Note: Results from the volume-augmented model. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 30: The K-NI: Model with one set of intercept dummy variables at July 1997

	Agro & Food Industry	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	1.0166***	0.9599***	1.0135***	0.9899***	0.9751***	1.0288***	0.9908***	1.1393***
β_{sb}	-0.0121	-0.0312*	-0.0364*	-0.0248	0.0356*	-0.0651***	-0.0115	0.0375
β_{sv}	0.0107	-0.0045	0.0161	-0.0077	0.0048	-0.0039	0.0199**	0.1961
β_{sf}	-0.0084	0.0438***	0.0030	0.0154	0.0597**	-0.0291	0.0260**	-0.0845
β_{co}	0.9718***	1.0086***	1.0186***	1.0147***	1.0494***	1.0257***	1.0034***	0.9935***
β_{cb}	0.0136**	-0.0689*	0.0049	0.0069	-0.0330	0.0090	0.0127	-0.0173**
β_{cf}	0.0505***	-0.0146	-0.0193	0.0061	-0.0669	0.0003	0.0061	-0.0019
β_{qo}	1.3511**	-0.1606	0.0225	1.4017**	1.0859	0.5553	1.4399**	-0.1677
β_{qb}	-0.8683	-1.5579*	-2.2045***	-0.5916	-1.2344*	-1.3766**	-1.9442***	-1.2789***
β_{qv}	2.2134**	-0.1102	-0.3449	-1.2182**	-0.2173	-0.1289	-0.7112**	-0.3937*
β_{qf}	-0.4570	1.1461***	1.3868***	-0.6134	0.3167	0.5403	0.8965	0.0370
σ_s	0.0820***	0.0314***	0.0504***	0.0557***	0.0716***	0.0572***	0.0562***	0.3264***
σ_c	0.0255***	0.0983***	0.1746***	0.1219***	0.1674***	0.1357***	0.1351***	0.0684***
Log-Likelihood	371.6198	396.2510	237.0399	324.6572	237.7032	267.1305	349.2452	237.9574
$(R1)\ \beta_{so} \neq \beta_{co}$	2.6720	3.9856**	0.0221	0.4646	2.2002	0.0093	0.1129	2.5992
$(R2)\ \beta_{cb} < 0$	0.0000	3.0843*	0.0000	0.0000	1.7850	0.0000	0.0000	5.4235**
$(R3)\ \beta_{sb} > \beta_{cb}$	0.0000	0.6864	0.0000	0.0000	3.9343**	0.0000	0.0000	0.2504
$(R4)\ \beta_{qb} < 0$	0.8763	4.2082**	20.4735***	0.6122	21.3781***	1.0923	11.6919***	11.6189***
$(R5)\ \beta_{qv} < 0$	0.0000	0.4431	2.0621	6.1420**	0.3353	0.3414	4.4572**	4.4878**
$(R6)\ \beta_{sv} > 0$	19.5517***	0.0000	2.6842	0.0000	0.0867	0.0000	5.5252**	3.1927*
Volatility regimes	24.2625***	38.5943***	39.5436***	21.9682***	21.4518**	14.5502	31.8008***	30.3031***
Mixture of normals	23.3920***	37.4168***	39.3035***	19.9358**	21.1505***	14.5490*	31.6713***	27.4140***
Fads	23.7886***	34.8760***	39.4534***	16.4196**	21.4187***	11.0837	31.3079***	23.6605***
VNS	20.6508***	25.7796***	24.7631***	10.5152*	12.4899**	7.0672	21.9451***	6.4306
Volume-augmented	10.4393**	23.6436***	20.3607***	4.6387	11.2995**	5.1974	8.7594**	0.5930
Starting observation	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Sep 1989
No. of observations	280	280	280	280	280	280	280	279

Note: Results from the model with one set of intercept dummy variables. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 31: The K-NI: Model with two sets of intercept dummy variables at September 1996 and August 1998

	Agro & Food Industry	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	1.0019***	0.9614***	1.0091***	1.0011***	0.9919***	1.0317***	0.9912***	1.1777***
β_{sb}	-0.0022	-0.0249*	-0.0449***	-0.0546**	0.0113	-0.0291	-0.0130	0.0208
β_{sv}	0.0124*	-0.0035	0.0116	-0.0064	0.0044	-0.0160	0.0158**	0.2517*
β_{sl}	-0.0614***	-0.0439*	-0.2045***	-0.0651***	-0.0877	-0.0951***	-0.0701***	-0.0814
β_{sf}	0.0781***	0.0855***	0.2124***	0.0805***	0.1167**	0.0717**	0.0990***	-0.0141
β_{co}	1.0241***	1.0141***	1.0757***	1.0057***	1.1188***	1.0184***	1.0262***	0.9997***
β_{cb}	-0.0185	-0.1192**	-0.1753*	-0.0004	-0.0312	0.0219	-0.0896	-0.0164**
β_{cl}	0.1738*	-0.0825**	-0.1314	-0.0302	-0.1711	0.0820	-0.1604	-0.0734***
β_{cf}	-0.2159**	0.0811**	0.2107	0.0443	0.0975	-0.0598	0.1558	0.0675***
β_{qo}	0.6287	-0.2390	0.4055	1.4014*	1.9175***	0.6182	1.2279**	-0.3596
β_{qb}	-0.5699	-1.4513	-2.1693***	-1.8059**	-1.1074**	-0.7639	-0.9161	-0.9572**
β_{qv}	-0.4869**	-0.0993	-0.1864	-1.1140**	-0.3550	0.2056	-0.7962**	-0.3005
β_{ql}	1.0177*	0.1073	1.5317*	-0.1462	-1.5101*	0.3082	-0.0677	-0.0658
β_{qf}	0.2276	1.3389**	-0.0205	-0.2243	1.7456**	0.3349	0.9890	-0.1478
σ_s	0.0495***	0.0315***	0.0582***	0.0496***	0.0816***	0.0658***	0.0548***	0.3454***
σ_c	0.1156***	0.0950***	0.1803***	0.1149***	0.2067***	0.1490***	0.1385***	0.0705***
Log-Likelihood	382.5044	410.0386	261.7234	335.0707	247.4343	271.5291	361.6977	242.1755
$(R1)\ \beta_{so} \neq \beta_{co}$	0.6223	4.0226**	2.6651	0.0197	1.2393	0.0814	0.5190	2.1397
$(R2)\ \beta_{cb} < 0$	0.1448	7.2466***	4.3440**	0.0003	0.6238	0.0000	1.9865	5.1307**
$(R3)\ \beta_{sb} > \beta_{cb}$	0.1032	3.6670*	2.1259	0.0000	0.8841	0.0000	1.3567	0.0766
$(R4)\ \beta_{qb} < 0$	1.0362	2.8947*	17.7272***	10.3834***	7.0896***	0.0763	1.7181	5.9532**
$(R5)\ \beta_{qv} < 0$	4.9417**	0.3191	0.7838	3.8235*	10.8208***	0.0000	5.9708**	2.6786
$(R6)\ \beta_{sv} > 0$	3.4526*	0.0000	2.0595	0.0000	4.9049**	0.0000	3.9829**	2.8682*
Volatility regimes	46.0316***	66.1694***	88.9105***	42.7951***	40.9141***	23.3474**	56.7059***	38.7393***
Mixture of normals	45.1612***	64.9919***	88.6704***	40.7628***	40.6128***	23.3461**	56.5763***	35.8501***
Fads	45.5578***	62.4511***	88.8203***	37.2465***	40.8810***	19.8808**	56.2129***	32.0967***
VNS	42.4199***	53.3547***	74.1300***	31.3421***	31.9522***	15.8643**	46.8501***	14.8668*
Volume-augmented	32.2084***	51.2187***	69.7276***	25.4657***	30.7618***	13.9946**	33.6645***	9.0291
One intercept DV	12.3845***	11.8127***	30.7343***	15.2897***	12.6683***	6.9997*	13.1408***	7.6567*
Starting observation	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Sep 1989
No. of observations	280	280	280	280	280	280	280	279

Note: Results from the model with two sets of intercept dummy variables. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

6.3. Conclusions

This chapter investigates the more disaggregated price indices in the Thai stock market, in order to find out which groups of businesses displayed bubble-like behaviour during the period studied by using the SET's industry group indices and sectoral indices, the Datastream-calculated indices, and the author's calculated K-NI series with the VNS model, the volume-augmented model, and – when applicable – the extended models with one or two sets structural breaks for the 1997 Asian Financial Crisis.

The evidence based on the SET's official industry group indices hinted signs of a bubble in at least five out the eight industry groups. However, these results are to be interpreted with caution, as the number of observations available was very small. On the other hand, the results based on the SET's official sectoral indices showed strong evidence of bubbles in the Banking, Industrial Materials & Machinery, and Information & Communication Technology sectors, as well as, some weaker evidence of bubbles in nine other sectors. That it, at least 12 out of 27 sectors in the Thai stock markets displayed some level of bubble-like behaviour. Interestingly, when the most fitting specification is considered, it appeared that the inclusion of structural breaks helped capture additional variation in the returns of 20 sectors – six of which with only one break in July 1997 and 14 other sectors with two breaks at September 1996 and August 1998. Meanwhile, three sectors including the Information & Communication Technology worked best with the basic VNS model, meaning both the abnormal volume included in timing the burst of the bubble, and the structural breaks were not significant.

Similar, results were found using the Datastream-calculated indices. The model with two structural breaks was most appropriate for six groups, while another group was most compatible with only one break. Regarding the bubble detection, several groups were found to contain bubbles, consistent with those obtained from the SET's official series. However, there was a major difference for the technology-related groups where the bubble was not detected with the Datastream-calculated indices. This is possibly due to the inclusion of only a few stock in the index, and they reported zero dividend yields during some periods of the series, thus, affecting the consistencies of fundamental values and bubble terms calculated.

Finally, the author's calculated K-NI was investigated. The results suggested strong evidence of bubbles in three industry groups, namely, Consumer Products, Property & Construction, and Technology, while there was some weaker evidence in five other industry groups. Again, the importance of structural breaks was noted. All industry groups were most consistent with the model allowing for two structural breaks, except for the Technology industry group. In fact, the Technology's estimates of standard deviations were unexpectedly larger in the bubble surviving regime than when they collapse, which implied more volatility when the bubbles continue to grow than when they finally burst. This is probably related to the uncertainty of the impacts to be brought about by an introduction of new innovations and differences of opinions by investors. Specifically, new products or services are regularly discovered by technology companies. Initially, commercial success and financial benefits these inventions could bring are not precisely known. Investors may have differing views, which potentially leads to higher volatility as a bubble is formed and continues to grow. The bubble could burst if the eventual realisation of how useful the innovation is does not justify the prior valuation. Moreover, as investors learn this information, their opinions converge and volatility would reduce. In other words, these could help explain why the standard deviation in the bubble-collapsing regime turns out to be lower than that in the bubble-surviving regime. The K-NI's Resources was the only one that did not contain a bubble-like behaviour. However, it is to be noted that the Mining sector which was a part of the Resources industry group was found to have some evidence of bubble presence. Therefore, on the whole, it could probably be summarised that the results were suggesting at least some evidence of bubbles in practically all industry groups with some inconsistencies between different sets of data and models utilised.

The next chapter will examine the linkages between industry groups and the transmission of bubbles from one industry group to another by extending the VNS and the volume-augmented models with bubble terms from other industry groups or the market-wide SET index as a proxy.

Chapter 7: Contagion in the Thai Market

7.1. Introduction

This chapter broadens the investigation of speculative bubbles in the Thai stock market conducted in the previous chapters. Firstly, it extends the standard regime-switching models to explore the contagion effects between the disaggregated groups within the Stock Exchange of Thailand. This is simply done by adding the relative bubble terms of other industry groups into both the two return equations and the probability function. Precisely, this will allow an examination of effects to return of an industry group coming from bubbles existed in other industry groups, as well as, the impact of such bubbles on the probability of the next-period return being realised in a bubble-surviving regime. However, it will not explain whether a bubble in one industry group will trigger a bubble in another industry group. Note that the term contagion, like a bubble, does not seem to have a universally agreed definition. Nonetheless, some of the empirical finance literature consider it as a significant increase of linkages between markets after a country is hit by a shock (Forbes and Rigobon, 2002) or the excessive co-movements that cannot be explained by fundamental factors (Bekaert et al., 2014). Such descriptions are different from what the models adopted in the chapter will pick up. Also, following the approach of Anderson et al. (2010), the terms contagion, transmission, spillover are used interchangeably here. In addition, to overcome the limitations faced with other datasets, this chapter will consider the K-NI series, which will include eight industry groups: Agro & Food (AGRO), Consumer Products (CONSUMP), Financials (FINCIAL), Industrials (INDUS), Property & Construction (PROPCON), Resources (RESOURC), Services (SERVICE), and Technology (TECH).

Besides, to supplement the results based on the bubble contagion models, the second part of this chapter also analyses the possible relationships between pairs of industry groups by utilising the bivariate Granger Causality tests based on both the returns and relative bubble sizes. They will offer evidence of whether a return of or a bubble in an industry group precedes that of another industry group. More particularly, while the test on returns would suggest whether the return in one industry group tends to follow that of another industry group, the test on bubbles might give some indication as to whether a bubble in one industry group may trigger a bubble in another industry group. In addition, as compared the structural models used in the first section, the standard Granger Causality tests are set up with the vector autoregressive (VAR) specifications – which do not include a regime-switching feature. Nonetheless, they do allow for impacts of lagged variables to be considered as well.

The next section presents empirical evidence based on the contagion models discussed in Chapter 4: Model A, Model M, and Model J. As the Model J is nested with the more complete Model A, the comparison between results obtained from the two models are analysed next. The following section then discusses the evidence from the Granger Causality tests, and the last section concludes the chapter.

7.2. Empirical Evidence

This section discusses evidence from all three bubble contagion models discussed in the previous chapter, namely, Model A, Model M, and Model J. This section will also consider results from Granger Causality tests on industry groups' returns and relative bubble terms.

The data utilised in this chapter is prepared in the same fashion as in the previous chapters. It covers the period starting from September 1988 or October 1988 until December 2012. The result tables will report the estimated coefficients from the regression, maximised log-likelihood statistics, results from block exogeneity tests, and robustness checks against more parsimonious specifications including the basic speculative bubble models without transmission of bubbles and the simplified model types P, R, and V where trading volume terms are left out.

7.2.1. Model including Data from All Industry Groups (Model A)

Evidence from the model including data from all industry groups (Model A), as formalised in equations (44) to (47), is presented in Table 32. Average returns (β_{so}^{i} and β_{co}^{i}) and standard deviations (σ_{s}^{i} and σ_{c}^{i}) are statistically significant in all industry groups. Specifically, the two regimes appear to be different as implied by the regime-switching speculative bubble model and the standard deviation in the surviving regime is smaller than that in the collapsing regime. For example, the parameters $\beta_{so}^{PROPCON}$ and $\beta_{co}^{PROPCON}$ for the

Property & Construction industry group are 1.0689 and 1.0030, respectively. They can be interpreted as the average net returns when there are no bubbles or abnormal trading volume in any of the other industry groups and are 6.89% and 0.30% in the surviving and collapsing regimes, respectively. Nonetheless, the average probability of bubble surviving parameters are not statistically significant for most industry groups, except for Industrials, Property & Construction, and Technology – where the β_{qo} actually turns out to be negative. The precise probability can be calculated using the cumulative normal distribution function, for instance, the average bubble-surviving probability for the Property & Construction industry group when there are no bubbles or abnormal trading volume in all industry groups is 98.59%.

The speculative bubble model also postulates that the bubbles should hurt returns when they do finally burst. However, in several cases, $\beta_{sbj} < \beta_{cbj}$ although β_{cbj}'s are largely statistically insignificant. The impact of abnormal trading volume on returns in the surviving regime captured by β_{svj} is typically statistically significant. Nevertheless, the signs of the parameters tend to be mixed, though the theory predicts positive parameters as investors should be compensated for the additional risks. Consider, for example, the Property & Construction industry groups where $\beta_{sb}^{PROPCON}, \beta_{cb}^{PROPCON}$ and $\beta_{sv}^{PROPCON}$ are -0.2652, 0.0191, and 0.1272, respectively, the parameters suggest that the existence of a bubble would reduce the expected returns in the surviving regime, but may increase returns when the bubble collapses although the estimate is not statistically significant. Precisely, when the relative bubble term is 0.5 or the bubble size is 50% of the actual price and there is no abnormal trading volume, the expected returns will change from 6.89% to -6.37% and 7.85% in the surviving and collapsing regimes, respectively. These results are indeed quite puzzling. The model assumes that, though β_{sb} could be positive or negative, it should be larger than β_{cb}, as investors would be punished when a bubble collapses. This problem is also found in many other industry groups such as Agro &Food, Financials, Industrials, Resources, and Services. It is likely due to the issue with maximum likelihood estimation, especially with a large number of parameters to be estimated. In fact, Anderson et al. (2010) presented a similar evidence in about half of the sectors in the S&P500 too. Nonetheless, the investors are compensated for additional risk when their holdings in the Property & Construction industry group observes abnormal trading volume. In this case, the expected return with trading volume in only the industry group increases by 50% and there is no bubble in any industry groups will be 13.25%.

Table 32: Model A, September 1989 – December 2012 (279 observations)

Independent Variables	Dependent Variables								
	Parameters	Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
Constant	β_{so}	1.0987***	1.0514***	1.2832***	1.0742***	1.0689***	1.0735***	1.0022***	1.3674***
	β_{co}	1.0044***	0.9896***	1.0115***	0.9981***	1.0030***	1.0054***	1.0001***	0.9749***
	β_{qo}	0.1786	1.6169	1.8264	2.4750*	2.1941**	1.3467	4.6581	-1.6249**
	σ_s	0.0064***	0.0046***	0.0038***	0.0205***	0.0201***	0.0305***	0.0177***	0.0020***
	σ_c	0.0673***	0.0678***	0.1211***	0.0796***	0.1114***	0.0999***	0.0753***	0.0923***
Agro & Food	β_{sb}	-0.1848***	-0.1682***	0.2599***	-0.0324	-0.1213***	-0.1650***	-0.0424**	-0.4001***
	β_{sv}	0.1010***	-0.0953***	0.2312***	0.0473**	-0.0474**	0.0747*	0.0948***	-0.1757***
	β_{cb}	0.0088	0.0023	-0.0132	0.0216	0.0293	-0.0428*	0.0061	0.0307
	β_{qb}	-2.3020	-0.1202	-1.6281	0.5164	-1.1672	-1.4253	1.1400	-0.9573
	β_{qv}	1.4327**	-0.7317	-1.1130	-0.2968	-0.8097	-2.6242	3.5222	0.0299
Consumer Products	β_{sb}	0.4546***	0.4534***	0.2644***	0.3466***	0.3237***	0.6304***	0.1917***	-0.3925***
	β_{sv}	-0.1091***	-0.0399***	0.0775***	-0.0723***	0.0192	0.1063***	-0.1144***	-0.0014**
	β_{cb}	-0.0399	-0.0906***	-0.0836*	-0.0556*	-0.1353***	0.0000	-0.0339	-0.1466***
	β_{qb}	-0.4386	-1.3892	-1.2487	-1.0429	-1.5432	-0.7335	0.8317	0.2717
	β_{qv}	0.5185	-1.2815	-0.9505	0.1478	-0.4129	-2.2406**	-8.9467	0.2412
Financials	β_{sb}	-0.3907***	-0.1155***	-0.4252***	-0.3110***	-0.2619***	-0.1968***	-0.1614***	-0.4908***
	β_{sv}	-0.1188***	-0.0098*	-0.0748***	-0.0727***	-0.1185***	-0.0295*	-0.0673***	0.0735***
	β_{cb}	0.0147	0.0009	-0.0743*	0.0148	-0.0230	-0.0472	-0.0021	0.0324
	β_{qb}	-1.7066	-1.0130	-1.1952	-1.2530	-1.3674	-3.3413	-13.9377	-0.0451
	β_{qv}	-0.7669	-1.0124	-0.7998	-0.6970	-1.0510***	1.1378	-0.5931	-0.0982
Industrials	β_{sb}	0.0461***	-0.0613***	0.2769***	-0.0985***	-0.1558***	-0.1244***	-0.0004	-0.0077
	β_{sv}	-0.0528***	0.0922***	-0.0248***	-0.1592***	-0.0862***	-0.1543***	-0.0826***	0.3937***
	β_{cb}	-0.0291***	0.0010	0.0063	-0.0086	-0.0070	0.0246	-0.0173	-0.0064
	β_{qb}	-3.2178	-1.2524	-1.2911	-1.6241	-1.0153	1.4339	-1.1303	-2.4458
	β_{qv}	0.0354	-0.5352	-0.7871	-0.3239	-1.2900**	-3.8535***	0.0111	-0.9571**
Property & Construction	β_{sb}	0.1546***	-0.1993***	-0.2476***	-0.0029	-0.2652***	-0.1958***	-0.0049	-0.2088***
	β_{sv}	-0.0065**	0.0086	0.0146*	0.0992***	0.1272***	-0.0151	0.0185	0.2597***
	β_{cb}	-0.0118	-0.0001	0.0140	0.0317*	0.0191	0.0057	-0.0005	-0.0169
	β_{qb}	-4.0399***	-0.8065	-1.8897	-3.0663***	-1.3015**	-5.3895**	-11.3204	3.2544***
	β_{qv}	-1.9090**	-0.3683	-0.8280	-1.7504***	-1.2925	-3.2569	-22.8919	0.4006

Table 32 (continued)

Independent Variables	Dependent Variables								
	Parameters	Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
Resources	β_{sb}	-0.1847***	-0.1025***	-0.2984***	-0.1628***	-0.2725***	-0.0895***	-0.1351***	-0.2222***
	β_{sv}	0.0790***	0.0364***	0.0184***	0.0542***	0.0676***	0.0665***	0.0387***	-0.1955***
	β_{cb}	0.0034	-0.0086	-0.0203	-0.0206	-0.0131	-0.0274	0.0011	0.0177
	β_{qb}	-1.0978***	-2.1092*	-1.3658	-1.7617	-1.2118	-3.8582*	-0.5558	-0.2680
	β_{qv}	-4.2623***	-1.9200*	0.3094	-0.7054	0.0900	0.3601	-0.5473	-0.0035
Services	β_{sb}	-0.0459***	-0.0222***	-0.1819***	-0.0419	-0.0226	-0.0063	-0.0463***	0.7660***
	β_{sv}	0.0033	-0.0016	-0.0539***	-0.0694***	-0.1571***	-0.0324	-0.0227**	-0.0174***
	β_{cb}	0.0050	0.0189	0.0687**	0.0043	0.0330	0.0203	0.0186	0.0318
	β_{qb}	0.1301	-1.5447	-1.2394	-1.3872	-1.6785**	-0.7469	-12.3864	0.8483
	β_{qv}	-1.6371	-0.3464	-0.8687***	-1.1334	-1.5549***	-4.2216*	0.8570	1.5116***
Technology	β_{sb}	0.0651***	0.1756***	0.1873***	0.1123***	0.2935***	0.1762***	0.1038***	0.5208***
	β_{sv}	-0.0005	0.0516***	-0.1194***	-0.0575***	-0.0865***	-0.1989***	-0.0397***	-0.0208***
	β_{cb}	-0.0055	-0.0146**	-0.0155	-0.0225**	-0.0218*	-0.0126	-0.0226**	-0.0271**
	β_{qb}	-0.3542***	-3.0833**	-2.0748**	-1.1807	-1.8851**	-2.2425	-8.3648	-3.0799***
	β_{qv}	-3.5042***	-1.3083	-0.6998	-0.7009*	-0.8624	-2.8869***	-8.4801	-0.2415
Log-Likelihood		415.1926	402.9800	248.2893	349.0687	254.6115	290.3846	385.3936	313.6687
Block Exogeneity Tests									
Agro & Food		72.9320***	17.5187***	18.7061***	3.6680	5.2475	5.5648	21.0432***	254.2627***
Consumer Products		33.9604***	10.0049*	17.4550***	4.3375	13.4040**	3.8528	2.7848	134.8473***
Financials		68.9821***	10.1642*	12.7034**	1.1347	10.5120*	5.3516	0.8926	259.3127***
Industrials		28.9540***	9.7431*	4.9525	16.7355***	9.1000	6.3511	8.4790	117.9626***
Property & Construction		36.0358***	15.8184***	51.7263***	5.5404	13.6857**	3.1787	3.8349	153.3607***
Resources		43.2803***	6.5610	5.1514	12.5594**	2.6017	8.9403	8.5208	137.6160***
Services		7.6133	0.7574	0.7932	5.8186	2.4082	0.9569	6.2182	144.6844***
Technology		49.0578***	8.3403	15.0904***	3.3184	18.3908***	2.3977	25.4814***	120.1936***
Robustness Checks									
Volatility regimes		115.1684***	54.3308*	64.9356**	73.5811***	58.2054**	64.1225**	107.1538***	181.7257***
Mixtures of normals		114.3249***	53.2097*	64.6697***	71.6114***	57.9085**	64.1213***	107.0357***	178.8365***
Fads		114.6461***	51.2050	64.8646***	68.1712***	58.1729**	60.6726**	106.7559***	175.0831***
VNS		111.5105***	41.8612	50.4839*	62.4039***	49.3166*	56.8876**	97.2340***	157.8532***
Volume-augmented		101.5108***	39.7789	46.1140*	56.5366**	48.0764*	55.0621**	84.1782***	153.0974***

Note: Results based on the Model A [equations (44) to (47)] ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Consider again the probability equation, not only the average probability of a bubble surviving in the next period that seems to be statistically insignificant, but also the impact of relative bubble size and abnormal trading volume shown by β_{qbj}^{i} and β_{qvj}^{i} as well. But, they usually have the expected negative signs. Specifically, the $\beta_{qb}^{PROPCON}$ and $\beta_{qv}^{PROPCON}$ are -1.3015 and -1.2925, respectively. They mean the expected surviving probability with relative bubble term of 0.5 would drop to just 54.34%, while the expected surviving probability with an abnormal trading volume of 50% may drop to 54.79% but the estimate is statistically insignificant. The effects from bubbles and trading volume in other industry groups can be interpreted in a similar manner.

Robustness checks compare Model A to the basic speculative bubble models without transmission channels from other industry groups. It is predominantly better, as the test is rejected, except for Consumer Products industry group where the Model A captures the additional variability of returns than the volatility-regimes and mixtures-of-normals models but not the fads, the VNS, or the volume-augmented models.

The main result for this section is the block exogeneity tests where linkages between industry groups can be detected. This is summarised in Table 33. The transmission goes from the bubbles from the industry group shown in the columns (independent variable) to the next-period gross return of industry group listed in the rows (dependent variable).

Firstly, the shaded diagonal shows the effect of the bubble in a particular industry group on its next-period return. The tests cannot be rejected in Resources and Services industry groups. This is consistent with the previous chapter where it picked up some weak evidence of bubbles in both industry groups.

Table 33: Block Exogeneity Test for Model A

Model A	**Independent Variables**							
		Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
Dependent Variables	Agro & Food	***	***	***	***	***	***		***
	Consumer Products	***	*	*	*	***			
	Financials	***	***	**		***			***
	Industrials				***		**		
	Property & Construction		**	*		**			***
	Resources								
	Services	***							***
	Technology	***	***	***	***	***	***	***	***

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Other key findings from this table are that the Resources industry group is not subject to bubble contagion from any other industry groups, though its bubbles will influence returns in Agro & Food, Industrials, and Technology industry groups. In fact, Technology industry groups appear to be sensitive to bubbles from all industry groups. This can be interpreted as when there are bubbles in any industry group, investors will later reallocate their holdings to Technology and push up returns, which is quite accurate. Meanwhile, bubbles form Technology stocks will spread to other industry groups, except for Consumer Products, Industrials and Resources. Another industry group with very limited linkages with others is Services. It is only affected by Agro & Food and Technology industry groups and passes on bubbles to Technology industry group only.

The 1997 Asian Financial Crisis in Thailand was believed to be partially caused by a real estate boom in the early 1990s and a banking crisis. Bubbles in Property & Construction industry group were revealed to be moving on to Agro & Food, Consumer Products, Financials, and Technology, while its returns receive impacts of bubbles from the same list of industry groups, except Agro & Food. Whereas, the Financials industry group, which include Banking and Finance & Securities sectors, is linked with Agro & Food, Consumer Products, Property & Construction, and Technology industry groups.

Finally, Table 34 details the Model A and the simplified models where abnormal volume terms are dropped. Robustness checks compare the full model to model types A-P, A-R and A-V

The tests against Model A-V are rejected in six out of eight industry groups, while the tests against Model A-R are not rejected in five industry groups. Moreover, there is one industry group which fails to reject tests against both Model A-R and A-P. That leaves two industry groups where the full Model A is simultaneously better than all three simpler model types. This suggests that the impact of bubble contagion captured by the abnormal trading volume in Model A seems to be coming through the return equation rather than the probability equation. In other words, when bubbles from other industry groups are contagious, they will influence return, rather than affecting the likelihood of whether the bubble in the industry group will collapse in the next period.

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Table 34: Comparison of Model A

		Agro & Food				Consumer Products			
		Model A	Model A-P	Model A-R	Model A-V	Model A	Model A-P	Model A-R	Model A-V
β_{so}		1.0987***	0.9969***	1.0188***	0.9648***	1.0514***	1.0642***	1.0107***	1.0219***
β_{sb}	AGR	-0.1848***	-0.7292***	-0.0476***	0.1286***	-0.1682***	-0.0880***	-0.0283***	0.0276*
	CON	0.4546***	0.3149***	0.1230***	0.1612***	0.4534***	0.4381***	0.1210***	0.0861**
	FIN	-0.3907***	0.3722***	0.1330***	-0.1698***	-0.1155***	-0.1211***	0.0597***	0.0604**
	IND	0.0461***	-0.2856***	-0.2277***	-0.0633***	-0.0613***	-0.0632***	-0.0413***	-0.1185***
	PRO	0.1546***	-0.0515***	-0.0679***	-0.0477***	-0.1993***	-0.2071***	-0.0590***	-0.0388***
	RES	-0.1847***	-0.3648***	-0.0470***	0.1258***	-0.1025***	-0.1045***	-0.0602***	0.0039
	SER	-0.0459***	0.1798***	-0.0330***	-0.1010***	-0.0222***	-0.0196	-0.0217***	-0.0230*
	TEC	0.0651***	0.3315***	0.0414***	-0.0076***	0.1756***	0.1652***	0.0054***	0.0231***
β_{sv}	AGR	0.1010***		0.0383***		-0.0953***		0.0417***	
	CON	-0.1091***		0.0119***		-0.0399***		-0.0182***	
	FIN	-0.1188***		-0.0281***		-0.0098*		-0.0245***	
	IND	-0.0528***		0.0288***		0.0922***		-0.0002	
	PRO	-0.0065**		0.0310***		0.0086		-0.0476***	
	RES	0.0790***		0.0043***		0.0364***		0.0127***	
	SER	0.0033		-0.1024***		-0.0016		-0.0072***	
	TEC	-0.0005		-0.0116***		0.0516***		0.0041***	
β_{co}		1.0044***	1.0035***	1.0017***	1.0116***	0.9896***	0.9872***	0.9914***	0.9873***
β_{cb}	AGR	0.0088	0.0057	-0.0038	0.0007	0.0023	0.0063	0.0079	0.0028
	CON	-0.0399	-0.0559**	-0.0409	-0.0409	-0.0906***	-0.0984***	-0.0951***	-0.1057***
	FIN	0.0147	-0.0020	-0.0102	-0.0142	0.0009	0.0068	-0.0001	0.0025
	IND	-0.0291***	-0.0144	-0.0144	-0.0224**	0.0010	-0.0001	-0.0002	0.0052
	PRO	-0.0118	-0.0063	0.0073	-0.0023	-0.0001	-0.0018	-0.0011	-0.0075
	RES	0.0034	-0.0007	0.0015	-0.0070	-0.0086	-0.0065	-0.0083	-0.0082
	SER	0.0050	0.0119	0.0054	0.0202	0.0189	0.0152	0.0185	0.0252
	TEC	-0.0055	-0.0109	-0.0187**	-0.0070	-0.0146**	-0.0151**	-0.0114	-0.0127

Note: Results based on the Model A and Model A-P, A-R, and A-V as discussed in p. 93. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 34 (continued)

		Agro & Food				Consumer Products			
		Model A	Model A-P	Model A-R	Model A-V	Model A	Model A-P	Model A-R	Model A-V
β_{qo}		0.1786	-2.2885	2.4223***	3.7969***	1.6169	2.5496	2.1062***	4.6817***
β_{qb}	AGR	-2.3020	-3.5619	-0.4807	-3.8547**	-0.1202	-4.3165	-0.7173	-6.1121**
	CON	-0.4386	-2.5572	-1.4041	-1.3323	-1.3892	-0.7523	-1.2945	-11.5531**
	FIN	-1.7066	1.8865	-1.4451	-3.2888*	-1.0130	-4.4857	-1.3979*	5.4288**
	IND	-3.2178	-3.3676	-2.1531**	-1.4375	-1.2524	-0.6072	-1.8095**	-11.5500***
	PRO	-4.0399***	-3.6726	-1.4102**	-1.7762*	-0.8065	-2.8722	-0.8898*	2.6464**
	RES	-1.0978***	-2.1087	-2.3836***	-3.4830**	-2.1092*	-6.2850***	-1.3513**	-11.4979***
	SER	0.1301	-2.1380	-0.6374	-1.8499	-1.5447	0.9096	-1.1678	3.5606**
	TEC	-0.3542***	-0.3650	-1.2778***	-1.3892***	-3.0833**	-7.2576**	-1.1796***	1.9640**
β_{qv}	AGR	1.4327**	1.6037			-0.7317	-5.6724**		
	CON	0.5185	-2.5237			-1.2815	-1.0238		
	FIN	-0.7669	-2.1633			-1.0124	-2.9972		
	IND	0.0354	0.6512			-0.5352	-0.3143		
	PRO	-1.9090**	1.9022			-0.3683	2.0480		
	RES	-4.2623***	-6.0878**			-1.9200*	-1.9576*		
	SER	-1.6371	-2.2862			-0.3464	-1.4479		
	TEC	-3.5042***	-3.6918*			-1.3083	-7.8244***		
Log-Likelihood		415.1926	405.6990	417.9935	377.3401	402.9800	391.5178	428.1151	416.1784

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 34 (continued)

	Agro & Food				Consumer Products			
	Model A	Model A-P	Model A-R	Model A-V	Model A	Model A-P	Model A-R	Model A-V
Block Exogeneity Tests								
Agro & Food	72.9320***	112.8324***	38.1354***	109.4456***	17.5187***	11.0712**	15.8740***	10.7569**
Consumer Products	33.9604***	97.1856***	45.6276***	8.1071**	10.0049*	15.6927***	5.4624	9.9881**
Financials	68.9821***	112.9123***	59.3164***	16.3020***	10.1642*	8.5315*	6.9417	4.7571
Industrials	28.9540***	116.7294***	115.3164***	11.8000***	9.7431*	1.5704	67.0272***	3.0949
Property & Construction	36.0358***	112.8567***	7.6750	19.7580***	15.8184***	17.2277***	72.6733***	9.6351**
Resources	43.2803***	112.9098***	3.2426	4.7712	6.5610	66.4410***	59.3588***	24.3825***
Services	7.6133	97.0137***	28.1004***	0.0468	0.7574	14.8152***	24.9475***	7.8241**
Technology	49.0578***	114.7093***	53.7470***	5.9637	8.3403	67.0137***	29.9457***	12.2421***
Robustness Checks								
Volatility regimes	115.1684***	96.1812***	120.7702***	39.4633**	54.3308*	31.4063	104.6010***	80.7276***
Mixtures of normals	114.3249***	95.3377***	119.9266***	38.6198**	53.2097*	30.2852	103.4799***	79.6065***
Fads	114.6461***	95.6589***	120.2479***	38.9411**	51.2050	28.2805	101.4752***	77.6018***
VNS	111.5105***	92.5233***	117.1123***	35.8054**	41.8612	18.9367	92.1314***	68.2580***
Volume-augmented	101.5108***	82.5236***	107.1126***	25.8057	39.7789	16.8545	90.0491***	66.1757***
Model A-P	18.9872**				22.9245***			
Model A-R	0.0000				0.0000			
Model A-V	75.7051***	56.7179***	81.3069***		0.0000	0.0000	23.8734***	

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 34 (continued)

		Financials				Industrials			
		Model A	Model A-P	Model A-R	Model A-V	Model A	Model A-P	Model A-R	Model A-V
β_{so}		1.2832***	0.9412***	0.9967***	1.0048***	1.0742***	0.8805***	1.0080***	0.9947***
β_{sb}	AGR	0.2599***	-0.0016	0.0457***	-0.0059	-0.0324	0.1827***	0.1214***	0.0143
	CON	0.2644***	0.0844***	0.0199***	0.0637	0.3466***	-0.2240***	0.0294***	0.3757***
	FIN	-0.4252***	0.3060***	0.0245***	-0.0376	-0.3110***	0.1417***	-0.1076***	0.0698***
	IND	0.2769***	-0.0069	-0.0785***	-0.0075	-0.0985***	-0.1324***	-0.2915***	-0.0748***
	PRO	-0.2476***	0.1606***	-0.0535***	0.0285	-0.0029	-0.2637***	-0.1591***	-0.2796***
	RES	-0.2984***	-0.0624***	0.0909***	-0.0142	-0.1628***	0.2346***	0.1496***	0.0003
	SER	-0.1819***	0.0177***	0.0638***	-0.0366	-0.0419	-0.2815***	-0.1494***	-0.1127***
	TEC	0.1873***	-0.0220***	-0.0252***	-0.0148	0.1123***	-0.0636***	0.0312***	0.0493***
β_{sv}	AGR	0.2312***		-0.0071***		0.0473**		-0.0429***	
	CON	0.0775***		0.0008**		-0.0723***		0.0429***	
	FIN	-0.0748***		-0.0591***		-0.0727***		-0.0276***	
	IND	-0.0248***		0.0579***		-0.1592***		0.0216***	
	PRO	0.0146*		0.0425***		0.0992***		0.0673***	
	RES	0.0184***		0.0718***		0.0542***		0.0303***	
	SER	-0.0539***		-0.0223***		-0.0694***		-0.1369***	
	TEC	-0.1194***		0.0217***		-0.0575***		-0.0450***	
β_{co}		1.0115***	1.0321***	1.0208***	1.0335***	0.9981***	1.0045***	1.0044***	1.0054***
β_{cb}	AGR	-0.0132	0.0046	0.0024	-0.0035	0.0216	0.0190	0.0132	0.0150
	CON	-0.0836*	-0.0922*	-0.1156**	-0.1471*	-0.0556*	-0.0455	-0.0464	-0.0502
	FIN	-0.0743*	-0.0841**	-0.0833**	-0.1389*	0.0148	0.0012	-0.0063	-0.0084
	IND	0.0063	-0.0005	0.0030	-0.0033	-0.0086	-0.0109	-0.0069	-0.0083
	PRO	0.0140	0.0041	0.0080	-0.0040	0.0317*	0.0286*	0.0292*	0.0274*
	RES	-0.0203	-0.0338*	-0.0293	-0.0460	-0.0206	-0.0189	-0.0192	-0.0222*
	SER	0.0687**	0.0826***	0.0829***	0.1499**	0.0043	0.0136	0.0186	0.0277
	TEC	-0.0155	0.0039	-0.0038	0.0483	-0.0225**	-0.0155*	-0.0174*	-0.0154*

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 34 (continued)

		Financials				Industrials			
		Model A	Model A-P	Model A-R	Model A-V	Model A	Model A-P	Model A-R	Model A-V
β_{qo}		1.8264	1.1937	2.3846***	-0.6341	2.4750*	1.7727	2.4975***	1.7092**
β_{qb}	AGR	-1.6281	-1.6702	-1.3437	-0.4181	0.5164	-1.3749	-1.7016	-1.4134
	CON	-1.2487	-1.6576	-1.0823	-3.2117	-1.0429	-1.4174	-1.3028	-3.2823
	FIN	-1.1952	-1.9603	-1.0031	1.1187	-1.2530	-1.1717	-2.1238**	-1.6054
	IND	-1.2911	-2.9381	-1.1657	-1.5986*	-1.6241	-1.6456	-0.9870	-2.2327*
	PRO	-1.8897	-0.4835	-1.7301**	-0.7940	-3.0663***	-1.9300	-0.5064	-2.8039**
	RES	-1.3658	-1.6619*	-2.0119***	-0.6311	-1.7617	-2.1229**	-1.4586**	-2.6983**
	SER	-1.2394	-1.5092	-1.5644	0.5731	-1.3872	-1.7472	-1.8055*	2.1829*
	TEC	-2.0748**	-0.7076	-1.1910***	3.3336***	-1.1807	-0.8462	-1.5692***	-0.1680
β_{qv}	AGR	-1.1130	0.1102			-0.2968	-0.7982		
	CON	-0.9505	-0.1295			0.1478	-0.5586		
	FIN	-0.7998	-0.6236			-0.6970	0.0676		
	IND	-0.7871	0.0094			-0.3239	0.2933		
	PRO	-0.8280	-0.3168			-1.7504***	-0.4649		
	RES	0.3094	-1.0921			-0.7054	-0.4153		
	SER	-0.8687***	0.3792			-1.1334	-0.4724		
	TEC	-0.6998	-1.6928*			-0.7009*	-0.0987		
Log-Likelihood		248.2893	218.9430	260.6031	252.8735	349.0687	342.1866	378.9970	332.3855

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 34 (continued)

	Financials				Industrials			
	Model A	Model A-P	Model A-R	Model A-V	Model A	Model A-P	Model A-R	Model A-V
Block Exogeneity Tests								
Agro & Food	18.7061***	0.6923	19.3102***	0.4367	3.6680	7.2759	41.2954***	2.5078
Consumer Products	17.4550***	14.7459***	32.3384***	5.7683	4.3375	10.7713**	4.5980	28.0676***
Financials	12.7034**	4.6693	20.3303***	5.7989	1.1347	32.4066***	68.6604***	4.6712
Industrials	4.9525	6.3597	70.2641***	3.9659	16.7355***	36.6860***	84.6700***	17.4384***
Property & Construction	51.7263***	29.7565***	66.1089***	3.5542	5.5404	79.8489***	65.9483***	7.2706*
Resources	5.1514	102.3320***	40.4674***	2.1432	12.5594**	16.2748***	21.7355***	9.6396**
Services	0.7932	0.5212	37.3950***	6.5774*	5.8186	35.3935***	19.2447***	20.5146***
Technology	15.0904***	34.3972***	67.4655***	5.4896	3.3184	10.2157**	16.8362***	21.8907***
Robustness Checks								
Volatility regimes	64.9356**	6.2430	89.5632***	74.1040***	73.5811***	59.8170***	133.4378***	40.2149**
Mixtures of normals	64.6697***	5.9771	89.2973***	73.8381***	71.6114***	57.8472***	131.4681***	38.2451**
Fads	64.8646***	6.1719	89.4922***	74.0330***	68.1712***	54.4070***	128.0279***	34.8049*
VNS	50.4839*	0.0000	75.1116***	59.6523***	62.4039***	48.6397**	122.2606***	29.0377
Volume-augmented	46.1140*	0.0000	70.7416***	55.2824***	56.5366**	42.7724**	116.3933***	23.1703
Model A-P	58.6926***				13.7642*			
Model A-R	0.0000				0.0000			
Model A-V	0.0000	0.0000	15.4592*		33.3662***	19.6021**	93.2230***	

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 34 (continued)

		Property & Construction				Resources			
		Model A	Model A-P	Model A-R	Model A-V	Model A	Model A-P	Model A-R	Model A-V
β_{so}		1.0689***	0.9292***	0.9443***	1.0343***	1.0735***	1.1242***	0.9898***	1.0623***
β_{sb}	AGR	-0.1213***	-0.1238***	-0.1272***	0.1186***	-0.1650***	-0.0334***	0.1682***	0.0849***
	CON	0.3237***	0.2808***	-0.0539***	-0.1336***	0.6304***	0.1413***	-0.1527***	0.1567***
	FIN	-0.2619***	-0.2427***	-0.0819***	-0.4192***	-0.1968***	-0.5113***	0.0873***	-0.2342***
	IND	-0.1558***	-0.0810***	-0.2607***	0.1099***	-0.1244***	0.0849***	-0.2834***	0.3487***
	PRO	-0.2652***	-0.5083***	-0.1532***	-0.1411***	-0.1958***	0.0850***	-0.0412***	0.3651***
	RES	-0.2725***	0.1853***	0.2470***	0.0951***	-0.0895***	-0.0363***	0.1070***	-0.0442***
	SER	-0.0226	-0.0831***	0.0219***	0.1207***	-0.0063	-0.0306***	-0.1214***	-0.0797***
	TEC	0.2935***	0.0668***	-0.0534***	0.0399*	0.1762***	-0.0817***	0.1579***	0.0772***
β_{sv}	AGR	-0.0474**		-0.0072***		0.0747*		-0.1868***	
	CON	0.0192		0.0121***		0.1063***		0.1029***	
	FIN	-0.1185***		0.0575***		-0.0295*		-0.1189***	
	IND	-0.0862***		0.0276***		-0.1543***		0.1382***	
	PRO	0.1272***		0.0175***		-0.0151		0.0533***	
	RES	0.0676***		0.0114***		0.0665***		0.0683***	
	SER	-0.1571***		-0.1572***		-0.0324		-0.0627***	
	TEC	-0.0865***		-0.0229***		-0.1989***		-0.0543***	
β_{co}		1.0030***	1.0149***	1.0087***	1.0073***	1.0054***	1.0129***	1.0137***	1.0134***
β_{cb}	AGR	0.0293	0.0172	0.0090	0.0135	-0.0428*	-0.0436**	-0.0494**	-0.0454**
	CON	-0.1353***	-0.1291***	-0.1347***	-0.1160**	0.0000	0.0348	0.0197	0.0333
	FIN	-0.0230	-0.0464	-0.0405	-0.0282	-0.0472	-0.0301	-0.0498	-0.0357
	IND	-0.0070	-0.0038	-0.0031	-0.0100	0.0246	0.0155	0.0240	0.0165
	PRO	0.0191	0.0165	0.0016	0.0095	0.0057	-0.0048	-0.0031	-0.0029
	RES	-0.0131	-0.0227	-0.0222	-0.0207	-0.0274	-0.0110	-0.0232	-0.0127
	SER	0.0330	0.0545**	0.0677**	0.0481	0.0203	0.0136	0.0289	0.0165
	TEC	-0.0218*	-0.0119	-0.0123	-0.0133	-0.0126	-0.0063	-0.0101	-0.0079

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 34 (continued)

		Property & Construction				Resources			
		Model A	Model A-P	Model A-R	Model A-V	Model A	Model A-P	Model A-R	Model A-V
β_{qo}		2.1941**	1.3897	2.5854***	1.6091*	1.3467	1.6219	2.1100***	1.3452
β_{qb}	AGR	-1.1672	-0.9232	-0.8681	-1.4234	-1.4253	-1.2743	-1.8882	-0.9756
	CON	-1.5432	-1.8168	-1.6056	2.1697	-0.7335	-1.4793	-1.8360	-3.6339
	FIN	-1.3674	-2.8114	-1.5654*	-2.9338**	-3.3413	-1.3918	-1.4442	-0.5994
	IND	-1.0153	-1.7206	-1.3943**	-0.9135	1.4339	-1.6512	-1.4522	-0.6307
	PRO	-1.3015**	-1.1481	-0.9358	-0.5811	-5.3895**	-0.8792	-0.7726	-3.0854**
	RES	-1.2118	-0.1625	-2.3339***	-0.6169	-3.8582*	-2.1848**	-1.2180*	-3.0799**
	SER	-1.6785**	-2.8660	-1.4788	-1.0711	-0.7469	-1.2221	-1.3179	1.1344
	TEC	-1.8851**	-1.9756**	-1.3803***	-1.9876*	-2.2425	-1.3755**	-1.1604***	-0.7426
β_{qv}	AGR	-0.8097	-1.0006			-2.6242	-0.4665		
	CON	-0.4129	-0.4367			-2.2406**	-1.1587*		
	FIN	-1.0510***	0.2631			1.1378	-0.1992		
	IND	-1.2900**	0.2121			-3.8535***	0.1771		
	PRO	-1.2925	-0.5715			-3.2569	0.0418		
	RES	0.0900	-0.7939			0.3601	-0.1511		
	SER	-1.5549***	-0.7027			-4.2216*	-0.6629		
	TEC	-0.8624	-0.3953			-2.8869***	-0.1579		
Log-Likelihood		254.6115	248.3794	285.9656	237.2151	290.3846	280.4672	309.2243	279.4777

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 34 (continued)

	Property & Construction				Resources			
	Model A	Model A-P	Model A-R	Model A-V	Model A	Model A-P	Model A-R	Model A-V
Block Exogeneity Tests								
Agro & Food	5.2475	117.4417***	26.4357***	35.1048***	5.5648	47.8770***	54.9832***	67.3763***
Consumer Products	13.4040**	44.0330***	28.8016***	10.2477**	3.8528	25.0583***	67.0287***	67.0681***
Financials	10.5120*	103.2577***	55.1179***	20.7170***	5.3516	17.2778***	91.9421***	63.9130***
Industrials	9.1000	32.1672***	3.6795	17.6444***	6.3511	4.9044	7.4298	67.1053***
Property & Construction	13.6857**	7.1119	55.3221***	34.5982***	3.1787	46.7495***	68.3160***	53.8454***
Resources	2.6017	21.9905***	53.9021***	20.7215***	8.9403	4.5555	69.8393***	42.7788***
Services	2.4082	5.1852	39.3857***	38.0017***	0.9569	8.1696*	21.8164***	66.4716***
Technology	18.3908***	37.3376***	46.0298***	21.4293***	2.3977	11.5842**	12.5051**	41.2611***
Robustness Checks								
Volatility regimes	58.2054**	45.7412*	120.9136***	23.4127	64.1225**	44.2877*	101.8020***	42.3087**
Mixtures of normals	57.9085**	45.4443*	120.6167***	23.1158	64.1213***	44.2864*	101.8007***	42.3075**
Fads	58.1729**	45.7087*	120.8811***	23.3802	60.6726**	40.8377	98.3520***	38.8587**
VNS	49.3166*	36.8524	112.0247***	14.5239	56.8876**	37.0528	94.5671***	35.0738**
Volume-augmented	48.0764*	35.6122	110.7846***	13.2837	55.0621**	35.2272	92.7416***	33.2483**
Model A-P	12.4642				19.8349**			
Model A-R	0.0000				0.0000			
Model A-V	34.7927***	22.3285***	97.5009***		21.8138***	1.9790	59.4933***	

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 34 (continued)

		Services				Technology			
		Model A	Model A-P	Model A-R	Model A-V	Model A	Model A-P	Model A-R	Model A-V
β_{so}		1.0022***	1.0160***	1.0383***	1.0073***	1.3674***	0.9794***	0.6034***	0.9742***
β_{sb}	AGR	-0.0424**	0.1024***	-0.0550***	0.2949***	-0.4001***	0.0221	0.5993**	0.0384*
	CON	0.1917***	-0.2026***	0.0999***	0.0958***	-0.3925***	-0.1208***	-0.1492	-0.1288***
	FIN	-0.1614***	-0.0226**	-0.1571***	-0.6342***	-0.4908***	0.0123	0.5431***	0.0435
	IND	-0.0004	-0.0103	-0.0273***	0.1163***	-0.0077	-0.0079	0.7328***	-0.0125
	PRO	-0.0049	0.0871***	0.2661***	0.1041***	-0.2088***	-0.0035	-1.0100***	-0.0064
	RES	-0.1351***	-0.0744***	-0.1613***	0.2215***	-0.2222***	0.0147	-0.0016	0.0133
	SER	-0.0463***	0.0296*	-0.1519***	-0.1156***	0.7660***	0.0204	1.7133***	0.0110
	TEC	0.1038***	-0.0380**	0.0307***	0.0745***	0.5208***	-0.0285***	1.2502***	-0.0270***
β_{sv}	AGR	0.0948***		0.0678***		-0.1757***		0.0860***	
	CON	-0.1144***		0.0071***		-0.0014**		0.3018***	
	FIN	-0.0673***		-0.1050***		0.0735***		-0.0638	
	IND	-0.0826***		-0.0650***		0.3937***		-0.0117	
	PRO	0.0185		-0.0527***		0.2597***		0.2610	
	RES	0.0387***		0.0906***		-0.1955***		0.1507***	
	SER	-0.0227**		-0.0929***		-0.0174***		0.0036	
	TEC	-0.0397***		-0.0064***		-0.0208***		-1.0211***	
β_{co}		1.0001***	1.0011***	1.0042***	1.0051***	0.9749***	1.7882***	0.9905***	1.5891***
β_{cb}	AGR	0.0061	-0.0080	0.0041	-0.0045	0.0307	0.0522	0.0176	0.1609***
	CON	-0.0339	-0.0282	-0.0416	-0.0520*	-0.1466***	-0.5248*	-0.1903***	-0.0038
	FIN	-0.0021	-0.0089	-0.0094	-0.0250	0.0324	-0.5386**	-0.0364	-0.8861***
	IND	-0.0173	-0.0122	-0.0204*	-0.0128	-0.0064	0.6545*	-0.0019	-0.1800***
	PRO	-0.0005	-0.0028	-0.0063	-0.0011	-0.0169	-0.5017**	-0.0015	-0.2003***
	RES	0.0011	0.0009	-0.0064	-0.0070	0.0177	-0.9912***	0.0099	-0.3549***
	SER	0.0186	0.0256	0.0350*	0.0414**	0.0318	0.5463**	0.0493**	0.5940***
	TEC	-0.0226**	-0.0220***	-0.0167**	-0.0201**	-0.0271**	0.5667**	-0.0292***	1.0964***

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 34 (continued)

		Services				Technology			
		Model A	Model A-P	Model A-R	Model A-V	Model A	Model A-P	Model A-R	Model A-V
β_{qo}		4.6581	-0.0063	1.7805**	5.0176***	-1.6249**	4.5075*	1.5893*	1.9396***
β_{qb}	AGR	1.1400	-2.0790	0.1340	-3.7902*	-0.9573	-0.0890	-2.5011*	0.3595
	CON	0.8317	0.4211	-0.8718	3.5833	0.2717	-0.8679	-1.7116	0.7967
	FIN	-13.9377	-1.9799	-1.7558*	-2.6757*	-0.0451	-1.0861	-1.1858	-1.7084*
	IND	-1.1303	0.5504	-0.3851	-2.9064*	-2.4458	-2.2069	-0.9206	-0.3483
	PRO	-11.3204	-0.2978	-1.0223	-2.3585*	3.2544***	-0.3781	-0.4220	-0.9492
	RES	-0.5558	-3.7122**	-1.1315	-3.5925**	-0.2680	-0.4687	-0.8187	-0.0377
	SER	-12.3864	-2.9560	-2.2052**	-4.5789**	0.8483	-1.1941	-1.9741	0.4222
	TEC	-8.3648	-4.6679*	-1.8690***	-3.0355***	-3.0799***	3.0970*	-1.2826***	1.2768**
β_{qv}	AGR	3.5222	-1.0922			0.0299	2.1254		
	CON	-8.9467	-0.2193			0.2412	0.0377		
	FIN	-0.5931	-0.4694			-0.0982	-1.0795		
	IND	0.0111	-2.2669			-0.9571**	-0.0584		
	PRO	-22.8919	-0.1610			0.4006	-1.9398*		
	RES	-0.5473	-5.8614**			-0.0035	0.2467		
	SER	0.8570	-0.9034			1.5116***	-2.5450*		
	TEC	-8.4801	-2.4948			-0.2415	0.7640		
Log-Likelihood		385.39	347.72	376.92	351.64	313.67	259.72	265.04	264.23

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 34 (continued)

	Services				Technology			
	Model A	Model A-P	Model A-R	Model A-V	Model A	Model A-P	Model A-R	Model A-V
Block Exogeneity Tests								
Agro & Food	21.0432***	30.9811***	23.8996***	5.7462	254.2627***	10.9121**	3.0568	3.7139
Consumer Products	2.7848	5.0380	31.5408***	4.4553	134.8473***	23.3111***	24.9225***	12.0451***
Financials	0.8926	27.5751***	22.2987***	27.6104***	259.3127***	20.9152***	43.4694***	37.4986***
Industrials	8.4790	22.0552***	50.8528***	150.3466***	117.9626***	9.9152**	261.1352***	2.1508
Property & Construction	3.8349	15.1091***	7.8627*	48.6760***	153.3607***	48.9926***	261.1352***	1.0126
Resources	8.5208	25.7714***	11.2359**	17.0059***	137.6160***	26.3288***	84.3029***	3.4853
Services	6.2182	34.5578***	94.1009***	22.6958***	144.6844***	22.7448***	217.9403***	62.5439***
Technology	25.4814***	1.7285	61.0521***	32.4269***	120.1936***	3.4871	232.0001***	183.0134***
Robustness Checks								
Volatility regimes	107.1538***	31.8087	90.1968***	39.6429**	181.7257***	73.8220***	84.4737***	82.8529***
Mixtures of normals	107.0357***	31.6906	90.0787***	39.5248**	178.8365***	70.9328***	81.5846***	79.9637***
Fads	106.7559***	31.4109	89.7989***	39.2450**	175.0831***	67.1793***	77.8311***	76.2102***
VNS	97.2340***	21.8889	80.2770***	29.7231*	157.8532***	49.9495***	60.6012***	58.9804***
Volume-augmented	84.1782***	8.8331	67.2212***	16.6673	153.0974***	45.1937**	55.8455***	54.2246***
Model A-P	75.3450***				107.9037***			
Model A-R	16.9570**				97.2520***			
Model A-V	67.5109***	0.0000	50.5539***		98.8728***	0.0000	1.6209	

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

7.2.2. Model including Market-wide Index's Data (Model M)

The second approach is to include the basic volume-augmented model bubble and trading volume terms of the market index (Model M) [equations (48) to (50)], instead of data from all other industry groups. They will serve as proxies for impacts of overall market condition on a particular industry group being investigated. Also, this modelling strategy helps reduce the number of parameters required to be estimated and thus makes the optimisation more efficient. The results are reported in Table 35. Overall, Model M seems to be appropriate, as the robustness checks against bubble models without linkages with the market are all rejected, except for the Agro & Food industry group that shows Model M be inferior to the basic volume-augmented model.

All individual mean returns (β_{so}^{i} and β_{co}^{i}) and residual standard deviation (σ_{s}^{i} and σ_{c}^{i}) estimates are statistically significant and have the plausible signs and magnitudes. Several bubble and volume parameters ($\beta_{sb}^{i}, \beta_{sv}^{i},$ and β_{cb}^{i}) in the return equations in both regimes are, however, statistically significant and have mixed signs which are not consistent with the theory. The probability equations, on the other hand, look to be fitting well with the mean probability of the bubble surviving parameters in seven out of eight industry groups turning out to be statistically significant. Moreover, most of the estimated β_{qb}^{i} are statistically significant and have the expected negative sign, while the parameters $\beta_{qv}^{i}$are less satisfactorily.

The results on the market index in the probability equation β_{qbM}^{i} and β_{qvM}^{i}) are very interesting. As the market index is a proxy for the conditions in the stock market and the general economy, any bubble component on the index could be expected to affect the disaggregated industry group. Specifically, as the relative size of a bubble in the market increases, the chance that a bubble in an individual industry group will continue growing in the next period may drop. The estimated parameters of market-wide index's bubbles on the probability that each industry group will be in the bubble-surviving regime (β_{qbM}^{i}) are all negative as expected, except in Industrials, though only four out of eight are statistically significant. Some of the estimates' size are quite large, such as those for Consumer Products and Financials.

Table 35: Model M

	Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	1.0257***	1.0030***	1.0312***	1.0129***	1.0782***	0.9774***	1.0464***	0.9956***
β_{sb}	0.0015	0.0291	0.1206***	-0.0515***	0.0632***	-0.0907***	0.0361***	-0.0154*
β_{sv}	0.0146	-0.0037	0.0239**	0.0025	0.0036	-0.0056	0.0238**	-0.0030
β_{co}	1.0157***	1.0247***	1.0222***	0.9895***	0.9648***	1.0457***	1.0078***	1.3076***
β_{cb}	-0.0420	-0.0789**	-0.0952**	0.0114	-0.0570	0.0080	-0.0069	0.2669
β_{qo}	1.0453**	2.7739***	1.9307***	1.3008*	3.2742***	1.2905**	2.3795***	0.6704
β_{qb}	0.0373	-4.2584**	-0.6897	-2.6625**	-1.7612***	-2.4608***	-1.5297**	1.1499***
β_{qv}	-0.5421**	0.1526	0.4342	-0.1739	0.3895	-0.3968	-0.1093	0.6081**
σ_s	0.0461***	0.0340***	0.0524***	0.0576***	0.0768***	0.0438***	0.0577***	0.0676***
σ_c	0.1118***	0.0903***	0.1635***	0.1247***	0.1868***	0.1198***	0.1592***	0.3340***
β_{sbi}	-0.0448***	-0.0039	-0.1551***	-0.0182	-0.1563***	0.0796**	-0.0849***	0.0003
β_{svi}	-0.0006	-0.0053	-0.0290	-0.0094	0.0008	-0.0580**	0.0012	-0.0130
β_{cbi}	0.0037	-0.0630	0.0571	0.0985	0.1033	-0.0645	-0.0515	-0.5559
β_{qbi}	-0.3580	-4.1420***	-3.5307***	1.8813*	-2.8852**	-1.2145	-0.2738	-0.6889
β_{qvi}	-0.7073*	-1.0847*	-0.8714	-1.4592***	-1.0809*	-0.7659	-0.7668**	-0.6537**
Log-Likelihood	373.1095	396.0635	240.0840	329.6103	243.9632	269.9758	357.8240	242.0000
AIC	-2.5579	-2.7219	-1.6077	-2.2472	-1.6355	-1.8213	-2.4487	-1.6272
SBIC	-2.6651	-2.8290	-1.7149	-2.3544	-1.7426	-1.9284	-2.5559	-1.7348
HQIC	-2.4798	-2.6438	-1.5296	-2.1691	-1.5573	-1.7432	-2.3706	-1.5489
Block exogeneity test	12.5553***	22.8865***	26.2580***	14.5616***	26.1018***	11.0898***	25.7700***	8.9843***
Volatility regimes	27.2418***	38.2193***	45.6317***	31.8744***	33.9718***	20.2407**	48.9585***	38.3882***
Mixture of normals	26.3713***	37.0418***	45.3916***	29.8421***	33.6704***	20.2394**	48.8289***	35.4990***
Fads	19.9245**	34.0312***	43.2477***	30.5851***	32.6248***	17.9152*	36.8476***	33.0669***
VNS	18.4174**	24.9868***	27.3640***	26.2043***	27.3997***	17.4149**	36.6272***	24.9842***
Volume-augmented	7.1995	16.7157***	19.6686***	10.1268*	24.4590***	15.3262***	26.3740***	20.1418***
Model M-P	2.7112	1.5355	3.9753	0.4282	0.1270	7.8372**	8.6441**	3.0360
Model M-R	10.4790***	5.5035*	3.0922	17.4712***	5.0327*	6.1833**	7.4565**	8.3081**
Model M-V	16.8420***	7.6356	6.4860	17.8891***	5.9585	9.7196**	18.8176***	10.6980**
Starting observation	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Sep 1989
No of observations	280	280	280	280	280	280	280	279

Precisely, they can be worked out that, when the market's relative bubble size is 0.5 or 50% of the total price index, while there are no bubble in the industry group, no abnormal trading volume in the industry group and in the market, the probability of being in a surviving regime would drop by about 23.90% and 41.86% in Consumer Products and Financials industry groups, respectively. The effect of market's abnormal trading volume on the probability (β^i_{qvM}) is even more convincing. All of them have the expected negative signs and six out of eight are statistically significant. Notable examples include Industrials and Technology industry groups. Assuming no bubbles in both the industry group and the market and the trading volume in the industry group is normal, the probability of surviving would fall by 20.73% and 15.25%, in those two industry groups respectively, when the trading volume in the market increases from the normal level by 50%.

The fact that the block exogeneity tests for all industry groups are rejected suggests that the contagion from the market index's bubble and volume terms are clearly important. However, it essentially works through the probability equation. This conclusion is drawn from the fact that most parameters in the return equations, namely, β^i_{sbM}, β^i_{svM}, and β^i_{cbM}, are also statistically insignificant and have mixed signs, like those with the industry group's bubble and volume parameters, while most of the estimated β^i_{qbM} and β^i_{qvM} have the expected negative signs and are statistically significant. Furthermore, the comparison with simplified model type M-P, M-R, and M-V are shown in Table 36. It reveals two industry groups where the full Model M is better than all other model types, five industry groups where the full Model M performs better than the Model M-R, and Financials is the one industry group where the full Model M does not capture additional explained variability from all Model M-P, M-R and M-V. The results from the block exogeneity tests with the three simplified model types do not change.

Table 36: Comparison of Model M

	Agro & Food				Consumer Products			
	Model M	Model M-P	Model M-R	Model M-V	Model M	Model M-P	Model M-R	Model M-V
β_{so}	1.0257***	1.0238***	1.0249***	1.0237***	1.0030***	1.0036***	1.0029***	1.0142***
β_{sb}	0.0015	0.0029	-0.0028	0.0015	0.0291	0.0192	0.0189	0.0039
β_{sbi}	-0.0448***	-0.0457***	-0.0487***	-0.0398**	-0.0039	-0.0068	-0.0018	-0.0513
β_{sv}	0.0146		0.0029		-0.0037		-0.0043	
β_{svi}	-0.0006		0.0175**		-0.0053		0.0010	
β_{co}	1.0157***	1.0232***	1.0185***	1.0237***	1.0247***	1.0206***	1.0163***	1.0064***
β_{cb}	-0.0420	-0.0467	-0.0460	-0.0473	-0.0789**	-0.0715**	-0.0675**	-0.0634**
β_{cbi}	0.0037	-0.0058	-0.0046	-0.0152	-0.0630	-0.0544	-0.0473	-0.0259
β_{qo}	1.0453**	0.9133*	0.7106	0.8690**	2.7739***	2.9396***	2.5260***	2.2664***
β_{qb}	0.0373	0.1495	0.1797	0.0767	-4.2584**	-5.0719*	-5.0384	-4.8676**
β_{qbi}	-0.3580	-0.2911	-0.1296	-0.3557	-4.1420***	-4.4064***	-4.5536**	-4.4740***
β_{qv}	-0.5421**	-0.4790			0.1526	0.1748		
β_{qvi}	-0.7073*	-0.7911**			-1.0847*	-1.1044*		
σ_s	0.0461***	0.0457***	0.0455***	0.0469***	0.0340***	0.0337***	0.0298***	0.0270***
σ_c	0.1118***	0.1085***	0.1160***	0.1167***	0.0903***	0.0895***	0.0856***	0.0839***
Log-Likelihood	373.1095	371.7539	367.8700	364.6885	396.0635	395.2958	393.3118	392.2458
AIC	-2.5579	-2.5625	-2.5348	-2.5263	-2.7219	-2.7307	-2.7165	-2.7232
SBIC	-2.6651	-2.6554	-2.6276	-2.6049	-2.8290	-2.8235	-2.8094	-2.8018
HQIC	-2.4798	-2.4948	-2.4671	-2.4691	-2.6438	-2.6630	-2.6488	-2.6659
Block exogeneity test	12.5553***	15.1158***	11.4522***	6.7881***	22.8865***	23.3888***	18.6975***	17.7690***
Volatility regimes	27.2418***	24.5306***	16.7628*	10.3998	38.2193***	36.6839***	32.7158***	30.5837***
Mixture of normals	26.3713***	23.6601***	15.8924**	9.5293	37.0418***	35.5063***	31.5383***	29.4062***
Fads	19.9245**	17.2133**	9.4456	3.0825	34.0312***	32.4957***	28.5277***	26.3956***
VNS	18.4174**	15.7062***	7.9385	1.5754	24.9868***	23.4513***	19.4833***	17.3512***
Volume-augmented	7.1995	4.4882	0.0000	0.0000	16.7157***	15.1803***	11.2122**	9.0801***
Model M-P	2.7112				1.5355			
Model M-R	10.4790***				5.5035*			
Model M-V	16.8420***	14.1308***	6.3630**		7.6356	6.1001**	2.1321	
Starting observation	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989
No of observations	280	280	280	280	280	280	280	280

Note: Results based on the Model M and Model M-P, M-R, and M-V as discussed in p. 93. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 36 (continued)

	Financials				Industrials			
	Model M	Model M-P	Model M-R	Model M-V	Model M	Model M-P	Model M-R	Model M-V
β_{so}	1.0312***	1.0266***	1.0303***	1.0276***	1.0129***	1.0127***	1.0161***	1.0162***
β_{sb}	0.1206***	0.1021***	0.1236***	0.1134***	-0.0515***	-0.0512***	-0.0499**	-0.0534**
β_{sbi}	-0.1551***	-0.1258***	-0.1486***	-0.1336***	-0.0182	-0.0168	-0.0282	-0.0280
β_{sv}	0.0239**		0.0200*		0.0025		-0.0019	
β_{svi}	-0.0290		-0.0169		-0.0094		0.0083	
β_{co}	1.0222***	1.0205***	1.0205***	1.0196***	0.9895***	0.9899***	0.9908***	0.9927***
β_{cb}	-0.0952**	-0.0988*	-0.0984**	-0.1003**	0.0114	0.0109	0.0051	0.0062
β_{cbi}	0.0571	0.0628	0.0584	0.0613	0.0985	0.0939	0.0727	0.0685
β_{qo}	1.9307***	1.9598***	1.9745***	1.9765***	1.3008*	1.4306*	1.2047**	1.0930**
β_{qb}	-0.6897	-0.7090	-0.7579	-0.7723	-2.6625**	-2.8433**	-2.0748**	-1.9220**
β_{qbi}	-3.5307***	-3.1888***	-3.7435***	-3.5658***	1.8813*	1.8061	0.2579	0.2265
β_{qv}	0.4342	0.1921			-0.1739	-0.1709		
β_{qvi}	-0.8714	-0.6709			-1.4592***	-1.4754***		
σ_s	0.0524***	0.0570***	0.0533***	0.0555***	0.0576***	0.0581***	0.0555***	0.0541***
σ_c	0.1635***	0.1718***	0.1634***	0.1667***	0.1247***	0.1258***	0.1214***	0.1192***
Log-Likelihood	240.0840	238.0963	238.5379	236.8410	329.6103	329.3962	320.8747	320.6658
AIC	-1.6077	-1.6078	-1.6110	-1.6131	-2.2472	-2.2600	-2.1991	-2.2119
SBIC	-1.7149	-1.7007	-1.7038	-1.6917	-2.3544	-2.3528	-2.2920	-2.2905
HQIC	-1.5296	-1.5401	-1.5433	-1.5559	-2.1691	-2.1923	-2.1314	-2.1546
Block exogeneity test	26.2580***	24.5921***	55.9035***	52.9243***	14.5616***	14.3096***	2.9502***	2.5323***
Volatility regimes	45.6317***	41.6564***	42.5395***	39.1457***	31.8744***	31.4462***	14.4033	13.9854*
Mixture of normals	45.3916***	41.4163***	42.2995***	38.9056***	29.8421***	29.4139***	12.3709	11.9530*
Fads	43.2477***	39.2724***	40.1556***	36.7617***	30.5851***	30.1569***	13.1139	12.6960**
VNS	27.3640***	23.3887***	24.2719***	20.8780***	26.2043***	25.7761***	8.7331	8.3152**
Volume-augmented	19.6686***	15.6933***	16.5764***	13.1826***	10.1268*	9.6986**	0.0000	0.0000
Model M-P	3.9753				0.4282			
Model M-R	3.0922				17.4712***			
Model M-V	6.4860	2.5107	3.3938		17.8891***	17.4608***	0.4179	
Starting observation	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989
No of observations	280	280	280	280	280	280	280	280

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 36 (continued)

	Property & Construction				Resources			
	Model M	Model M-P	Model M-R	Model M-V	Model M	Model M-P	Model M-R	Model M-V
β_{so}	1.0782***	1.0783***	1.0788***	1.0789***	0.9774***	0.9847***	0.9825***	0.9873***
β_{sb}	0.0632***	0.0631***	0.0648***	0.0634***	-0.0907***	-0.0810**	-0.0861***	-0.0767**
β_{sbi}	-0.1563***	-0.1559***	-0.1610***	-0.1608***	0.0796**	0.0687	0.0645	0.0543
β_{sv}	0.0036		0.0180		-0.0056		-0.0316***	
β_{svi}	0.0008		-0.0149		-0.0580**		0.0062	
β_{co}	0.9648***	0.9679***	0.9543***	0.9673***	1.0457***	1.0467***	1.0510***	1.0514***
β_{cb}	-0.0570	-0.0540	-0.0775	-0.0601	0.0080	0.0091	0.0144	0.0157
β_{cbi}	0.1033	0.0967	0.1479	0.1113	-0.0645	-0.0686	-0.0682	-0.0734
β_{qo}	3.2742***	3.2152***	3.6980***	3.3061***	1.2905**	1.5601**	1.0270*	1.1223**
β_{qb}	-1.7612***	-1.7373***	-1.9311**	-1.7131**	-2.4608***	-2.7074**	-1.8263***	-1.8139**
β_{qbi}	-2.8852**	-2.8139**	-3.4742**	-3.1876**	-1.2145	-1.3749	-0.7236	-0.8854
β_{qv}	0.3895	0.3928			-0.3968	-0.2906		
β_{qvi}	-1.0809*	-1.1140**			-0.7659	-0.5960		
σ_s	0.0768***	0.0764***	0.0815***	0.0789***	0.0438***	0.0506***	0.0494***	0.0515***
σ_c	0.1868***	0.1864***	0.1878***	0.1870***	0.1198***	0.1220***	0.1247***	0.1263***
Log-Likelihood	243.9632	243.8997	241.4468	240.9839	269.9758	266.0572	266.8841	265.1160
AIC	-1.6355	-1.6493	-1.6318	-1.6427	-1.8213	-1.8076	-1.8135	-1.8151
SBIC	-1.7426	-1.7421	-1.7246	-1.7213	-1.9284	-1.9004	-1.9063	-1.8937
HQIC	-1.5573	-1.5816	-1.5641	-1.5855	-1.7432	-1.7399	-1.7458	-1.7578
Block exogeneity test	26.1018***	29.1540***	22.4597***	27.4425***	11.0898***	4.4928***	4.7053***	3.0380***
Volatility regimes	33.9718***	33.8448***	28.9391***	28.0133***	20.2407**	12.4035	14.0573	10.5211
Mixture of normals	33.6704***	33.5435***	28.6378***	27.7120***	20.2394**	12.4022	14.0561*	10.5198
Fads	32.6248***	32.4978***	27.5922***	26.6664***	17.9152*	10.0780	11.7319	8.1956
VNS	27.3997***	27.2727***	22.3670***	21.4412***	17.4149**	9.5777*	11.2316**	7.6953*
Volume-augmented	24.4590***	24.3320***	19.4263***	18.5005***	15.3262***	7.4890*	9.1429**	5.6066**
Model M-P	0.1270				7.8372**			
Model M-R	5.0327*				6.1833**			
Model M-V	5.9585	5.8315*	0.9258		9.7196**	1.8824	3.5363	
Starting observation	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Aug 1989
No of observations	280	280	280	280	280	280	280	280

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 36 (continued)

	Services				Technology			
	Model M	Model M-P	Model M-R	Model M-V	Model M	Model M-P	Model M-R	Model M-V
β_{so}	1.0464***	1.0454***	1.0460***	1.0472***	0.9956***	0.9969***	0.9977***	0.9983***
β_{sb}	0.0361***	0.0386***	0.0308*	0.0344**	-0.0154*	-0.0146*	-0.0144*	-0.0141*
β_{sbi}	-0.0849***	-0.0858***	-0.0860***	-0.0846***	0.0003	-0.0073	-0.0050	-0.0108
β_{sv}	0.0238**		0.0254***		-0.0030		-0.0043	
β_{svi}	0.0012		0.0015		-0.0130		-0.0088	
β_{co}	1.0078***	1.0551***	1.0168***	1.0227***	1.3076***	1.3006***	1.2982***	1.2919***
β_{cb}	-0.0069	0.0170	0.0119	0.0059	0.2669	0.2630	0.2567	0.2519
β_{cbi}	-0.0515	-0.0854	-0.0505	-0.0556	-0.5559	-0.5407	-0.5440	-0.5301
β_{qo}	2.3795***	1.9705***	2.3493***	2.1933***	0.6704	0.6912	0.6699	0.6877
β_{qb}	-1.5297**	-1.3099*	-1.5370**	-1.3448**	1.1499***	1.1311***	1.1379***	1.1273***
β_{qbi}	-0.2738	0.1269	-1.0833	-0.9002	-0.6889	-0.7110	-0.9415	-0.9666
β_{qv}	-0.1093	-0.4917			0.6081**	0.5659**		
β_{qvi}	-0.7668**	-0.8644*			-0.6537**	-0.6368**		
σ_s	0.0577***	0.0567***	0.0569***	0.0583***	0.0676***	0.0682***	0.0667***	0.0671***
σ_c	0.1592***	0.1429***	0.1480***	0.1515***	0.3340***	0.3352***	0.3299***	0.3300***
Log-Likelihood	357.8240	353.5020	354.0957	348.4152	242.0000	240.4820	237.8459	236.6510
AIC	-2.4487	-2.4322	-2.4364	-2.4101	-1.6272	-1.6307	-1.6118	-1.6176
SBIC	-2.5559	-2.5250	-2.5293	-2.4887	-1.7348	-1.7239	-1.7050	-1.6964
HQIC	-2.3706	-2.3645	-2.3687	-2.3528	-1.5489	-1.5628	-1.5439	-1.5601
Block exogeneity test	25.7700***	25.1685***	21.8715***	20.2852***	8.9843***	8.7461***	4.4018***	3.8177***
Volatility regimes	48.9585***	40.3144***	41.5019***	30.1409***	38.3882***	35.3522***	30.0801***	27.6902***
Mixture of normals	48.8289***	40.1848***	41.3724***	30.0113***	35.4990***	32.4630***	27.1910***	24.8010***
Fads	36.8476***	28.2035***	29.3911***	18.0300***	33.0669***	30.0309***	24.7588***	22.3689***
VNS	36.6272***	27.9831***	29.1707***	17.8097***	24.9842***	21.9482***	16.6761***	14.2862***
Volume-augmented	26.3740***	17.7299***	18.9175***	7.5564***	20.1418***	17.1058***	11.8338***	9.4438***
Model M-P	8.6441**				3.0360			
Model M-R	7.4565**				8.3081**			
Model M-V	18.8176***	10.1735***	11.3610***		10.6980**	7.6620**	2.3899	
Starting observation	Aug 1989	Aug 1989	Aug 1989	Aug 1989	Sep 1989	Sep 1989	Sep 1989	Sep 1989
No of observations	280	280	280	280	279	279	279	279

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

To sum up, while the Model A shows that the effects of bubbles and trading volume from all other industry groups work through the return equation, the Model M implies bubbles and abnormal trading volume of the entire market influence each industry group through probability equation by making them less likely to be in a surviving regime in the next period. In other words, a bubble component in the index suggests an increased instability of the market as a whole. This would push a return path of the industry group more towards a bubble-collapsing state. In contrast, a bubble in a related industry group would directly affect the level of performance to be realised by investors.

7.2.3. Model including Data from Two Industry Groups (Model J)

As noted earlier, the contagion model with all industry groups (Model A) is the fullest model, but it may be sub-optimal in terms of maximum likelihood estimation as it contains 45 parameters to be estimated for eight industry groups, which also makes the interpretation difficult. This section attempts to deal with this issue by including only the industry groups of interest and one additional industry group as the independent variables at a time (Model J) [equations (51) to (53)]. This reduces the number of parameters to be estimated from 45 to just 15. Implicitly, this means the Model J ignores the impacts from all other industry groups not included in the particular specification. Still, it is believed to offer some partial evidence of contagion between industry groups.

The results of Model J are presented in Table 37. There are 56 specifications in total from eight industry groups as the dependent variable, and seven other industry groups take turn to act as the additional independent variable. Overall, the average return parameters (β_{so}^{ij} and β_{co}^{ij}) are statistically significant in all specifications. Almost all of them have the financially meaningful magnitude and the two regimes are somewhat different as assumed by the theory with the estimates of β_{so}^{ij} greater than β_{so}^{ij} in about 41% of all the cases. For example, the parameters $\beta_{so}^{AGRO,INDUS}$ and $\beta_{so}^{AGRO,INDUS}$ are estimated to be 1.0157 and 1.0098 in the case of Agro & Food as dependent variable and Industrials as the additional independent variable (AGRO-INDUS). They suggest the average net returns are 1.57% and 0.98%, respectively. The standard deviations in both regimes are all statistically significant as well. As expected, the standard deviations in the collapsing regime are higher than those in the surviving regime, except for the cases of CONSUMP-TECH, TECH-AGRO, TECH-

INDUS, TECH-PROPCON, TECH-RESOURC, and TECH-SERVICE. In other words, there appears to be a problem when estimating regressions with Technology industry group as the industry group of interest since if the surviving regime is more volatile than the bubble actually collapses.

The results for the bubble parameters from the industry group being studied, β_{sb}^{ij} and β_{cb}^{ij}, and from the additional industry group, β_{sbj}^{ij} and β_{cbj}^{ij} , in the return equations are less well-fitting. Many of them are statistically insignificant. The influence of the bubble terms on returns in the collapsing regime are negative as hypothesised in about 60% of the cases. The theory also postulated that β_{sb}^{ij} should be larger than β_{cb}^{ij} and that appears to be supported by the data in about 50% of all the cases. The effects of abnormal trading volumes on the returns are also unconvincing. The estimates for the industry group whose return is being investigated are positive in 61% but only statistically significant in about 38% of all the cases, while those for the additional industry group are positive in only 39% and statistically significant in 13% of the cases.

Consider the probability equation, the average probability of bubble surviving denoted β_{qo}^{ij} tend to be positive. Particularly, they are greater than zero, which implies an average probability of more than 50% in 84% of the cases, and greater than one (average probability of more than 84.13%) in 55% of all the cases. Moreover, they are statistically significant in 43 cases. Out of the other 13 cases where β_{qo}^{ij} are statistically insignificantly different from zero, there are five cases where Technology industry group as the dependent variable. This perhaps points out the uniqueness of the industry group again.

As predicted by the theory, the average probability that a bubble will survive in the next period tends to fall as the bubble size increases. This is shown by the estimates of β_{qb}^{ij} turning out to be negative in 84% and are statistically significant in 63% of all the cases, while the β_{qbj}^{ij} which implies linkages with another industry group are negative in 71% but only statistically significant in 32% of all the cases. The effect of the abnormal normal trading on the probability is again less convincing. Although the β_{qv}^{ij} and β_{qvj}^{ij} are negative in 84% and 57% of the cases, respectively, they are only statistically significant in 32% and 20%, respectively.

Table 37: Model J

Dependent Variable: Agro & Food								
Independent Variables	Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}		1.0097***	1.0163***	1.0157***	1.0061***	1.0108***	1.0096***	1.0024***
β_{sb}		0.0057	0.0239**	0.0140	-0.0018	0.0030	0.0054	-0.0102
β_{sv}		0.0180*	0.0201**	0.0189*	0.0135	0.0215**	0.0097	0.0179**
β_{co}		1.0153***	1.0159***	1.0098***	1.0152***	1.0168***	1.0140***	1.0064***
β_{cb}		0.0232	-0.0518*	-0.0407	-0.0323	-0.0330	-0.0357	-0.0263
β_{qo}		0.9568**	-0.7217	0.9756	0.7783*	0.8013*	1.1659***	0.0078
β_{qb}		0.4331	4.5555	-0.2788	0.0736	-0.0001	0.2861	0.2336
β_{qv}		-1.0200***	-0.5793	-0.5555	-0.6917**	-0.7093**	-0.4048	-0.6389**
σ_s		0.0463***	0.0434***	0.0446***	0.0460***	0.0461***	0.0476***	0.0458***
σ_c		0.1158***	0.0884***	0.1040***	0.1135***	0.1145***	0.1216***	0.1198***
β_{sbj}		-0.0085	0.0261*	-0.0271***	-0.0111	-0.0148**	-0.0070	-0.0138***
β_{svj}		-0.0008	0.0127	0.0038	0.0062	-0.0065	0.0143	0.0040
β_{cbj}		-0.0901	-0.0359*	-0.0284	-0.0133	-0.0121	0.0052	-0.0039
β_{qbj}		-1.3993	-2.2560	-0.3070	-0.1064	-0.0426	-1.0150*	1.0132**
β_{qvj}		0.7329**	-2.4463	-1.0466	0.1293	0.1791	-0.0800	0.5826*
Log-Likelihood		369.1420	369.6538	375.0039	366.6018	368.5308	367.6554	375.1558
AIC		-2.5387	-2.5423	-2.5807	-2.5204	-2.5343	-2.5280	-2.5818
SBIC		-2.6462	-2.6498	-2.6882	-2.6280	-2.6418	-2.6355	-2.6893
HQIC		-2.4603	-2.4640	-2.5024	-2.4421	-2.4560	-2.4497	-2.5034
Volatility regimes		23.0671**	24.0907**	34.7909***	17.9867*	21.8448**	20.0940**	35.0946***
Mixture of normals		22.2235**	23.2472***	33.9474***	17.1432*	21.0013**	19.2505**	34.2511***
Fads		22.5448**	23.5684***	34.2686***	17.4644*	21.3226**	19.5718**	34.5724***
VNS		19.4092***	20.4328***	31.1330***	14.3288**	18.1869**	16.4361**	31.4367***
Volume-augmented		9.4095*	10.4331*	21.1333***	4.3291	8.1872	6.4364	21.4370***
Model J-P		4.4512	5.3773*	1.0264	5.2645*	5.5847*	7.9246**	8.2546**
Model J-R		11.9040***	13.3123***	15.7713***	8.5794**	8.8076**	2.5780	0.0000
Model J-V		14.9771***	15.0282***	18.2669***	11.4815**	10.6504**	10.2860**	4.5310
Starting observation		Sep 1989	Sep 1989	Sep 1989	Sep 1989	Sep 1989	Sep 1989	Sep 1989
No of observations		279	279	279	279	279	279	279

Note: Results based on the Model J [equations (51) to (53)] ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 37 (continued)

Dependent Variable: Consumer Products								
Independent Variables	Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	0.9986***		0.9990***	0.9988***	0.9951***	0.9970***	0.9983***	1.0056***
β_{sb}	-0.0120		0.0091	-0.0086	-0.0187	-0.0058	-0.0035	-0.0506
β_{sv}	-0.0056		-0.0060	-0.0054	-0.0063	-0.0058	-0.0058	-0.0040
β_{co}	1.0010***		0.9864***	0.9963***	1.0037***	1.0074***	0.9963***	0.9745***
β_{cb}	-0.1700*		-0.1184**	-0.1134	-0.0917	-0.1290*	-0.1499*	-0.0658***
β_{qo}	1.0253**		1.1606***	1.3047***	0.6251	1.2489***	1.3957***	0.9189*
β_{qb}	-2.2364		-1.1119	-1.8612*	-2.5218**	-1.9929*	-1.5097	0.7488
β_{qv}	-0.0582		-0.0352	-0.0770	-0.2300	-0.0889	0.0325	-0.2208
σ_s	0.0420***		0.0397***	0.0432***	0.0413***	0.0424***	0.0420***	0.0932***
σ_c	0.1145***		0.1060***	0.1196***	0.1128***	0.1167***	0.1139***	0.0321***
β_{sbj}	0.0020		0.0066	-0.0118	-0.0070	-0.0162***	-0.0028	-0.0119
β_{svj}	0.0009		0.0037	0.0020	-0.0006	-0.0063	0.0026	0.0198
β_{cbj}	0.0586		0.0170	0.0071	-0.0161	-0.0442	0.0335	-0.0218***
β_{qbj}	0.4537		-0.9011	-0.1790	1.2284**	0.1045	-0.5757	-1.6209***
β_{qvj}	-0.1506		-0.5349	-0.2379	-0.0070	-0.3348	-0.8745**	-0.0406
Log-Likelihood	384.2292		385.9260	384.8625	387.3164	391.0015	388.2407	399.4167
AIC	-2.6468		-2.6590	-2.6513	-2.6689	-2.6954	-2.6756	-2.7557
SBIC	-2.7543		-2.7665	-2.7589	-2.7765	-2.8029	-2.7831	-2.8632
HQIC	-2.5685		-2.5807	-2.5730	-2.5906	-2.6170	-2.5972	-2.6774
Volatility regimes	16.8291		20.2227**	18.0958*	23.0035**	30.3737***	24.8521***	47.2041***
Mixture of normals	15.7080		19.1017**	16.9747*	21.8824**	29.2527***	23.7310***	46.0831***
Fads	13.7033		17.0969*	14.9700	19.8777**	27.2479***	21.7263**	44.0784***
VNS	4.3595		7.7531	5.6262	10.5339	17.9041**	12.3825*	34.7345***
Volume-augmented	2.2772		5.6709	3.5440	8.4516	15.8219***	10.3003*	32.6523***
Model J-P	1.4944		1.6373	1.0114	2.2118	3.3120	1.2416	2.3701
Model J-R	0.7298		3.5123	1.5019	1.6684	0.0000	9.3605***	1.6328
Model J-V	1.9868		5.5966	2.0865	3.3490	5.7645	10.5340**	4.1111
Starting observation	Sep 1989		Sep 1989	Sep 1989	Sep 1989	Sep 1989	Sep 1989	Sep 1989
No of observations	279		279	279	279	279	279	279

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 37 (continued)

	Dependent Variable: Financials							
Independent Variables	Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	1.0129***	1.0142***		1.0124***	1.0215***	1.0215***	1.0165***	0.9973***
β_{sb}	-0.0325	-0.0492**		-0.0200	-0.0556	-0.0495	-0.0413	-0.0185
β_{sv}	0.0167	0.0196*		0.0065	0.0177*	0.0284**	0.0145	0.0150*
β_{co}	1.0154***	1.0024***		1.0105***	1.0091***	1.0091***	1.0346***	1.0118***
β_{cb}	0.0005	0.0100		0.0028	0.0039	-0.0054	-0.0582	-0.0082
β_{qo}	1.1195***	1.0961***		1.0479***	0.4561	1.6276***	1.0038***	-1.1976*
β_{qb}	-0.6130	-0.6620		-1.5972***	-1.7855***	-1.9218***	-1.1189**	-0.8689
β_{qv}	-0.4160	-0.2727		-0.0359	-0.2719	-0.3240	-0.1564	0.1048
σ_s	0.0578***	0.0566***		0.0588***	0.0528***	0.0448***	0.0571***	0.0561***
σ_c	0.1820***	0.1819***		0.1932***	0.1771***	0.1589***	0.1854***	0.1782***
β_{sbj}	0.0125	0.0082		-0.0255**	0.0112	0.0002	0.0209	-0.0138*
β_{svj}	-0.0025	-0.0129*		0.0036	-0.0201*	-0.0274***	0.0016	-0.0058
β_{cbj}	0.0044	-0.0569		-0.0123	-0.0016	-0.0129	0.0648	0.0316
β_{qbj}	-1.7256	-3.0233*		-0.0005	0.6856*	-2.7306***	-0.7070	2.3730***
β_{qvj}	-0.1823	0.0387		-0.5358***	-0.1537	0.0804	-0.4163	-0.1315
Log-Likelihood	227.7673	229.9807		232.8103	228.4165	233.3333	229.4615	243.2113
AIC	-1.5252	-1.5411		-1.5614	-1.5299	-1.5651	-1.5374	-1.6359
SBIC	-1.6327	-1.6486		-1.6689	-1.6374	-1.6726	-1.6449	-1.7435
HQIC	-1.4469	-1.4628		-1.4830	-1.4516	-1.4868	-1.4590	-1.5576
Volatility regimes	23.8917**	28.3185***		33.9777***	25.1900***	35.0235***	27.2801***	54.7796***
Mixture of normals	23.6257***	28.0526***		33.7118***	24.9241***	34.7576***	27.0142***	54.5137***
Fads	23.8206***	28.2475***		33.9067***	25.1189***	34.9525***	27.2091***	54.7086***
VNS	9.4400	13.8668*		19.5260***	10.7383	20.5719***	12.8284*	40.3280***
Volume-augmented	5.0700	9.4969*		15.1561***	6.3684	16.2019***	8.4585	35.9580***
Model J-P	2.3409	6.1129**		0.7540	4.3070	11.9790***	2.2636	3.2828
Model J-R	0.7930	1.3290		10.4723***	3.0190	0.9605	3.7388	0.2494
Model J-V	4.1807	7.6451		13.2527**	7.0243	11.3216**	6.7231	3.3067
Starting observation	Sep 1989	Sep 1989		Sep 1989	Sep 1989	Sep 1989	Sep 1989	Sep 1989
No of observations	279	279		279	279	279	279	279

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 37 (continued)

				Dependent Variable: Industrials				
Independent Variables	Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	1.0083***	0.9998***	0.9985***		0.9970***	1.0028***	1.0017***	0.9953***
β_{sb}	-0.0652**	-0.0258**	-0.0299**		-0.0245*	-0.0517**	-0.0275**	-0.0297
β_{sv}	-0.0183	-0.0063	-0.0047		-0.0160	0.0004	-0.0089	-0.0121
β_{co}	1.0134***	1.0281***	1.0090***		1.0218***	1.0132***	1.0262***	1.0141***
β_{cb}	0.0045	0.0211	-0.0008		-0.0018	0.0044	0.0099	0.0005
β_{qo}	1.0425**	1.8298***	1.6156**		1.0288*	0.9601**	1.5001***	1.2835*
β_{qb}	-1.6861**	-0.6176	-0.6005		-0.5391	-1.7362*	-0.5591	-1.9948
β_{qv}	-1.2030**	-1.3505**	-0.9925		-1.6434	-0.9716**	-0.9616	-1.3162**
σ_s	0.0507***	0.0585***	0.0579***		0.0553***	0.0401***	0.0569***	0.0537***
σ_c	0.1112***	0.1276***	0.1267***		0.1151***	0.1030***	0.1256***	0.1136***
β_{sbj}	0.0298**	0.0180	0.0148		-0.0044	-0.0335***	0.0194	-0.0120*
β_{svj}	-0.0113	-0.0103	-0.0054		0.0035	-0.0224***	-0.0036	0.0017
β_{cbj}	-0.0084	0.0007	0.0469		0.0311	-0.0090	0.0309	-0.0029
β_{qbj}	-0.1174	-2.6389*	-1.1694		-0.3869	-0.8382	-0.5906	-0.1248
β_{qvj}	-0.4821	-0.1327	-0.3186		0.2895	0.1184	-1.1105**	0.1283
Log-Likelihood	325.1433	325.1114	325.7236		322.2619	327.4015	327.1896	322.6651
AIC	-2.2232	-2.2230	-2.2274		-2.2026	-2.2394	-2.2379	-2.2055
SBIC	-2.3308	-2.3305	-2.3349		-2.3101	-2.3470	-2.3454	-2.3130
HQIC	-2.1449	-2.1447	-2.1491		-2.1243	-2.1611	-2.1596	-2.1272
Volatility regimes	25.7305***	25.6665***	26.8909***		19.9675**	30.2469***	29.8230***	20.7740**
Mixture of normals	23.7607***	23.6968***	24.9212***		17.9978*	28.2771***	27.8532***	18.8042**
Fads	20.3205**	20.2566**	21.4810**		14.5576	24.8369***	24.4130***	15.3640
VNS	14.5532**	14.4893**	15.7137**		8.7903	19.0696***	18.6458***	9.5968
Volume-augmented	8.6859	8.6220	9.8464*		2.9230	13.2023**	12.7784**	3.7294
Model J-P	2.7930	2.6622	0.5364		0.9511	7.1024**	0.6225	0.4476
Model J-R	7.0775**	0.0000	4.7909*		3.8844	7.9093**	8.8107**	3.9883
Model J-V	7.1648	4.4152	8.2334*		4.1438	11.6985**	8.8746*	4.4927
Starting observation	Sep 1989	Sep 1989	Sep 1989		Sep 1989	Sep 1989	Sep 1989	Sep 1989
No of observations	279	279	279		279	279	279	279

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 37 (continued)

Dependent Variable: Property & Construction								
Independent Variables	Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	1.0045***	1.0009***	0.9881***	1.0050***		1.0116***	1.0091***	1.1110***
β_{sb}	-0.0050	-0.0087	-0.0153	0.0026		0.0308**	-0.0029	-0.0118***
β_{sv}	0.0144	0.0061	0.0005	0.0075		0.0057	0.0008	0.1836***
β_{co}	1.0115***	1.0011***	1.0333***	1.0285***		1.0407***	1.0123***	1.0042***
β_{cb}	-0.0090	-0.0056	0.0025	0.0023		-0.0328	-0.0091	0.0229*
β_{qo}	2.7347***	1.8632***	1.9154***	1.9174***		8.0734*	1.7608***	-1.4890***
β_{qb}	-1.1235**	-0.7802*	-0.8298	-1.0656**		-2.2814**	-0.9597*	1.9168***
β_{qv}	-0.1609	-0.1184	0.0455	-0.0749		0.4080	-0.0194	-0.5896
σ_s	0.0753***	0.0746***	0.0763***	0.0850***		0.0846***	0.0793***	0.0051***
σ_c	0.1753***	0.1747***	0.1831***	0.2051***		0.1703***	0.1923***	0.0971***
β_{sbj}	0.0041	0.0192	0.0741	-0.0110		-0.0793***	0.0421	0.1673***
β_{svj}	-0.0082	-0.0093	-0.0002	-0.0040		-0.0091	-0.0037	0.5474***
β_{cbj}	-0.0066	-0.1066	-0.0493	-0.0727		0.0259	-0.0256	-0.0192**
β_{qbj}	-4.2197***	-3.9999**	-1.6380*	-0.4048		-8.8264	-0.6314	-2.9005***
β_{qvj}	0.2994	0.1228	-0.4640	-0.2419		-0.9955	-0.6434	-0.1764
Log-Likelihood	238.2307	237.3528	239.5700	232.1676		245.2265	236.0743	261.6985
AIC	-1.6002	-1.5939	-1.6098	-1.5568		-1.6504	-1.5848	-1.7684
SBIC	-1.7077	-1.7015	-1.7173	-1.6643		-1.7579	-1.6923	-1.8760
HQIC	-1.5219	-1.5156	-1.5315	-1.4784		-1.5721	-1.5064	-1.6901
Volatility regimes	25.4437***	23.6881**	28.1224***	13.3176		39.4354***	21.1311**	72.3795***
Mixture of normals	25.1468***	23.3912***	27.8255***	13.0207		39.1385***	20.8342**	72.0826***
Fads	25.4113***	23.6557***	28.0899***	13.2852		39.4030***	21.0986**	72.3470***
VNS	16.5549**	14.7993**	19.2336***	4.4288		30.5466***	12.2423*	63.4907***
Volume-augmented	15.3148***	13.5592**	17.9934***	3.1887		29.3065***	11.0021*	62.2505***
Model J-P	1.5115	1.4238	0.0012	0.3329		0.7125	0.0505	67.8672***
Model J-R	0.8679	0.4010	2.8682	0.9860		0.9967	3.8730	49.8871***
Model J-V	2.4987	1.7826	3.0372	2.0352		1.7106	4.2998	69.6681***
Starting observation	Sep 1989	Sep 1989	Sep 1989	Sep 1989		Sep 1989	Sep 1989	Sep 1989
No of observations	279	279	279	279		279	279	279

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 37 (continued)

Independent Variables	Dependent Variable: Resources							
	Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	1.0063***	1.0042***	0.9959***	1.0102***	1.0092***		1.0073***	1.0152***
β_{sb}	-0.0783***	-0.0683***	-0.0912***	-0.0275*	-0.0747***		-0.0710***	-0.0703***
β_{sv}	-0.0004	-0.0047	-0.0320***	-0.0150	-0.0018		-0.0385***	-0.0072
β_{co}	1.0180***	1.0274***	1.0343***	1.0176***	1.0271***		1.0170***	1.0176***
β_{cb}	0.0007	0.0013	0.0065	-0.0109	0.0188		0.0080	0.0375
β_{qo}	1.0193**	0.8827**	0.4022	8.0541**	0.9877**		0.3975	0.5793
β_{qb}	-2.0332***	-1.9653**	-1.1092**	-10.4045**	-2.0350***		-2.1084***	-2.0458**
β_{qv}	-0.4127	-0.2780	0.2000	-3.2057*	-0.5337		0.0245	-0.2430
σ_s	0.0535***	0.0541***	0.0461***	0.0650***	0.0580***		0.0422***	0.0617***
σ_c	0.1285***	0.1299***	0.1159***	0.1277***	0.1324***		0.1143***	0.1346***
β_{sbj}	-0.0153	-0.0378	0.0693***	0.0064	0.0132		0.0389***	0.0116
β_{svj}	-0.0166**	-0.0054	0.0035	-0.0112	-0.0043		-0.0227	0.0043
β_{cbj}	-0.0343	0.0148	-0.0441**	0.0034	-0.0230		-0.0589**	-0.0490
β_{qbj}	-0.0988	0.4356	-0.6529	-8.2385*	0.2688		0.5804	0.8525*
β_{qvj}	0.1982	0.1235	0.4248*	-2.0475*	0.9295**		-0.4613	0.4915
Log-Likelihood	265.9017	263.6028	267.1910	268.8621	267.0869		267.3488	267.2573
AIC	-1.7986	-1.7821	-1.8078	-1.8198	-1.8071		-1.8090	-1.8083
SBIC	-1.9061	-1.8896	-1.9153	-1.9273	-1.9146		-1.9165	-1.9158
HQIC	-1.7203	-1.7038	-1.7295	-1.7415	-1.7288		-1.7306	-1.7300
Volatility regimes	15.1568	10.5590	17.7354*	21.0775**	17.5271*		18.0510*	17.8679*
Mixture of normals	15.1555	10.5577	17.7341*	21.0763**	17.5259*		18.0497*	17.8666*
Fads	11.7068	7.1090	14.2854	17.6276*	14.0771		14.6010	14.4179
VNS	7.9218	3.3240	10.5005	13.8426*	10.2922		10.8160	10.6330
Volume-augmented	6.0963	1.4985	8.6750	12.0171**	8.4667		8.9905	8.8075
Model J-P	4.6897*	1.2692	6.0716**	1.4407	0.4390		7.3808**	0.6242
Model J-R	1.7503	0.2774	4.6933*	7.0900**	1.8101		1.5875	2.7020
Model J-V	5.5217	2.3027	7.5947	8.6055*	8.7377*		8.4506*	4.4600
Starting observation	Sep 1989	Sep 1989	Sep 1989	Sep 1989	Sep 1989		Sep 1989	Sep 1989
No of observations	279	279	279	279	279		279	279

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 37 (continued)

	Dependent Variable: Services							
Independent Variables	Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	1.0126***	1.0120***	1.0164***	1.0118***	1.0087***	1.0106***		1.0171***
β_{sb}	-0.0019	-0.0035	0.0040	-0.0067	0.0198	0.0137		0.3204***
β_{sv}	0.0252***	0.0299***	0.0299***	0.0203**	0.0283***	0.0220**		0.0484***
β_{co}	0.9581***	0.9271***	1.0033***	0.9962***	0.9851***	0.9732***		1.0004***
β_{cb}	-0.0105	0.0238	0.1321	0.0064	0.0045	-0.0345		-0.0006
β_{qo}	2.3769***	2.4064***	2.2723***	1.9673***	2.0509***	2.2763***		-1.2651**
β_{qb}	-1.7829**	-1.5130**	-2.0935***	-1.9617***	-1.7639***	-1.2523*		-0.3708
β_{qv}	-0.6598	-0.7658*	-0.3797	-0.3360	-0.5455	-0.7010*		0.2801
σ_s	0.0608***	0.0612***	0.0598***	0.0551***	0.0590***	0.0608***		0.0127***
σ_c	0.1558***	0.1538***	0.1422***	0.1336***	0.1534***	0.1745***		0.0677***
β_{sbj}	0.0125	0.0192	-0.0212	-0.0306***	-0.0212***	-0.0233***		0.1094***
β_{svj}	0.0006	-0.0067	-0.0038	0.0001	-0.0043	-0.0043		0.0242***
β_{cbj}	-0.0350	-0.2176	-0.1933	-0.0003	-0.0202	0.0211		-0.0214***
β_{qbj}	-0.2178	-0.5809	0.3488	-0.0684	0.2310	-0.0794		-0.5417
β_{qvj}	0.0873	0.3371	-0.3267	-0.5310	-0.0872	-0.0004		0.1621
Log-Likelihood	344.3840	345.5936	346.8427	349.4071	347.9680	348.2696		347.7018
AIC	-2.3612	-2.3698	-2.3788	-2.3972	-2.3869	-2.3890		-2.3850
SBIC	-2.4687	-2.4774	-2.4863	-2.5047	-2.4944	-2.4966		-2.4925
HQIC	-2.2829	-2.2915	-2.3005	-2.3189	-2.3086	-2.3107		-2.3066
Volatility regimes	25.1345***	27.5537***	30.0518***	35.1807***	32.3025***	32.9056***		31.7702***
Mixture of normals	25.0164***	27.4356***	29.9337***	35.0626***	32.1844***	32.7875***		31.6521***
Fads	24.7366***	27.1559***	29.6540***	34.7829***	31.9046***	32.5078***		31.3723***
VNS	15.2147**	17.6339**	20.1321***	25.2609***	22.3827***	22.9858***		21.8504***
Volume-augmented	2.1589	4.5781	7.0763	12.2051**	9.3269*	9.9301*		8.7946
Model J-P	8.5935**	9.4860***	11.3549***	4.9687*	9.0747**	6.2999**		0.0000
Model J-R	2.1475	3.6045	2.0242	5.9136*	2.8563	3.9980		4.6177*
Model J-V	13.6858***	15.5180***	16.9029***	14.2622***	14.4060***	11.8983**		13.5545***
Starting observation	Sep 1989	Sep 1989	Sep 1989	Sep 1989	Sep 1989	Sep 1989		Sep 1989
No of observations	279	279	279	279	279	279		279

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 37 (continued)

Dependent Variable: Technology								
Independent Variables	Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	1.1085***	0.9901***	0.9922***	1.1038***	1.0627***	1.0998***	1.0834***	
β_{sb}	0.0564	-0.0195***	-0.0163***	0.0984	0.2049*	0.0804	0.0462	
β_{sv}	0.2197*	-0.0043	-0.0051	0.2068*	0.1450	0.1978	0.1824	
β_{co}	0.9919***	1.0102***	1.0700***	0.9917***	0.9925***	0.9925***	0.9927***	
β_{cb}	-0.0172***	0.0771	0.1350	-0.0167***	-0.0214***	-0.0168**	-0.0168***	
β_{qo}	-0.1067	0.2563	0.6138*	-0.6482**	-0.4230	-0.1741	-0.2097	
β_{qb}	-1.2938***	1.3105***	1.0743***	-1.6088***	-1.6419***	-1.2861***	-1.2751***	
β_{qv}	-0.4159*	0.3641	0.4745**	-0.5541**	-0.6588**	-0.4529**	-0.8093***	
σ_s	0.3254***	0.0646***	0.0677***	0.3304***	0.3048***	0.3259***	0.3161***	
σ_c	0.0682***	0.3217***	0.3436***	0.0697***	0.0675***	0.0682***	0.0670***	
β_{sbj}	0.0287	-0.0425	0.0174	-0.0799	-0.1772**	-0.0275	0.0361	
β_{svj}	-0.0393	-0.0099	-0.0112	-0.0237	0.0378	-0.0263	0.0489	
β_{cbj}	-0.0029	-0.2240	-0.1117	-0.0067	0.0102	0.0000	0.0040	
β_{qbj}	-0.0688	-0.9920	-0.7271*	1.3965**	0.8288**	0.0328	0.0193	
β_{qvj}	0.0404	-0.0181	-0.2720	0.4811**	0.4450*	0.1854	0.8444**	
Log-Likelihood	237.8930	242.2538	241.6435	245.8369	245.1723	238.2418	241.5299	
AIC	-1.5978	-1.6291	-1.6247	-1.6547	-1.6500	-1.6003	-1.6239	
SBIC	-1.7053	-1.7366	-1.7322	-1.7623	-1.7575	-1.7078	-1.7314	
HQIC	-1.5195	-1.5507	-1.5464	-1.5764	-1.5717	-1.5220	-1.5456	
Volatility regimes	30.1743***	38.8960***	37.6752***	46.0620***	44.7328***	30.8720***	37.4481***	
Mixture of normals	27.2852***	36.0068***	34.7860***	43.1729***	41.8437***	27.9828***	34.5589***	
Fads	23.5317***	32.2533***	31.0326***	39.4194***	38.0902***	24.2293***	30.8055***	
VNS	6.3018	15.0235**	13.8027*	22.1895***	20.8604***	6.9995	13.5756*	
Volume-augmented	1.5461	10.2677*	9.0469	16.3519***	16.1046***	2.2437	7.7380	
Model J-P	3.3756	4.3789	4.5198	3.2353	3.1928	3.2382	4.0865	
Model J-R	4.3271	3.8601	5.5552*	0.0000	2.6904	5.0045*	10.5229***	
Model J-V	6.0917	7.6796	9.9282**	12.6683**	9.4417*	6.8973	13.2161**	
Starting observation	Sep 1989	Sep 1989	Sep 1989	Sep 1989	Sep 1989	Sep 1989	Sep 1989	
No of observations	279	279	279	279	279	279	279	

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

The robustness checks against other models reveal that Model J is better than most of the simpler specifications, namely the volatility regime, the fads, and the VNS models. However, it only improves from the basic volume-augmented models in about 48% of all the cases. This test against the volume-augmented models also serves as block exogeneity test for Model J. The results are also summarised in Table 38. In general, it shows several linkages to and from the Industrials, Services and Technology to other industry groups, while the Resources industry group receives very limited influence from others but develops bubbles before some of them. Remarkably, the test picks up only a few linkages between the Financials industry group with others. Moreover, it discovers only a couple of cases of transmission from Property & Construction industry group although it is affected by bubbles in all other industry groups except Industrials.

The robustness tests against the Model types P, R, and V – where the volume terms are dropped – are only statistically significant in about 32%, 34%, and 48% of all the cases, respectively. This is consistent with the majority of the trading-volume parameters being statistically insignificant as discussed earlier.

When considering the results for each industry group, there are a number of points to take note of. Firstly, the specifications with Agro & Food industry group as the dependent variable always yield positive $\beta_{sv}^{AGRO,j}$, which are statistically significant in five out of seven cases, and $\beta_{qv}^{AGRO,j}$ which are all negative and statistically significant in four cases. Similarly, the $\beta_{sv}^{FINCIAL,j}$ for Financials industry group as the dependent variable are all positive with four cases of statistical significance. These suggest the importance of abnormal trading volume of Agro & Food and Financials industry groups in determining their own returns. In the cases where Agro & Food industry group is included as the additional independent industry group, the models are not better than basic volume-augmented models, except for a case with Property & Construction. Thus, Agro & Food industry group has a very limited linkage to others.

Table 38: Block Exogeneity Test for Model J

Model J	**Independent Variables**								
Dependent Variables		Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
	Agro & Food	N/A	*	*	***				***
	Consumer Products		N/A				***	*	***
	Financials		*	N/A	***		***		***
	Industrials			*	N/A		**	**	
	Property & Construction	***	**	***		N/A	***	*	***
	Resources				**		N/A		
	Services				**	*	*	N/A	
	Technology		*		***	***			N/A

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively. This is equivalent to performing the log-likelihood ratio test between Model J and the basic Volume-augmented model.

The impact from the bubble on Industrials industry group tends to work through the return equation, while the influence of the trading volume appears to affect the probability of surviving. This is shown by the results that β_{sb}^{ij} and β_{qv}^{ij} are always positive, as expected, and they are statistically significant in six and four cases, respectively. It is the opposite for the Services industry group, where β_{sv}^{ij} and β_{qb}^{ij} are very important in many cases, which suggest strong effects of trading volume on returns and bubble on the probability instead.

The effect of bubble size on the probability of bubble surviving, β_{qb}^{ij}, when investigating the Property & Construction industry group is very crucial. The estimates are negative in almost all the cases, except for PROPCON-TECH, and are also statistically significant in almost all the cases, except for PROPCON-FINCIAL. Meanwhile, the effect from bubble from another industry group, β_{qbj}^{ij}, tend to be quite large and four cases are statistically significant. For instance, they are -4.2197, -3.9999, -1.6380, and -2.9005 in the cases of PROPCON-AGRO, PROPCON-CONSUMP, PROPCON-FINCIAL, and PROPCON-TECH, respectively. This means the expected probabilities of a bubble in the Property & Construction industry group surviving are heavily affected by the bubble contagious from several other industry groups.

Besides, the trading volumes of either the Property & Construction or any additional independent variable industry groups, except for Technology, do not seem to be relevant in explaining the returns of the industry group. This is reflected by the fact that all the volume-related parameters ($\beta_{sv}^{ij}, \beta_{qv}^{ij}, \beta_{svj}^{ij}$and β_{qbj}^{ij}) turned out to be statistically insignificant and the tests against the model type P, R, and V where volume terms are left out were also not rejected. A similar result is found in the case of Consumer Products industry group as a dependent variable. There, out of 28 parameters, only the $\beta_{qv}^{CONSUMP,SERVICE}$ was found to be statistically significant.

The Resources industry group is strongly influenced by the relative bubble terms. When investigating the Resources industry group, the $\beta_{sb}^{RESOURC,j}$are all statistically significant although they are all negative and smaller than $\beta_{cb}^{RESOURC,j}$, contradicting the intuition from the theory, while the $\beta_{qb}^{RESOURC,j}$ are all statistically significant and negative as expected. However, it is important to also note that the specifications almost always are not better than simpler fads, VNS, and volume-augmented models, except for the case with Industrials industry group. This explains the limited linkage from other industry groups to the Resources. When the Resources industry group is the additional independent variable, it yields six cases of negative $\beta_{sb}^{RESOURC,j}$, except for Financials, and five of them are statistically significant, except for Financials and Technology. It also correlates with cases of all negative $\beta_{qb}^{RESOURC,j}$and they are all statistically significant, except for Agro & Food as a dependent variable.

Finally, the Technology industry group is the most notable in several ways. Investigation of the returns in Technology industry group found five cases of negative and statistically significant effect of relative bubble on the return in the collapsing regime ($\beta_{cb}^{TECH,j}$), while the other two cases of positive $\beta_{cb}^{TECH,j}$are found to be statistically insignificant. In the probability equation, both the $\beta_{qb}^{TECH,j}$and $\beta_{qv}^{TECH,j}$ are all statistically significant, though they are unexpectedly negative in the cases where Consumer Products and Financials are the additional industry group. However, the average probability estimates, $\beta_{qo}^{TECH,j}$, are mostly statistically insignificant, suggesting the average probability that is no different from 50%. The magnitudes of the standard deviations in the two regimes, as reported earlier, are contradicting the expectations in many cases. The surviving regime was found to be more volatile than when the bubble collapses, except for TECH-CONSUMP and TECH-FINCIAL again.

For the specifications where Technology was included as the second industry group, the effects of relative bubble terms from Technology on returns of the particular industry group being studied are quite strong. The impact on the state-determining probability equation ($\beta_{qb}^{i,TECH}$), are statistically significant in five cases although they only have the expected negative signs in CONSUMP-TECH and PROPCON-TECH. The influence on the returns when the bubble survives ($\beta_{sb}^{i,TECH}$) are also statistically significant in five cases, though they have mixed signs as well. The parameter, $\beta_{cb}^{i,TECH}$, which illustrate the impact of a bubble from Technology on returns of another in other industry group, are negative as expected, except for Financials. However, only three of them are statistically significant, namely, the cases with Consumer Products, Property & Construction, and Services.

The contagion from Technology to other industry groups via trading volume is quite limited. This is shown by the parameter $\beta_{sv}^{i,TECH}$. While they have the expected positive signs in almost all the cases, except for Financials, the estimates are only statistically significant in two cases of Property & Construction and Services. Moreover, the estimates of $\beta_{qv}^{i,TECH}$, which captures the effect of Technology's trading volume on the probability equations, are almost always statistically insignificant and have mixed signs.

7.2.4. Comparison of Results from Model A and Model J

As the Model J is actually nested in the Model A, results from the two models can be compared with Log-likelihood Ratio (LR) test to determine whether the Model A offers an improvement over the more parsimonious Model J. The results are presented in Table 39.

Overall, the evidence reveals 30 cases of LR test rejection, which suggests the Model A is mostly preferred to Model J, while the null hypothesis that Model J is the true model is not refuted in four other cases – two in Financials and two others in Property & Construction and Services. There are also 22 other cases (approximately 39% of all the cases) which were reported as invalid. This refers to a situation where maximised likelihood statistics from the Model J is unexpectedly higher than that of the comparable Model A. This is totally counterintuitive because the larger model should, at least, have the same likelihood statistics at optimal. The problem is believed to be caused by the inefficient estimations of the Model A in that it may contain too many parameters to be efficiently estimated. Even though attempts to reiterate the optimisations with multiple sets of randomised starting values were included in the MATLAB code, it is extremely difficult to predict in advance the suitable magnitudes of 45 different parameters. The issue is observed primarily in cases where Financials, Industrials, Property & Construction, Resources, and Technology industry groups are the independent variables, and Consumer Products and Services are the dependent variables. Therefore, these results are to be interpreted with some caution.

Table 39: Log-Likelihood Ratio Test – Model A vs. Model J

H_o: The reduced model (i.e. Model J) is true

LR Test	Independent Variables								
Dependent Variables		Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
	Agro & Food	N/A	67.6761***	Invalid	Invalid	Invalid	Invalid	35.4763	Invalid
	Consumer Products	61.9269***	N/A	Invalid	Invalid	Invalid	Invalid	Invalid	Invalid
	Financials	374.8506***	345.9985***	N/A	232.5167***	52.3901***	114.1027***	311.8641***	140.9148***
	Industrials	180.0985***	155.7373***	Invalid	N/A	Invalid	Invalid	116.4080***	Invalid
	Property & Construction	353.9239***	331.2543***	17.4386	233.8022***	N/A	90.3162***	298.6385***	103.9403***
	Resources	298.5818***	278.7544***	Invalid	160.4132***	Invalid	N/A	236.0896***	92.8228***
	Services	141.6172***	114.7728***	Invalid	Invalid	Invalid	Invalid	N/A	Invalid
	Technology	354.5992***	321.4523***	13.2917	206.4637***	18.8784	104.2855***	287.7274***	N/A

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 40 shows the results from the Model A and Model J, as well as, the LR tests between them. Firstly, the evidence is somewhat alike. On the whole, they offer the same conclusions in 28 cases – which is 50% of all the cases – with 15 cases of no contagion detected and 13 cases of some level of linkages between industry groups.

Secondly, test invalidity occurs in 22 cases, as pointed out previously. However, there are nine cases where the two models have the same implication. Precisely, they include four cases of some evidence of contagion and five other cases of no evidence at all. This leaves only 13 cases of inconclusive results.

Lastly, the shaded cells in Table 40 indicate a presence of contagion as detected by the preferred model or that both models found some evidence of linkages. Table 41 concludes the number of cases where each industry group is found to be connected with others. It also considers the cases of inconclusive results as possible linkages.

Table 40: Comparison between Model A and Model J

	Independent Variables	Agro & Food		Consumer Products		Financials		Industrials		Property & Construction		Resources		Services		Technology	
Dependent Variables	**Test\Model**	**A**	**J**	**A**	**J**	**A**	**J**	**A**	**J**	**A**	**J**	**A**	**J**	**A**	**J**	**A**	**J**
Agro & Food	**BE**	N/A		***	*	***	*	***	***	***		***				***	***
	LR			*A*		*Invalid – S*		*Invalid – S*		*Invalid*		*Invalid*		*J*		*Invalid – S*	
Consumer Products	**BE**	***		N/A		*		*		***			***		*		***
	LR	*A*				*Invalid*		*Invalid*		*Invalid*		*Invalid*		*Invalid*		*Invalid*	
Financials	**BE**	***		***	*	N/A			***	***			***			***	***
	LR	*A*		*A*				*A*		*A*		*A*		*A*		*A*	
Industrials	**BE**						*	N/A				**	**		**		
	LR	*A*		*A*		*Invalid*				*Invalid – N*		*Invalid – S*		*A*		*Invalid – N*	
Property & Construction	**BE**		***	**	**	*	***			N/A			***		*	***	***
	LR	*A*		*A*		*J*		*A*				*A*		*A*		*A*	
Resources	**BE**								**			N/A					
	LR	*A*		*A*		*Invalid – N*		*A*		*Invalid – N*				*A*		*A*	
Services	**BE**	***							**		*		*	N/A		***	
	LR	*A*		*A*		*Invalid – N*		*Invalid*		*Invalid*		*Invalid*				*Invalid*	
Technology	**BE**	***		***	*	***		***	***	***	***	***		***		N/A	
	LR	*A*		*A*		*J*		*A*		*J*		*A*		*A*			

Note: *BE* stands for Block Exogeneity Tests, while *LR* refers to Log-likelihood Ratio Tests where *A* and *J* mean either Model A or Model J is preferred, respectively, and *Invalid* denotes cases where the maximised likelihood statistics from Model A were unexpectedly lower than Model J's, while *Invalid – S* and *Invalid – N* are cases where the LR tests are invalid, but the results from both models found either some level of linkages (*S*) or no linkage between the two industry groups (*N*) at all, respectively. The shaded cells are specifications with contagion detected. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 41: Total Number of Linkages To and From Industry Groups

Industry Group	Contagion To	Contagion From	Total Linkages	With Possible Additional Contagion To	With Possible Additional Contagion From	Total Possible Linkages
Agro & Food	4	4	8	6	4	10
Consumer Products	1	4	5	7	4	11
Financials	4	2	6	4	4	8
Industrials	1	2	3	2	4	6
Property & Construction	3	2	5	3	5	8
Resources	0	2	2	0	5	5
Services	1	1	2	5	2	7
Technology	6	3	9	6	5	11

Note: *Possible additional contagion* refers to cases where the LR test is invalid, and the results from Model A and Model J are inconclusive.

As per general view, the Technology industry group is found to be the most interconnected with contagion to six other industry group (except Financials) and from three industry groups, which can potentially increase to five. Consumer Products, Financials, and Property & Construction are also reasonably contagious with several other industry groups, as expected, although the result for Consumer Products could change dramatically with the cases of test invalidity. On a contrary, the results of the Agro & Food industry group is rather surprisingly. The evidence suggests that it is quite heavily linked with other industry groups.

Finally, Resources is the most isolated industry group, as it does not seem to pass on effect to returns of any other industry groups, though it appears to develop bubbles following a few others. Services and Industrials are also found to have quite limited linkages with other industry groups, although that may be different with the inconclusive results.

7.2.5. Granger Causality Tests

An alternative methodology for analysing contagion between industry groups is to conduct Granger Causality tests. It detects an existence of the independent variable in the past preceding the dependent variable and therefore can be used as evidence of spillovers. Both the returns and relative bubble terms were investigated.

The results from the pairwise Granger Causality tests using returns from different industry groups are reported in Table 42. In general, they are similar to those obtained from the Model A discussed above. Resources industry group remains essentially isolated – now with no connection to other industry groups although a link to Consumer Products was detected – while Technology still is the most interconnected industry group having had its returns preceded several industry groups and followed many of them. The results for Services industry group show additional links to three other industry groups and from several new industry groups.

Fewer cases of directions from Financials and Industrial industry groups were picked up, but additional cases of influence on them from other industry groups were also detected. Lastly, Property & Construction was found to be more independent from others, but there are still flows to and from Financials and to Technology industry groups.

Table 43 presents evidence from the Granger Causality tests on the relative bubble term. Overall, the test reveals slightly fewer cases of linkages between bubbles from different industry groups than those detected with the Model A, but comparable to the Granger Causality tests on returns although the exact pairs are somewhat different. Financials, Industrials, Property & Construction, and Technology industry groups remain heavily connected with others, as their bubbles form before the existence of a bubble in many other industry groups. However, bubbles in these industry groups only follow bubbles in only a few others. Meanwhile, Resources and Services industry groups are shown to have limited linkages with others, in terms of bubble formation.

In conclusion, the results from Granger Causality tests partially support evidence suggested by the speculative bubble models. Precisely, Financial, Industrials, and Technology industry groups are found to be strongly linked with several other industry groups in the market, although the evidence on the returns and the bubble terms are less clear on the lead-lag relationships between them. Resources industry group is predominantly unconnected to others in all sets of evidence. Property & Construction and Services industry groups have somewhat inconsistent results. The former is unexpectedly shown to be quite cut off from other industry groups with the Granger Causality on returns, while the same analysis also reveals additional links of Services with other industry groups although other sets of results seem to imply it is relatively isolated.

Table 42: Granger Causality Test: Returns

H_o: The independent variable does not Granger-cause the dependent variable

Returns	**Independent Variables**								
		Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
Dependent Variables	Agro & Food	N/A	3.2495*	0.5553	0.4496	0.0353	1.6846	1.0621	5.3724***
	Consumer Products	5.8171***	N/A	0.2261	0.0516	1.9113	0.8617	0.2389	5.4961***
	Financials	2.8638*	2.7405*	N/A	2.9218*	4.7280**	2.4585	6.8082***	2.9122*
	Industrials	10.9360***	9.4524***	0.0488	N/A	1.7089	0.8016	4.7033**	1.1342
	Property & Construction	1.6723	2.4224	3.9286**	1.6540	N/A	1.2126	4.4632**	2.2176
	Resources	0.3646	3.7404*	0.3276	1.0314	0.6128	N/A	0.3656	0.9496
	Services	0.8266	4.3660**	5.4512***	4.6178**	0.0987	2.0805	N/A	5.4674***
	Technology	6.6457***	5.3542***	5.9705***	0.0885	7.4298***	0.4757	5.8736***	N/A

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table 43: Granger Causality Test: Relative Bubble Terms

H_o: The independent variable does not Granger-cause the dependent variable

Bubbles	**Independent Variables**								
Dependent Variables		Agro & Food	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
	Agro & Food	N/A	5.5251***	6.8009***	8.2156***	9.4919***	2.2141	5.1967**	9.8415***
	Consumer Products	8.4421***	N/A	4.5324***	4.4578**	8.1480***	2.3358	0.4391	6.5735***
	Financials	1.7802	4.6295**	N/A	0.8814	2.1928	0.2451	1.2898	0.2358
	Industrials	2.7535*	2.5919	5.8541***	N/A	4.3671**	2.1134	2.1970	4.2712**
	Property & Construction	4.0859**	8.0386***	1.5177	5.3416***	N/A	1.5627	1.0479	3.1127*
	Resources	0.5257	1.0582	5.1846**	0.1129	0.2280	N/A	4.8513**	0.2522
	Services	0.8352	0.0219	10.4853***	1.1729	5.2175***	0.5636	N/A	6.3534***
	Technology	1.3044	1.3730	3.2692*	3.2928*	2.0183	6.8936***	1.7605	N/A

Note: ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

7.3. Conclusions

The previous chapter tested the existence of speculative bubbles in various sectors or industry groups in the Thai stock market and found most of them with at least some evidence of bubbles. This chapter sets out to investigate the contagion or the transmission of bubbles between them. The analysis includes both variants of speculative bubble models and the Granger-Causality tests.

Specifically, the channels for the effects coming other industry groups or the overall market index are built into the basic regime-switching models. The first specification, Model A, allows for impacts from all other industry groups. However, the model would include a large number of parameters to be estimated. Therefore, a simpler Model J is also adopted to study the linkages between two industry groups at a time. Overall, the evidence implies that Technology is the most contagious industry group, while Resources is the most isolated. This may suggest a distinction between the characteristics of the new-economy, tech-related shares and those in the traditional resource-based sectors. Meanwhile, Financials, Industrials, and Property & Construction are moderately linked with several other industry groups. Moreover, it also reveals that the Agro & Food and Consumer Products are quite heavily interconnected with other industry groups, which is somewhat unexpected. Unfortunately, the results are rather inconclusive for the Services industry group.

The chapter also explores an alternative approach to capture impact from outside a particular industry group by assuming the market-wide index as a proxy in Model M. The baseline specification yields an expected result that all industry groups are affected by the market as a whole. However, the three model sub-types, based on different sets of abnormal volume term dropped, offer an interesting insight. With the Model A, several industry groups are affected by all other industry groups through their return equations, rather than via the probability equation, whereas the opposite finding is discovered when Model M is applied. In other words, a bubble in the overall market is associated with a bubble in individual industry group collapsing in the next period, while the bubbles in other industry groups tend to directly affect the next-period return of a particular industry group.

The last part of the chapter examined the linkages between industry groups with the Granger Causality tests. In general, the evidence is fairly in support of the conclusion found in the previous section. Specifically, the results based on returns of the different pair of industry groups reveal that the return of the Consumer Products precedes return of six other industry groups. This is reasonable as the performance of this industry group relies on purchasing power of consumers, and a strong demand for consumption could support profits in other industry groups as well. In contrast, the performance of financial intermediaries typically lags behind the economy. For example, after the economy slows down, non-performing loans at commercial banks would begin to rise. This is supported by the evidence that return of the Financials industry group follows six others. As for the results based on the bubble terms, the evidence indicates that bubbles in Financials and Technology industry groups precede most of the others, which would be in line with the popular opinion.

Chapter 8: Conclusions

This study was set out to examine the existence and the transmission of bubbles in the Thai stock market from its foundation in April 1975 until December 2012. It has applied several variants of regime-switching bubble models to detect bubble-like behaviour, as well as, the linkages between bubbles in different industry groups in the Thai market.

The first empirical chapter investigated a bubble in the aggregate market index. The results from the volume-augmented regime-switching bubble model suggested some evidence of a bubble in the SET index. The chapter also presented various robustness checks, as well as, extensions to the base model. Particularly, some of the specifications allowed for structural breaks in the Thai stock returns. Thailand replaced the fixed exchange rate regime for a managed float system in July 1997. Indeed, the model including one intercept dummy variable as a proxy for the break starting from July 1997 was proved to better at capturing return variability than the standard model. However, when the breakpoint was set to be determined by the model, it was revealed to be in at the end of June 1990 which overlapped with the period when the Thai government introduced financial liberalisation policies. More interestingly, the model with two endogenous breaks was able to illustrate the important effect of the 1997 Asian Financial Crisis by pointing out September 1996 and August 1998 as the most appropriate structural breaks. The analysis of implied probabilities statistics from the regime-switching models was also shown to be mostly consistent with the actual performance of the index, which supports the methodology choice.

The second empirical chapter analysed the disaggregated indices. Series from different datasets were investigated, and the general conclusion was that there was at least some evidence in various segments in the Thai stock market. The first set was the official SET's industry group. However, the complete data suitable for the volume-augmented regime-switching bubble models was only available from December 2007. Once allowed for an initial burn-in period for fundamental value computations, it only contained 49 observations, which was arguably too short to produce convincing evidence. The disaggregated SET's sectoral indices were considered next. The eight industry groups can be sub-divided into 27 sectors. The majority of the sectoral indices are most fitting with the model with two structural breaks on September 1996 and August 1998. Financials, Industrials, and

Technology are three industry groups which had one of their sectors (Banking, Industrial Materials & Machinery, and Information & Communication Technology, respectively) detected with strong evidence of bubble presence. Some evidence were also found in many other sectors from every industry groups. Then, the Datastream-calculated indices were investigated. Similarly, more than half of the indices were found to work best with the model with two intercept dummy variables. The results showed strong evidence of bubbles in Consumer Goods, Consumer Services, and Financials stocks, while some evidence were also detected in Health Care, Industrials, and Utilities. However, these outcomes are to be interpreted with caution, as there was an issue with dividend yields reported as zero for extended periods in some of the indices. The classification of stocks by Datastream was also inconsistent with the official SET's indices.

All the different datasets had certain limitations, for instance, availability of the industry group indices, tractability working with 27 sectoral indices, and reliability of the Datastream-calculated indices. As a result, a new set of indices, called the K-NI, was proposed by the author. It was constructed by imitating the computations of the SET's industry group and sectoral indices but only grouped into eight industry groups and extended as far back as 1988. All the K-NI industry groups were best suited to the model with two structural breaks, except for the Technology industry group where it was no better than the basic volume-augmented model. The results showed at least some level of evidence in every industry groups, except the Resources.

Comparing the evidence from these first two chapters on the aggregate market index and the disaggregated indices, they were consistent with Jung and Shiller (2005) who put forward that aggregation would average out impacts from individual constituent stocks or indices and make evidence of bubbles less apparent.

Transmission of bubbles between industry groups within the Thai stock market was studied in the third empirical chapter. The standard regime-switching models were extended in three key settings. The first was to include impacts of all other industry groups, called the Model A. Model M was the second specification, and it allowed for influence from the market index on individual industry groups. Lastly, the pairwise contagion between each two industry groups was assessed with Model J. Moreover, as the Model J is nested within the full Model A,their results can be compared with log-likelihood ratio tests. The main findings were that Technology appeared to be most heavily linked with other industry groups, while some evidence of contagion were found in other popular industry groups, namely, Financials, Industrials, and Property & Construction, as well. Surprisingly, evidence of bubble transmission was also detected in Agro & Food and Consumer Products. The results for Services was ambiguous, which leaves Resources to be the only industry group that is relatively separated from others.

In addition, as the number of parameters to be estimated in the complete bubble contagion models was quite large, the more parsimonious models where the volume terms were removed in certain ways were also taken into considerations. It revealed an interesting feature of the different influence of other industry groups and the main market to a particular industry group. Precisely, the impact of bubbles in other related industry groups was primarily observed in the returns, while the bubble in the market as a whole appeared to chiefly affect the probability of the industry group's bubble collapsing in the next period.

The insights gained from analysing stock market bubbles could have several important implications. The understanding of asset price evolution and bubble behaviour can help improve the functioning of the financial markets. The cost of a bursting bubble is massive. Several authors had offered recommendations to policy makers and regulators. For instance, Scherbina (2013) pushed for the removal of various conditions for bubble formation like short sale constraints or perverse incentives and providing better financial education to the public to reduce irrationality. Jones (2014) emphasised on the additional role of monitoring quantity indicators, such as quality of financial asset issuance and underwriting standards. However, given various issues, the ability of the policy makers to recognise ongoing bubble is far from perfect. Also, the financial markets are continuously evolving both in terms of size and depth. Hence, policy makers should be aware that the next threat to financial stability could be different from what encountered in the past.

Future research could take several paths. Firstly, it could focus on developing a surveillance framework for bubble detection. Identification of bubbles is a complicated undertaking and probably cannot be reduced to a single equation. The introduction of new indicators, as well as, comparative studies of different market scenarios, would be valuable. Monitoring efforts should also be updated frequently, as price patterns can change in relatively short time. Secondly, investors would benefit from having trading rules that can detect different stages of bubble developments and time the eventual collapse, as well as, track flows of funds from one sector to another. They should be tested against other investment strategies to validate their financial usefulness through both explosive and dormant phases. Particularly, it would also be desirable to be able to parameterise the models more parsimoniously. However, it should be noted that if all investors assume the same strategies, bubbles may never be formed in the first place. Finally, additional works in terms of theoretical literature are still needed. For instance, the relationship between actual price and fundamentals could be subjected change in investor preference, and this can be modelled with the game theoretical approach (Brooks and Katsaris, 2003a).

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Appendices

Appendix 1: Results based on SET's Industry Group Indices

This appendix discusses the results based on eight industry group indices of the Stock Exchange of Thailand. Based on the evidence presented in Table A1-1, there are five main panels. The top panel presented the estimated parameters with asterisks denoting different levels of statistical significance. The next panel showed the log-likelihood statistics at optimum and different information criteria. The coefficient restriction tests and the robustness checks against simpler specifications were presented in the next two panels. The bottom panel reported the starting observation and the number of observations included in the estimation.

Consider the results for Financials industry group, for example, the coefficients β_{so} and β_{co} are 1.0364 and 0.9579, respectively. This suggests that the average net monthly return in the surviving and collapsing regimes for the Financials industry group are 3.64% and a loss of 4.21% per month or 53.58% and -40.32% per year, respectively. The estimated parameters of the relative bubble term (β_{sb} and β_{cb}) are both statistically significant – particularly, β_{cb} is negative and is smaller than β_{sb} as postulated by the theory. The parameter β_{qo} shows the average probability for the next period to be in a surviving regime. It is estimated to be 2.1368 which suggests the cumulative normal distribution probability of 98.37%. However, as the bubble grows, this probability drops very quickly, as shown by the estimated β_{qb} of -2.9979. Unexpectedly, the standard deviations of the Financials industry group in the surviving regime, σ_s, turns out to be higher than that in the collapsing regime, σ_c. Results from all other industry groups can be interpreted in a similar manner.

Table A1-1: SET's Industry Group Indices: VNS model

	Agro & Food Industry	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}		1.0192***	1.0364***	1.0649***	1.0783***	1.0369***	1.0469***	0.9021***
β_{sb}		-0.0403	-0.1077**	-0.0556*	-0.1136***	0.0798***	-0.0323	-0.3039***
β_{co}		1.0365***	0.9579***	0.8641***	0.9560***	1.0119***	0.9521***	1.0702***
β_{cb}		0.8583***	-0.1345***	-0.0768***	-0.0277	-0.1886***	-0.0703***	0.0942
β_{qo}		0.4129	2.1368**	2.0063***	0.8561*	-0.6591	5.7691**	-0.4460
β_{qb}		8.2436*	-2.9979	-1.4852**	-0.9579	0.7963	-9.0113*	0.4464
σ_s		0.0359***	0.0616***	0.0754***	0.0444***	0.0173***	0.0506***	0.0329***
σ_c		0.0003***	0.0108**	0.0406***	0.0347***	0.0676***	0.0058**	0.0556***
Log-Likelihood		107.0412	68.1609	48.7891	66.7613	69.5707	78.4869	70.7060
AIC		-4.0425	-2.4555	-1.6649	-2.3984	-2.5131	-2.8770	-2.5594
SBIC		-4.3690	-2.7821	-1.9914	-2.7250	-2.8396	-3.2035	-2.8860
HQIC		-3.9253	-2.3384	-1.5477	-2.2812	-2.3959	-2.7598	-2.4422
$(R1)\ \beta_{so} \neq \beta_{co}$		17.0162***	2.8022*	5.1492**	4.1215**	11.5540***	7.4223***	2.3644
$(R2)\ \beta_{cb} < 0$		0.0000	2.8022*	5.1492**	0.7249	10.1949***	7.4223***	0.0000
$(R3)\ \beta_{sb} > \beta_{cb}$		0.0000	2.8022*	5.1492**	0.0000	13.0815***	7.4223***	0.0000
$(R4)\ \beta_{qb} < 0$		0.0000	2.8022*	5.1492**	10.5349***	0.0000	7.4223***	0.0000
Volatility regimes		37.2999***	7.8738*	4.2717	15.1239***	19.5435***	7.8229*	8.1701*
Mixture of normals		5.4230	0.0000	2.7286	15.1239***	19.2023***	0.0000	5.2808
Fads		37.0077***	2.8022	4.0564	10.5349**	17.7449***	7.4223*	5.9522
Starting observation	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008
No. of observations	49	49	49	49	49	49	49	49

Note: Results from the VNS model [equations (13) to (17)]. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

The evidence appears to suggest that VNS model is explaining the return behaviour of certain industry groups reasonably well. For example, the model worked quite well with Industrials, Services, Financials, and, slightly less so with Resources, Property & Construction and Consumer Products. However, the standard deviations in almost all of these industry groups – except for Resources – in the surviving regime is higher than in the collapsing regime, which is counterintuitive. Moreover, results from Industrials, Services and Financials are hardly more informative when compared to simpler models like volatility regimes, mixtures of normal, or fads models. Astonishingly, the results suggest only a weak evidence of bubbles in the Technology index. Note also that there is no result available for Agro & Food industry group from the model estimation as the maximum likelihood statistics failed to converge, which is probably due to lack of data.

The results with the volume-augmented model are shown in Table A1-2. The model now includes two new parameters. The coefficients β_{sv} and β_{qv} indicate the impact of abnormal trading volume in the return function when the bubble survives and the probability of the bubble continues to grow in the next period, and they are expected to be positive and negative, respectively. Overall, it suggests bubble-like behaviour in Financials and Technology industries. Weaker evidence is also found in Industrials, Resources and Services.

However, the results seem to imply that there were no bubbles in Property & Construction and Consumer Products industries. Moreover, the estimation still did not return any results for Agro & Food industry group.

There are still issues with estimated standard deviations. The specification offers an improvement over the VNS model. Precisely, the restriction tests are statistically significant in four out of seven industry groups and comparisons with simpler models showing stronger evidence in favour of the volume-augmented model, except for Industrials.

Table A1-2: SET's Industry Group Indices: Volume-augmented model

	Agro & Food Industry	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}		1.0172***	1.0207***	1.0667***	1.0661***	1.0357***	1.0232***	0.9822***
β_{sb}		-0.0152	-0.0421	-0.1038***	-0.2662***	0.0770***	0.0019	-0.1371**
β_{sv}		-0.0135	-0.0028	-0.0798**	-0.0154	-0.0023	-0.0370	-0.0268
β_{co}		1.0365***	1.1041***	1.0101***	1.0384***	1.0122***	1.1079***	1.0653***
β_{cb}		0.8583***	-0.0856***	-0.0053	-0.0331	-0.1927***	-0.0351	0.1262*
β_{qo}		0.4075	2.5805**	1.7694*	1.1711	-0.6566	0.5577	119.3708
β_{qb}		8.7579*	-3.2415	-3.2920*	-3.9531	0.7712	4.9228	-187.7880
β_{qv}		-0.6254	-2.2143**	-1.1287	-3.0648	0.4923	-2.9858	-117.3053
σ_s		0.0354***	0.0586***	0.0583***	0.0437***	0.0181***	0.0483***	0.0566***
σ_c		0.0003***	0.0097***	0.1139***	0.0816***	0.0678***	0.0175***	0.0390***
Log-Likelihood		108.4365	73.7026	51.1069	66.4105	69.8762	81.9008	74.1539
AIC		-4.0178	-2.6001	-1.6778	-2.3025	-2.4439	-2.9347	-2.6185
SBIC		-4.4260	-3.0083	-2.0860	-2.7106	-2.8521	-3.3429	-3.0267
HQIC		-3.8713	-2.4536	-1.5314	-2.1560	-2.2974	-2.7882	-2.4720
$(R1)\ \beta_{so} \neq \beta_{co}$		31.4317***	10.2454***	4.3646**	0.8890	4.6508**	5.4790**	3.4555*
$(R2)\ \beta_{cb} < 0$		0.0000	10.2454***	0.0233	0.6344	8.8323***	2.2142	0.0000
$(R3)\ \beta_{sb} > \beta_{cb}$		0.0000	10.2454***	0.0000	0.0000	0.1002	1.3577	0.0000
$(R4)\ \beta_{qb} < 0$		0.0000	10.2454***	9.4061***	0.0327	0.0000	0.0000	36.4396***
$(R5)\ \beta_{qv} < 0$		1.6032	10.2454***	1.0239	3.5895*	0.0000	9.9044***	9.1597***
$(R6)\ \beta_{sv} > 0$		0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Volatility regimes		40.0905***	18.9572***	8.9073	14.4223**	20.1546***	14.6507**	15.0659**
Mixture of normals		8.2136	7.5929	7.3642	14.4223**	19.8134***	0.0000	12.1766**
Fads		39.7983***	13.8857**	8.6920	9.8333*	18.3560***	14.2500**	12.8480**
VNS		2.7906	11.0835***	4.6356*	0.0000	0.6111	6.8278**	6.8958**
Starting observation	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008
No. of observations	49	49	49	49	49	49	49	49

Note: Results from the volume-augmented model [equations (22) to (24)]. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Overall, there is some evidence of bubble-like behaviour in many industry groups, namely Financials, Industrials, Property & Construction, Resources, Services, and Technology from either the VNS or the volume-augmented models. This leaves only Consumer Products, which neither models seems to be fitting well and the Agro & Food industry group which no results were obtained from estimations. However, these sets of results are to be interpreted with great caution. The availability of data was extremely limited. The validity of these results is compromised as this can potentially lead to estimation inefficiency, meaning the distribution of the estimator is wider than it would have been with a larger sample. Results from several industry groups did not always capture more variability of returns than simpler specifications, or they yield standard deviations in the surviving regime that are larger than those in the collapsing regime, which is rather counterintuitive. Moreover, the appropriate breaks for the models with dummy variables as analysed in the previous chapter are before the start of this industry group dataset by the SET. Therefore, those extensions are not applicable here.

Appendix 2: Results based on the K-NI (Replicating observations only)

In order to evaluate the results with the K-NI, only the observations that are comparable to the available SET's Industry Group indices were used in the estimations. The results from the VNS and the volume-augmented models are presented in Table A2-1 and Table A2-2. As a conclusion, based on the most fitting specification for each industry group, the results with the last 49 observations of the K-NI revealed evidence of bubbles in Agro & Food, and Services industry groups, and some evidence in Industrials, Property & Construction, and Resources industry groups. However, due to the limited number of observations, the results for three industry groups, namely, Consumer Products, Financials, and Technology, did not converge. These results are mostly identical to those obtained with SET's original industry group indices. Specifically, both sets of data showed at least some evidence of bubbles in Industrials, Property & Construction, Resources, and Services industry groups. Unfortunately, the results for four other industry groups were not available either with the SET's industry group indices or the K-NI and, thus, cannot be directly compared.

Table A2-1: The K-NI (Replicating observations only): VNS model

	Agro & Food Industry	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	1.0472***			1.0302***	1.0701***	1.0703***	1.0517***	
β_{sb}	-0.0871**			-0.0012	-0.1826***	-0.2006***	-0.0054	
β_{co}	0.9118***			1.0643***	1.0308***	0.9741***	0.9900***	
β_{cb}	-0.2530***			0.2151	0.1298***	0.0195	-0.2468***	
β_{qo}	3.2245***			0.4096	2.4140***	0.6424	1.3544*	
β_{qb}	-6.3543*			0.6487	-3.4652*	-1.2036	0.9184	
σ_s	0.0474***			0.0501***	0.0748***	0.0518***	0.0546***	
σ_c	0.0025**			0.1427***	0.0015**	0.0660***	0.0015**	
Log-Likelihood	80.7130			54.4305	62.7641	63.6666	73.2989	
AIC	-2.9679			-1.8951	-2.2353	-2.2721	-2.6653	
SBIC	-3.2944			-2.2217	-2.5618	-2.5986	-2.9918	
HQIC	-2.8507			-1.7779	-2.1181	-2.1549	-2.5481	
$(R1)\ \beta_{so} \neq \beta_{co}$	12.4026***			0.3397	12.9095***	3.7280*	7.1379***	
$(R2)\ \beta_{cb} < 0$	12.4026***			0.0000	0.0000	0.0000	7.1379***	
$(R3)\ \beta_{sb} > \beta_{cb}$	12.4026***			0.0000	0.0000	0.0000	7.1379***	
$(R4)\ \beta_{qb} < 0$	12.4026***			0.0000	12.9095***	50.6510***	0.0000	
Volatility regimes	14.3843***			2.7416	17.9569***	7.8446*	7.3595	
Mixture of normals	12.8240***			2.7205	17.9569***	7.4919*	0.0000	
Fads	11.5527***			2.3111	12.9095***	6.3657*	7.1379*	
Starting observation	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008
No. of observations	49	49	49	49	49	49	49	49

Note: Results from the VNS model [equations (13) to (17)]. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.

Table A2-2: The K-NI (Replicating observations only): Volume-augmented model

	Agro & Food Industry	Consumer Products	Financials	Industrials	Property & Construction	Resources	Services	Technology
β_{so}	1.0398***			1.0295***	1.0678***	1.0179***	1.0307***	
β_{sb}	-0.0958**			-0.0345***	-0.1919***	0.1249***	0.0049	
β_{sv}	0.0272			-0.0508***	-0.0082	-0.0162	-0.0544	
β_{co}	1.0633			1.0561***	1.0344***	1.0502***	1.0959***	
β_{cb}	-1.0040			0.0750*	0.1381***	-0.2424***	-0.0628	
β_{qo}	2.9636***			0.1149	2.4935***	-0.5284	1.2316	
β_{qb}	0.8107			-0.6871	-3.4443	0.1153	-0.4135	
β_{qv}	-1.2346			-0.0611	-1.5010*	0.8014	-2.4189	
σ_s	0.0541***			0.0179***	0.0747***	0.0163***	0.0527***	
σ_c	0.0000			0.1138***	0.0090***	0.0723***	0.0506***	
Log-Likelihood	95.2424			58.2268	61.8184	69.1869	70.8985	
AIC	-3.4793			-1.9684	-2.1150	-2.4158	-2.4857	
SBIC	-3.8874			-2.3766	-2.5232	-2.8240	-2.8938	
HQIC	-3.3328			-1.8220	-1.9686	-2.2693	-2.3392	
$(R1)\ \beta_{so} \neq \beta_{co}$	38.2649***			5.5443**	10.4205***	6.1793**	0.7484	
$(R2)\ \beta_{cb} < 0$	38.2649***			0.0000	0.0000	8.0448***	0.5549	
$(R3)\ \beta_{sb} > \beta_{cb}$	38.2649***			0.0000	0.0000	0.2195	0.5894	
$(R4)\ \beta_{qb} < 0$	0.0000			2.3183	10.4205***	0.0000	41.9608***	
$(R5)\ \beta_{qv} < 0$	38.2649***			7.4728***	10.4205***	0.0000	2.1086	
$(R6)\ \beta_{sv} > 0$	41.4615***			0.0000	0.0000	0.0000	0.0000	
Volatility regimes	43.4432***			10.3343	16.0656**	18.8853***	2.5588	
Mixture of normals	41.8829***			10.3131*	16.0656***	18.5326***	0.0000	
Fads	40.6116***			9.9037*	11.0183*	17.4064***	2.3372	
VNS	29.0589***			7.5926**	0.0000	11.0407***	0.0000	
Starting observation	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008	Nov 2008
No. of observations	49	49	49	49	49	49	49	49

Note: Results from the volume-augmented model [equations (22) to (24)]. ***, **, * denote statistically significant at 1%, 5% and 10%, respectively.