Asset Price Bubbles and Portfolio Optimization: Issues and Evidence

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Dedicated to my Family

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DECLARATION

I, Hafsal K, hereby declare that this thesis entitled "**Asset Price Bubbles and Portfolio Optimization: Issues and Evidence**" submitted by me under the guidance and supervision of Prof. S. Raja Sethu Durai of University of Hyderabad, is a *bonafide* research work, which is also free from plagiarism. I also declare that it has not been submitted previously in part or full to this University or any other University or Institution for the award of any degree or diploma. I hereby agree that my thesis can be deposited in Shodganga/INFLIBNET.

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A. Publications:

1. Hafsal K. and S. Raja Sethu Durai (2020). "Fundamental beta and portfolio performance: evidence from an emerging market", *Macroeconomics and Finance in Emerging Market Economies*, 13(3), 264-275. doi: 10.1080/17520843.2020.1760913

B. Presentations in conferences:

1. Presented a paper: "Explosive Bubbles in Equity Markets: Evidences from the Asian Countries" at international conference on contemporary issues of economic policy in developing economies. Organized by Moulana Azad national Urdu university (March 2018).
2. Presented a paper: "Does volatility in Asian forex market transmit to India" at 52nd annual conference of the Indian Econometric Society (TIES), IIM-Kozhikode, (January 2016).

Further, the student has passed the following courses towards fulfillment of coursework requirement for Ph.D./was exempted from doing coursework (recommended by Doctoral Committee) on the basis of the following courses passed during his M.Phil. program and the M.Phil. degree was awarded:

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HAFSAL K

CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

INTRODUCTION

"Federal Reserve policymakers should deepen their understanding about how to combat speculative bubbles to reduce the chances of another financial crisis."

- Donald Kohn (Former Vice Chairman of the United States Federal Reserve Board)

1.1. Introduction

Advanced and emerging economies were shocked by financial crises over the last two decades. The Asian financial crisis, the dot-com bubble, the global financial crisis and the European sovereign debt crisis are prime examples. The distortions in the asset prices increased the apprehensions of both the practising and academic economists. Economists have a diverging opinion on what determines the asset prices; many argue that an asset's fundamental factors drive its prices. However, there is a plethora of contrasting evidence, particularly the possibility of speculative bubbles. The asset price bubble is generally considered the price that cannot be justified by the fundamental factors. Empirical features of a bubble episode are widely considered as an unprecedented increase in asset prices in the initial phase along with an unexpected crash; this phenomenon has been noted in different financial markets, including stock, commodity, and real estate. It indicates that the boom and associated burst of an asset price bubble will have a detrimental effect on the financial system, which leads to a severe crisis in the economy. The presence of a bubble in an economy has substantial implications on an economy and market participants and possibly affect the economic decisions of consumption, saving, and investment.

Apart from direct market participants, the topic of bubbles is also in the concerns of financial intermediaries, like fund managers, investment banks, brokers, and mutual funds. A boom period in the market generates greater trading activity and creates the space for a potential hike in the fee. Understanding the nature and behaviour of the price bubbles allows participants to make profit by riding the bubble and exiting before the burst. Bubbles, therefore, are an area of great interest to academics in formulating models for asset pricing. Their research focuses on providing information to improve investor` behaviour and the resulting bubbles. Further, questions on how the bubble movement dynamics differ for different asset classes, sectors, and groups of the economy and whether any contagion exists between them? As the damages due to the bubble burst were substantial and increased in recent times, attracted more attention by the regulators and policymakers.

This thesis attempts to explain the stock price behaviour and its impact on different sections of the economy by decomposing the asset price into fundamental and bubble components to understand whether fundamentals drive the market or not. Most of the existing studies are testing the presence of a bubble in the market, and only very few studies attempt to extract the bubble component from the asset prices. This thesis proposes two innovative measures to decompose the fundamental and bubble components, one from a time-series and another from a cross-section point of view. This thesis also tries to understand the dynamic relationship between fundamentals and bubble components of different countries. Furthermore, it also gives investors insight into how this information on fundamentals and bubbles is useful in creating a better portfolio optimization.

1.2. A Historical view of Bubbles, Crashes, and Crises

Historically, asset price bubbles, crashes, and crisis happened with striking frequency. The evidence shows that the presence of bubbles occurred in all stages of development in the financial and economic system, irrespective of developed, underdeveloped, and emerging economies. The first documented bubble date back to the early 17^{th} century in the Netherlands; Tulip Mania (1636-37) is considered the initial bubble example. Exorbitant prices for tulip bulbs prevailed during 1636 and in 1637, they collapsed all of a sudden. Soon after, in 1719-20, the Mississippi Bubble in France and the South Sea Bubble in England were seen as notable bubbles in history. These companies' initial periods achieved a significant growth rate, but later, the price drastically collapsed. After these two great episodes of bubbles, another historically notable bubble occurred in 1840; British Railway Mania, the railroad construction company's stock value went up, which resulted in a boom in the market. Subsequently, the central bank's intervention in the interest rate affected the stock price, and the stock price crashed. The three bubbles mentioned above are formally considered the initial examples of the asset price bubble in history.

During the early 20^{th} century, in the 1920s, the U.S. market witnessed a boom in the stock market, specifically from 1927 to 1929. Soon after, the market experienced a severe Crash, termed as "the great depression." Before the crash, the stock market experienced an unimaginable level of growth in the stock prices. For instance, the Dow Jones price doubled during these periods. The euphoria ended with Black Tuesday with an approximately 40 percent loss in the value and continued until 1933. It also indicates the unstable price in the market will not sustain, and the consequences are harmful.

Closer to our time, the global financial system is more fragile and experienced a series of bubbles from the 1980s. In the mid-1980s, the Real estate and stock markets of Japan experience a price boom. The unexpected rise in market price increased investors' attention; subsequently, the real estate and stock price collapsed, leading to a severe crisis in Japan and related economies. The Japanese economy suffered a substantial loss during market crashes, with a 20 percent decline in the GDP [Hoshi and Kashyap, 2004]. Another recent and prominent example in bubble history is the dotcom bubble. In the 1990s, the U.S. stock market's internet sector Dotcom stocks experienced an unusual increase in all key indices, particularly the NASDAQ index. The term "new economy" of the internet and computational technologies increased investors' interest in these stocks, causing a boom in the market [Philips et al., 2011]. The most celebrated word in the literature of asset price bubbles coined by Alan Greenspan, the former Fed Chairman on December 5, 1996, *"Irrational Exuberance," was* used to explain the dotcom bubbles of the 1990s. Philips et al. (2011), Ofek and Richardson (2003), Perez (2009), and many other researchers theoretically and empirically proved it as a bubble.

Very recently, the unsustainable growth in the U.S. housing market and consequent financial turmoil of 2007 -09 led to a severe economic crisis since after the great depression of 1929, which created massive repercussions on the world economy [Brunnermeier, 2009]. Due to the low-interest rate, mortgage securitization, and global saving, glut attributed a boom in housing prices. Eventually, that led to the crash. Furthermore, the housing price bubble led to the default of many companies, such as Lehman Brothers and AIG, which led to the government writing off an amount. Subsequently, the stock values of these companies drastically fallen. This crash led to the most extended period of recession in the US economy and was the immediate cause of the so-called Global Financial Crisis [Sornette and Cauwels, 2014]. Given the bubbles' detrimental effects and following crises, economic researchers and policymakers have been seeking for a mechanism to empirically identify bubble structure to take proper actions to depress bubbles before they collapse. Hence the topic of asset price bubbles is still important, and continuing research in Financial Economics.

As noted by Evanoff et al. (2012), "We still do not have a good definition of an asset bubble, and we still do not know how to identify them, what causes them to grow or burst, and what their welfare implications are." Stigliz (1990) provides a formal definition for a bubble when an asset's market price exceeds its underlying fundamental values. Simply a bubble means the persistent overvaluation or mispricing of the financial or real assets [Brunnermier and Ohmke, 2003]. In the presence of a bubble, the overconfident investors purchase the assets at a higher price, thinking they can sell the asset at even higher prices. When it crashes, the magnitude of the adverse shock from the financial sector to the real economy is vast and devastating, as witnessed by the recent financial crisis.

1.3. Why is Bubble identification important?

The importance of understanding the presence of bubbles in the asset price is to avoid adverse effects due to the natural relationship between the asset prices and the overall functioning and performance of the financial system and economy. For instance, since the financial market is directly or indirectly linked with the economy and society, the bubble burst in it not only impacts the people who are directly related, but it also spreads to other parts of the economy. Most of the companies will go bankrupt, which will increase the unemployment rate, decrease business activities, and diminish the level of consumption that may lead to a severe economic recession. Therefore, timely and proper understanding of the asset price bubble is an indispensable part of the modern era. As everyone knows, the primary objective of any countries central bank is to ensure a healthy economy, price stability, and encourage the financial system's stability. It is highly imperative to have a stable financial system for a well-functioning economy.

Identifying asset price bubbles has become an important concern for policymakers, central banks alike. Early identification makes possible the prevention of the collapse of asset prices, to this purpose, numerous econometric tests have been developed and tested. Nevertheless, there is no consensus among researchers on how to detect and measure bubbles statistically. A significant chunk of the literature defines bubbles as a divergence of asset prices from its fundamentals; at the same time, the definition of the fundamental value varies for a different asset class such as stocks, exchange rates, and commodities, etc. Moreover, researchers used various measures to quantify fundamentals for the same asset class. To get it clear, we need first to understand the different definitions and the theoretical underpinning in defining the bubbles.

1.4. Definition and Theoretical Background

As noted by Stiglitz (1990), "If the reason that the price is high today is only because the investors believe that the selling price will be higher tomorrow when fundamental factors do not seem to justify such a price, then a bubble exists." The topic of asset price bubbles is a very controversial subject in economics; there is no consensus in the arguments and theory behind the bubbles. Asset bubbles imply a prolonged deviation between an asset's fundamental value and its market value. This definition enables simple mathematical expression and quantifies asset price bubbles as the deviation of actual price from its fundamentals. The topic of the speculative bubble in asset prices arises because of uncertainties to the "fundamentals." For example, in the stock market, a stock buyer is ready to pay a price that he thinks to be equivalent to the "fundamental" price. In evaluating this "fundamental" value, the buyer will collect the knowledge on dividend flows and future price changes. Inevitably, his/her evaluation must depend on expectations about some relevant forthcoming events. Since these market participants' expectations are subjective, it may not reflect the real value, and hence, all the evaluation of market fundamentals is subjective [Shiller, 2001].

Due to the difficulties arise in identifying the correct fundamental value, economists define bubbles differently. Still, the literature's dominant paradigm shows that all the temporary mispricing in the asset markets are not bubbles. The most popular theory in economics, the Efficient Market Hypothesis (EMH) developed by Fama (1970), argues that in an efficient market, an asset's fair value reflects all the available information and the expectations of an asset's prospects. If any differences arise between the fundamental and market value will be quickly corrected through arbitrage. There is no profit chance to be exploited; hence there is no incentive for speculation. The historical evidence challenges the EMH and shows the presence of bubbles in the financial markets. Abreu and Brunnermeier (2003) outline that bubbles can survive despite rational arbitrageurs who are collectively both well-informed and well-financed.

The asset bubble theories are broadly classified into three, rational bubbles, heterogeneous beliefs, and behavioural bubbles. These theories are based on the fundamental value of an asset. Therefore, understanding an asset's fundamental or fair value is the prime element in the bubble detection process [Brunnermeier,2008; Brunnermeier and Oehmke,2013].

1.5. Types of Bubbles

1.5.1. Rational bubbles

The rational bubble is the foremost approach used to explain the emergence of the bubble in the asset markets initially proposed by Blanchard and Watson (1983). Theoretically, the rational bubble assumes that all the agents are rational, and they decomposed the asset price into fundamental and bubble component. Later on, Campbell et al. (1997) modelled it as follows:

If the net return on a stock can be written as:

$$R_{t+1} = \frac{P_{t+1} - P_t + D_{t+1}}{P_t} \tag{1.1}$$

Where R_{t+1} indicates the return on asset between t and $t+1$; P_t is price or price of a share at time period t while D_{t+1} denotes the next period's dividend. An important assumption that expected return on the stock equals to R, a constant is held:

$$E_t(R_{t+1}) = R \tag{1.2}$$

where Et is conditional expectation at time t. Combining equations (1.1) and (1.2) and rewriting $E_t(R_{t+1})$ as:

$$E_t(R_{t+1}) = \frac{E(P_{t+1} + D_{t+1}) - P_t}{P_t} = R \tag{1.3}$$

By rearranging equation (1.3), we obtain an equation known as "expectational difference equation," which shows the relationship between the stock price at period *t* and expected stock price and dividend at time *t+1*.

$$P_t = E_t\left[\frac{P_{t+1} + D_{t+1}}{1+R}\right] \quad (1.4)$$

Based on the Law of Iterated Expectations - $E_t\big[E_{t+1}[X]\big] = E_t[X]$ to remove future-dated expectations and solving forward for K periods, now it follows:

$$P_t = E_t\left[\sum_{i=1}^{K}\left(\frac{1}{1+R}\right)^i D_{t+i}\right] + E_t\left[\left(\frac{1}{1+R}\right)^K P_{t+K}\right] \quad (1.5)$$

The right-hand side of the equation $E_t\left[\left(\frac{1}{1+R}\right)^K P_{t+K}\right]$, indicates the discounted value of the price of the stock, K periods from the present. It is assumed that as K increases, that will converge to zero.

$$\lim_{K \to \infty} E_t\left[\left(\frac{1}{1+R}\right)^K P_{t+K}\right] = 0 \quad (1.6)$$

The fundamental price of a stock (P_t^f) or expected present value is equal to the expected value of the future discounted dividends, as shown in the below equation.

$$P_t^f = E_t\left[\sum_{i=1}^{K}\left(\frac{1}{1+R}\right)^i D_{t+i}\right] \quad (1.7)$$

It tells us that present value of the expected future dividend must be equal to the current stock price. But once our assumption of convergence in equation (1.6) is violated, the equation (1.4) is written as:

$$P_t = P_t^f + B_t \quad (1.8)$$

Where $B_t = E_t\left[\frac{B_{t+1}}{1+R}\right]$. Then the second term in equation (1.8), B_t is known as the rational bubble. Therefore, in rational bubble models, price comprises of both fundamental (P_t^f) and (B_t) and bubble components.

1.5.2. Heterogeneous beliefs bubbles

The heterogeneous belief theory of bubble argues that the agents disagree on the fundamental value of the assets. It can be due to different reasons such as psychological biases or the prediction of uncertain futures. Harrison and Kreps (1978) say that bubbles and crashes are due to heterogeneous beliefs. In a market, when disagreements about an asset's fundamental value prevail among the agents, coupled with short-selling constraints. Then the agents are ready to pay a price greater than his anticipation of an assets fundamental value with an expectation of reselling the same at a higher price in future. Such kind of activities and behaviour causes the emergence of bubble in the asset prices. This method does not require large aggregate expectational errors, but rather develop on variations in investors' heterogeneous beliefs. In fact, while investors' aggregate beliefs may be unbiased, intense variations in their heterogeneous beliefs may generate a bubble component on account of frenzied trading. Scheinkman and Xiong(2003) extended it in a time series framework and empirically proved that bubbles follow a higher trading volume.

1.5.3. Periodically Collapsing Bubbles

Another important class of bubble is Evans (1991) periodically collapsing bubbles. According to him, rational asset price bubbles are always positive in nature but periodically collapse, and defined as follows:

$$B_{t+1} = (1+r)B_{t\mu_{t+1}}, \text{ if } B_t \le \alpha \tag{1.9}$$

$$B_{t+1} = [\delta + \pi^{-1}(1+r)\theta_{t+1} \times (B_t - (1+r)^{-1}\delta)]\mu_{t+1}, \text{ if } B_t > \alpha \tag{1.10}$$

Where δ and α represents the positive parameters with $0 < \delta < (1+r)\alpha, \mu_{t+1}$ is an exogenously defined i.i.d random positive process with $E_t U_{t+1} = 1$ and $\theta_{t+1}$is an exogenously defined i.i.d Bernoulli process, where the parameters value lies 1 and 0 with probability π and $1-\pi$ respectively, where $0 < \pi \le 1$. when $B_t \le \alpha$ represents bubble grows at a mean rate of $(1+r)$ and when $B_t > \alpha$, the bubble grows with a faster mean rate of $\pi^{-1}(1+r)$, it collapses with a probability of $1-\pi$. δ represents the mean rate at which the bubble falls while it collapses, and later the bubble process restarts again. Evans (1991) demonstrated that the conventional unit root and cointegration fails to identify the periodically collapsing bubbles.

1.5.4. Intrinsic bubbles

Froot and Obstfeld (1991) found a special kind of rational asset price bubbles in US stock prices, which depends only on the changes in fundamentals. For a change in fundamentals, it causes asset prices to overreact. They explain intrinsic bubbles as follows:

Log dividends are generated through geometric martingale:

$$d_{t+1} = \mu + d_t + \varepsilon_{t+1} \tag{1.11}$$

Where μ is trend growth in dividends. log of dividends is denoted by d_t represents log dividend at time t, while ε_{t+1} represent a random process with zero mean and variance σ^2. The present value of stock price will be directly proportional to dividends if period *t* dividends are known when P_t is set.

$$P_t^{pw} = kD_t \tag{1.12}$$

Where $k = (e^r - e^{\mu+\sigma^2/2})^{-1}$ and r is a real interest rate and $r > \mu + \sigma^2/2$.

Suppose function $B(D_t)$ is defined as

$$B(D_t) = cD_t^{\lambda} \tag{1.13}$$

Where λ denotes quadratic equation have positive root $\lambda^2\sigma^2/\,2 + \lambda\mu - r = 0$ and c is an arbitrary constant. The basic stock price equation can be written in the following form:

$$P(D)_t = P_t^{pw} + B(D_t) = kD_t + cD_t^{\lambda} \tag{1.14}$$

Here, $B(D_t)$ contains intrinsic bubble component where $c \neq 0$ and $P(D)_t$ is derived as a function that depends solely on dividends and is not influenced by any other extraneous variable.

1.6. Bubble Detection Methods

1.6.1. Variance Bounds Tests

The variance bound tests introduced by Shiller (1981) and Leroy and Porter (1981) were the first tests with regard to rational bubbles. These tests match the variance of fundamental prices computed using ex-post data against the variance of actual prices, then proceed to check whether dividend flows can justify the volatility of the observed prices. When the actual price is determined by the expected dividends and not by the forecast errors, then there exists no bubble in the market. Shiller (1981) proved that the actual price volatility is higher when compared to the bounds imposed on the volatility of the fundamentals

1.6.2. West's Two-Step Test

West (1987) introduced a two-step method to detect the presence of bubbles in asset prices. According to him the parameters to estimate the expected dividend price can be calculated in two ways. The first equation can be estimated to obtain the expected future dividend is Eulers equation with no arbitrage condition. The second equation parameters estimate the discounted future dividend is by an ARIMA model. Here one set of estimating the discounted present value of dividend, contain no bubble hypothesis and the other set contains the bubble hypothesis. If the estimated parameters from both coincide (excluding sampling error) indicates no bubble in the asset prices. If the parameters are different in the estimation indicates the presence of bubble in the asset price series.

1.6.3. Non-stationarity and Cointegration Tests

Cointegration is another important method used to detect the presence of bubble in asset price. Generally, in cointegration based test is classified into two, the first approach is residual based test, this approach is generally use unit root test to the residuals obtained from the regression between the asset price and the dividend process. If the residual has unitroot, indicates the presence of bubble in the asset prices. Therefore, if cointegration exists between asset price and dividend indicates absence of bubble. Another method is to check the presence of bubble is to examine the unit root in the dividend price ratio. If dividend price ratio shows unitroot represents the presence of bubble. Diba and Grossman (1988) analysed the explosivity of the asset prices with the dividend process. If the explosivity in asset price is more than the dividend process indicates the presence of bubble. They tested this to US stock price and concluded with bubble.

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Evans (1991) in his study of market bubbles found that the traditional cointegration and unit root tests fail to capture prices with periodically decaying bubbles with mean reverting property. Hence, prices are not explosive and tend to be stationary. Furthermore, traditional cointegration methods fail to capture intrinsic bubbles inherent in dividend process thereby decreasing the power of such tests.

In view of the above limitations, Taylor and Peel (1998) proposed a cointegration test which incorporated the phenomenon of collapsing bubbles and found no evidence of bubbles in their study. Similarly, Wu and Xiao (2008) developed a test based on stationarity of residuals of the decaying bubbles based on the intuition that bubbles, though stationary, would still be huge and the test failed to detect the presence of bubble.

1.6.4. Regime-switching Test

Van Norden and Schaller (1993) developed a regime-switching model to identify bubbles by bifurcating asset returns in two regimes, namely i) a surviving state where a functional relationship between the size expected bubble and current bubble is assumed, and ii) a decaying state where a relationship between probability of survival and size of the bubble is assumed. The proposed model specifies the time varying nature of asset bubbles in both regimes and makes it possible to compute the conditional expected returns of asset holdings.

The VNS model, with its roots in models of Blanchard (1979) and Blanchard and Watson (1982), consists of a speculative bubble framework where the probability of the bubble's survival and transition to next period is q and the bubble bursts with probability 1-q. Under this framework, evidence of bubbles was detected in the U.S stock market. In the light of certain limitations of the VNS model, Brooks and Katsaris (2005a, 2005b) elaborated the method by incorporating the abnormal level as a sign of collapsing phase and by including a third regime where bubble emerge gradually in dormant state. Evidence of near-bubble dynamics in S&P 500 prices and sectoral indices is presented in the volume augmented model of Anderson et al. (2010).

1.6.5. Right tailed unit-root test

Evans (1991) criticized the ADF test's power in identifying the mildly explosive behaviour, particularly in a periodically collapsing bubble. Therefore, Philips and Yu (2011) extended the model in (1.16) to SADF statistic with a test strategy based on a two-step process. Firstly, detect the explosiveness in the price using the ADF statistic. If we found that the series is explosive, the next step is to identify the windows which this period occur. The SADF statistics follow a forward recursive estimation with the predefined minimum window size.

Phillips et al. (2011) proposed a right-tailed unit-root test, where the test follow the given Augmented Dickey-Fuller equation

$$\Delta P_t = \alpha_{r1,r2} + \beta_{r1,r2} P_{t-1} + \sum_{i-1}^{k} \varphi_{r1,r2}^{i} \Delta P_{t-i} + \varepsilon_t, \;\; \varepsilon_t \sim^{iid} N(0, \sigma_{r1,r2}^2) \qquad (1.15)$$

P_t denotes the asset's price, r_1 and r_2 indicate window fractions of the total sample size, which specify the starting and ending points of each window, while k denote the lag length used to avoid the effects of autocorrelation from the model, and α_{r1r2}, β_{r1r2} and $\varphi_{r1\,r2}^{i}$ are regression coefficients. The method is focusing on the following test statistics:

$$ADF_{r1}^{r2} = \frac{\hat{\beta}_{r1,r2}}{s.e(\hat{\beta}_{r1,r2})} \qquad (1.16)$$

Here null hypothesis of a unit root in P_t, $H_0{:}\beta_{r1,\ r2}=0$, against the alternative of mildly explosive behaviour, $H_1{:}\beta_{r1,\ r\ \ 2}>0$.

The SADF statistic is defined as:

$$SADF(_{r0}) = \sup_{r_2 \epsilon [r_{0,} 1]} ADF_0^{r2} \tag{1.17}$$

The SADF is the supremum from all independent and forwardly recursive ADF statistics.

If the SADF stats is greater than the right tailed critical value indicate the presence of bubble or the series is explosive. The critical value is derived from the following limit distribution.

$$\sup_{r_2 \epsilon [r_{0,} 1]} \frac{\int_0^{r2} WdW}{\int_0^{r2} W^2} \tag{1.18}$$

Latter Phillips et al. (2015) identified that the SADF statistics is inadequate to detect multiple bubble episodes. They extended the model into a generalized SADF (GSADF) statistic. The GSADF process follows a repeated estimation of ADF in a recursive format. Moreover, the GSADF changes subsample's initial observation (r1) and changes the endpoint (r_2). The GSADF statistic is defined as follows:

$$GSADF(_{r0}) = \sup_{r_2 \epsilon [r_{0,} 1], r_1 \epsilon [0, r_2 - r_{0,}]} ADF_0^{r2} \tag{1.19}$$

If the GSADF stat is greater than the critical value from the limit distribution indicates the presence bubble.

1.7. Scope and relevance of the study

In recent times, the financial market has been challenged by frequent bubbles, crashes, and crises worldwide. The presence of bubbles and busts in the financial market have become a focusing issue for the policymakers, market regulators, investment risk and fund managers, and financial institutions, as it affects all the sections of the economy. So, the analysis of the formation, identification, and impact of bubbles and crashes in financial markets attracted great interest in finance and economics. Financial markets' functioning can be improved, and the costs of a bubble burst can be mitigated through a clear understanding of asset price movements and bubble behaviour. The loss of investors' confidence due to bubbles would affect the economy with an increase in the cost capital for businesses. Based on these inferences, the real problem is whether we have proper tools and methods to identify the bubbles' intensity, their dynamic relationship across the countries, and how to use this information for designing better investment strategies.

At first glance, one would find it is beneficial for the central banks and the government to control of bubble burst when prevention fails. However, such measures are quite complicated. Firstly, an appropriate method for evaluating asset prices' behaviour are far from known, and it is very difficult to define bubbles with conclusively as an economy goes through various phases. Moreover, large ups and downs of asset prices need not coincide with booms and recessions. Expansionary economic policies can help reduce the severity of any potential downturn, while the use of such measures contributes to forming the next bubble [Meltzer, 2002; Jones, 2014].

On the other hand, the benefits of speculations in stock markets cannot be ignored. They could provide potential benefits to the economy. Consider a financing constrained economy, the start-ups and innovative companies may never get sufficient funding. Though, with its inherent tendency of risk-sharing and diversification, stock markets allow new technologies to be adopted, contributing to better long-term economic growth [Komaromi, 2006].

With this background, the scope and relevance of this study are as follows: (i) It focuses on developing two new ways to decompose fundamental and bubble components from stock prices that can be easily extended to any other asset prices and testing it for an emerging economy, India. (ii) With this decomposition, a better understanding is derived from these fundamental and bubble components' dynamic relationship across the countries. (iii) Further, it also examines the effectiveness of this information in investment strategies and its usefulness in portfolio optimization.

1.8. Objectives of the study

The main objectives of the thesis are as follows:

1) To examine and establish the Common Trend method's usefulness in identifying and extracting the theoretical speculative bubbles.
2) To decompose the stock price's fundamental and bubble components using a Common Trends approach for India, the US, and Japan to understand the dynamic relationship of it among these countries.
3) Develop a new approach towards identifying the fundamental and bubble component using the cross-sectional information of the stock prices.

4) To examine and establish the usefulness of this decomposition in forming effective investment strategies through portfolio optimization.

1.9. Organization of the Thesis

The thesis is organized as follows:

Chapter 1 gives an introduction and background on the theoretical framework and existing types of financial bubbles and its importance. Further, it also provides the scope and relevance of the study and its main objectives.

Chapter 2 introduces the Common Trends approach of Warne (1993) and examines its usage in identifying the periodically collapsing theoretical bubbles proposed by Evans (1991) and Rotterman et al. (2015). The Common Trends approach's usefulness in decomposing the asset price into a permanent component and transitory component extracts the fundamental and bubble trajectory effectively are discussed.

Chapter 3 provides an application of the Common Trends approach in identifying the fundamental and bubble components of stock prices for India, the US, and Japan. The identified fundamental and bubble components of these stock markets are further evaluated with the Diebold and Yilmaz (2012) return and volatility spillovers along with the wavelet coherency analysis to examine the dynamic relationship among these countries' stock markets. The implications of this dynamic relationship are discussed elaborately.

Chapter 4 attempts to propose an alternative approach to decompose the fundamental and bubble components of stock prices. Following Ball and Mankiw (1995), this study considers the cross-sectional skewness of component stock returns as aggregate shocks that induce transitory deviation in the returns from its fundamental values. The proposed method uses the methodology developed by Rather et al. (2016) for extracting core inflation is applied to the components of the Dow Jones Industrial index to identify the fundamental return by minimizing the cross-sectional skewness. The efficacy of this approach is validated with other methods, and the advantages are discussed.

Chapter 5 extends Anderson and Brooks (2014) bubble CAPM model to a static and dynamic time-varying framework and examines its usefulness in evaluating the portfolio performance. This method's effectiveness in constructing the portfolio is analysed using the data from an emerging market, India. The construction of the time-varying market, fundamental and bubble beta, is first of its kind from an emerging market perspective that provides a simple, parsimonious alternative towards combining portfolio optimization with fundamental and bubble factors.

Finally, chapter 6 summarizes this study's overall findings with policy implications, limitations of the study and provides suggestions for future research.

Chapter 2

BUBBLE IDENTIFICATION USING COMMON TREND APPROACH

2.1. Introduction

Historically, asset price bubbles, a phenomenon experiencing explosiveness and a crash, are present in the commodity, stock, real estate, and forex markets. Recently, the global financial world undergoing regular asset price bubbles became much popular in their dynamics and its impacts on the real world. Therefore, many economists tried to understand the bubble dynamics, identifying and predicting bubbles to minimize their impact when they burst. However, there is no consensus regarding the definition, identification, and causes of the bubbles. All the bubble detection methods explained in chapter 1 have one common disadvantage, as these methods are only date stamps the bubble periods, and no technique traces the bubble path. This chapter addresses these problems of identification and introduces the Common Trend method to extract the bubble path for some theoretical bubbles. Two theoretical bubbles are examined, namely the periodically collapsing bubbles of Evans (1991) and Rottermann and Wilfling (2018).

Researchers proposed plenty of theoretical models to understand the presence of speculative bubbles, their growth, and consequences in the economy. Moreover, many empirical studies provide econometric or statistical methods for the identification of bubbles using real data. Theoretical bubble models are developed to examine these statistical models' validity and efficacy in identifying different kinds of bubbles. In the real world, we cannot precisely determine the bubbles' shape, so if these statistical models are good enough to trace the theoretical bubbles, we presume that they can do the same for the real data.

Evans (1991) questioned the test method proposed by Diba and Grossman (1998) are not enough to identify an important type of speculative bubbles, known as periodically collapsing bubbles. The traditional unit-root and cointegration methods, with a high probability, conclude the absence of bubbles in the asset prices. Evans used a Monte Carlo simulation to shows the unit root, and the cointegration test fails to identify the bubbles in the presence of a periodically collapsing bubble. The analysis of bubble detection is based upon the standard unit root testing procedures where cointegration tests assume a null of unit root. The alternative hypothesis, which is a linear AR process, fail to encompass the non-linearity of periodically collapsing bubbles thereby failing to correctly capture the presence of bubbles. Due to the lack of models that capture non-linearities within cointegration analysis, the study by Evans (1991) does not provide evidence of the presence of bubbles that collapse periodically in the stock prices of US. Therefore, there is a need to empirically examine the presence of such bubbles in stock prices.

Rotermann and Wilfling (2018) proposed another set of theoretical bubbles in contrast to the Evans (1991) type with recurringly explosive and stochastically deflating trajectories. They argued that periodically collapsing bubbles are so systematic and not reflect the real-world data. This chapter considers the Common Trend framework of Warne (1995) to identify the type of Evans (1991) theoretical periodically collapsing bubble as well as Rotermann and Wilfling (2018) recurringly explosive and stochastically deflating bubbles to extract the bubble path. The Common Trend method uses the cointegrating relationship between the asset price and its fundamental factors to decompose the asset price into permanent and transitory components is proven to capture the characteristics of both these bubbles empirically.

This chapter is organized as follows: Section 2.2 and Section 2.3 describes the theoretical framework of periodically collapsing bubbles of Evans (1991) and recurringly explosive with stochastically deflating bubbles of Rotermann and Wilfling (2018), respectively. Section 2.4 discusses the Common Trend methodology and its application to extract the theoretical bubbles' paths and explain its effectiveness. Finally, section 2.5 summarizes and concludes the chapter.

2.2. Periodically Collapsing Bubble

The model proposed by Evans (1991) incorporates the present value analysis with rational expectations. Pt is the stock price at time t

$$P_t = \frac{1}{1+r}[E_t(P_{t+1})E_t(D_{t+1})] \tag{2.1}$$

Here D_{t+1} represents dividend payment of the stock at t and t+1 $E_t(\cdot)$ represents the conditional expectations of all available market information till time t. The compensatory rate of return, where risk of stock is incorporated, is given by r (Campbell et al., 1997). Equation 2.1 is modified by incorporating future prices in a forward recursion. Based on the expected value of discounted future dividends, P_{ft} the fundamental component of stock price and the bubble term by B_t , the traditional present value representation of stock price at time t can be derived.

$$P_t = P_t^f + B_t\left(\frac{1}{1+r}\right)^i E_t(D_{t+1}) + B_t \tag{2.2}$$

The bubble, B_t, can be interpreted from (2.2) as the divergence of current stock price Pt from its current fundamental value, Pf_t. Equation 2.2 is the class of solutions for the Euler equation (2.2) where B_t is stochastic variable which is in conformity with the discounted martingale property.

$$E_t(B_{t+1}) = (1 + r)\, B_t\ ,\ \text{Or } B_t = \left(\frac{1}{1+r}\right) E_t(B_{t+1}) \qquad (2.3)$$

Since B_t in (2.2) satisfies the rational expectations property, and called as a rational bubble To understand the impact of rational bubbles on stock prices is demonstrated in Evans (1991), where a class of bubbles with characteristics non-linearity, non-negativity, periodically collapsing, and martingale, as given in equation (2.3), is discussed. By characterising the discount factor as $\psi = (1 + r) - 1$, the Evans bubble can be written in the following form:

$$B_t = \begin{cases} \frac{1}{\psi} B_{t-1} u_t, & \text{if } B_{t-1} \leq \alpha \\ \left[\theta + \frac{1}{\pi\psi}\left(B_{t-1} - \theta\psi\right)\nu_t\right] u_t, & \text{if } B_{t-1} > \alpha, \end{cases} \qquad (2.4)$$

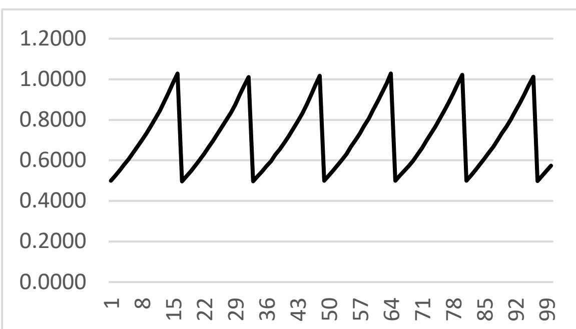
where θ and α denotes the real constants terms such that $0 < \theta < (1 + r)\alpha\ and\ \{u_t\}_{t-1}^{\infty}$ is an exogenously defined $i.i.d$ random process $0\, u_t > 0$ and $E_t - 1(u_t) = 1$ for all t. We assume $\{u_t\}$ to follow a lognormal distribution and is adjusted to have a unit mean, i.e., $u_t =$ exp $(y_t - i^2/2)$ with $\{y_t\}_{t-1}^{\infty}$being i.i.d. $N(0,\ i^2)$). $\{\nu t\}_{t=1}^{\infty}$ is $i.i.d$ Brenoulli and is independent of $\{u_t\}_{t-1}^{\infty}$ with $Pr(\nu t = 1) = \pi\ and\ Pr(\nu t = 0) = 1 - \pi$ for $0 < \pi \leq 1$. The $\{\nu t = 1\}$ indicates the growing phase the bubble, but the bubble collapse in the event of $\{\nu t = 0\}$.

Using equation (2.4), Evans (1991) simulated a periodically collapsing bubble and exposed that the traditional unit-root tests fail to detect these bubbles.

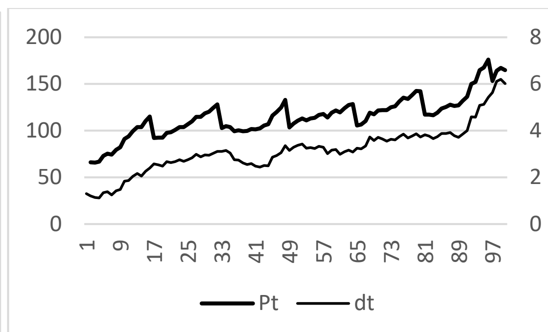
Figure 2.1 shows the simulated bubble model with the given parameters. Bubbles in prices are shown in panel A whereas panel B shows simulated price and dividend series. The following parameters are used for simulating the model: μ = 0.0373, σ^2_D = 0.0010, α = 1, ρ = 0.985, b = 1, B_0 = 0.50, π = 0.85, ζ = 0.50, τ = 0.05,

Figure. 2.1: Simulated Periodically Collapsing Bubbles and corresponding Asset Price and Dividend Process

Panel A



Panel B



2.3. Recurringly Explosive and Stochastically Deflating Bubble

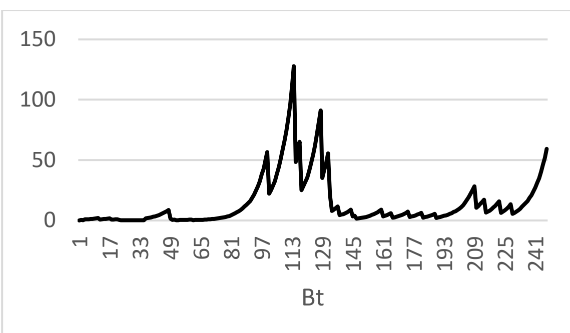
Roterman and Wilfling (2018) questioned Evans' bubble, depicted in equation (2.4), based on the features of two distinct rates of growth. For $B_{t-1} \leq \tau$, the bubble grows at the mean rate $\frac{1}{\psi} - 1 = r$. For $B_{t-1} > \tau$, the bubble grows at the faster rate $\frac{1}{\pi\psi} - 1 > r$ (if π < 1), then bubble collapses with probability 1 – π rate per period. Based on the above arguments, the bubble process of Evan's collapses completely within a single period and certainly come back to the same point expected at level θ after collapsing, from where the process restarts. Rotermann and Wilfling (2018) proposed a new and alternative bubble process, based on a strictly positive and recurringly explosive and stochastically deflating nature.

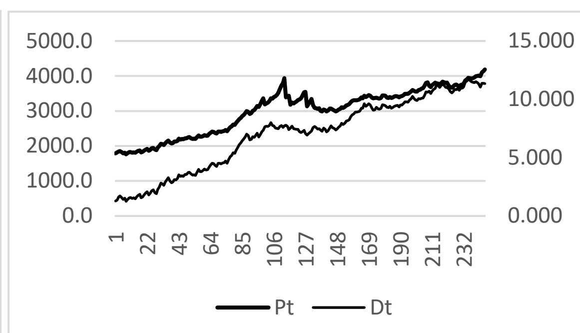
$$B_t = \begin{cases} \frac{\alpha}{\psi\pi} B_{t-1} u_t & \text{, with probability } \pi \\ \frac{1-\alpha}{\psi(1-\pi)} B_{t-1} u_t & \text{, with probability } 1-\pi \end{cases} . \tag{2.5}$$

Using the Bernoulli process $\{vt\}$, the equation (2.5) can be converted into one single equation as $B_t \left[\left(\left[\frac{\alpha}{\psi\pi} - \frac{1-\alpha}{\psi(1-\pi)} \right] v_t + \frac{1-\alpha}{\psi(1-\pi)} \right) B_{t-1} \right] u_t$ (2.6).

Figure. 2.2: Simulated Recursively Explosive and Stochastically Collapsing Bubbles and corresponding Asset Price and Dividend process

Panel A **Panel B**





Here the model assumes that $0 < \alpha < 1$. The constraint provides that the bubble will not collapse to zero and reinflate. The simulated model of bubbles with the following parameters are displayed in figure 2.2. Panel A explains the bubbles in the price series, and panel B explains the simulated price and dividend series. The parameter value, r = 0.02 so that β = 1/r = 50, ψ = 1/(1+r) = 0.9804, t2 = 0.001, θ = 1.1, π = 0.98 and α = 0.91.

2.4. Common Trends Method

The basic idea is derived from the Gonzalo and Granger (1995) disposition on the decomposition of a time series. Consider the following series x_t, integrated of order one and decomposed such that

$$x_t = x_t^P + x_t^T \tag{2.7}$$

$$\Delta x_t^P = \sum_{i=0}^{\alpha} \varphi e_{t-i}^P, x_t^T = \omega_i e_{t-i}^T, \tag{2.8}$$

Here x_t^P is a nonstationary process and is x_t^T a stationary process. The error terms, e_t^p and e_t^T, are assumed to be i.i.d stationary series and follows N (0, σ_i; i = 1, 2). Given the autoregressive representation of Δx_t^p and x_t^T in equation (2.8) uncorrelated among them means that in the long run the x_t will affect the shock from the innovation term e_t^p. In contrast, shocks from e_t^T do not have an effect on the long-run forecast of x_t, in other words, do not have any permanent impact on x_t Therefore, the component x_t^p is described to as the permanent component and x_t^T as a transitory component of x_t.

This analysis employs the methodology suggested by Warne (1993) and Blix (1995). Consider an N-dimensional vector $x_t$of I (1) variables that have r < N cointegrating relations among the variables, then the unrestricted VAR of order p is

$$A(L)x_t = \rho + \varepsilon_t$$

Under cointegration assumption, VAR become VECM as

$$A^*(L)\Delta x_t = \rho - \gamma z_{t-1}\varepsilon_t$$

where $\Delta = 1 - L$; L is the lag operator; and the matrix polynomial $A_i^* = -\sum_{j-t+1}^{p} A_j$ is related to A(λ) through for i = 1, ……, p-1.

$$A^*(\lambda) = I_n - \sum_{i=1}^{p-1} A_i^* \lambda^i$$

A stationary process can be expressed as an invertible distributed lag of serially uncorrelated disturbances under the Wold Representation Theorem.

$$\Delta x_t = \delta + C(L)\varepsilon_t$$

By recursive substitution, we can derive

$$x_t = x_0 + C(1) \sum_{j=0}^{t-1} \varepsilon_{t-j} + c^*(L)\varepsilon_t \tag{2.9}$$

where$c^*(L) = \sum_{j-0}^{\infty} c_j L^j$, and C_j^*=$\sum_{j-i+1}^{\infty} c_j$, C_j^* helps to capture the long-run effect of the reduced form disturbances in ε_t on the variable x_t, and x_0 is the initial observation in the sample.

Warne (1993) derived the following Common Trends representation $x_t = x_0 + \Gamma_t \tau_t + \phi(L)\varphi_t$ The growth component from the equation $\Gamma_t \tau_t$ can be defined as: $\tau_t = \mu = \tau_{t-1} + \psi_t$. It is an n-dimensional random walk model with drift μ. The dimension of the loading matrix Γ_g is n x k with rank k and can be derived from the consistent estimation of C (1).

The Estimated Equation

$$\binom{D}{P} = \binom{D}{P}_0 + \binom{k_{11}}{k_{21}} (\tau_d)_t + \phi(L) \binom{\psi}{\nu}_t \tag{2.10}$$

Where the fundamental component is $P_t^{CT} = P_0 + \hat{\kappa}_{21}\hat{\tau}_{dt}$ and the bubble component is $P_t^b = P_t - P_t^{CT}$.

2.4.1. Tracing the periodically collapsing bubble

Our study's methodological framework needs a permanent component in data series; that means all the series are non-stationary in nature. To this purpose, the study use unit root tests to identify whether the simulated asset prices and dividend series follow a non-stationary process. The Augmented Dickey-Fuller (ADF) unit root test is applied to test the null hypothesis that the data series is non-stationary. We cannot reject the null hypothesis of unit root in levels for the dividend and prices data at the 1% significance in the ADF tests. Later, we tested the first-differenced data, and there the null of unit root hypothesis is statistically rejected. Hence, the results from the ADF exhibit that the simulated dividend and asset prices follow non-stationary processes. It indicates that for each data series, we can obtain the permanent and transitory components. According to the log-linear present value approach, the dividend and asset prices are cointegrated, which can be validated theoretically. We use the Johansen (1991) cointegration maximum likelihood approach to examine cointegration among these variables. The lag lengths are picked based on the criteria of serially uncorrelated residuals.

The finding based on the trace test statistics and reported in Table 2.1. indicate that the price and dividend series are cointegrated. Moreover, the tested values of the cointegrating coefficients are stable for all the cointegration techniques used.

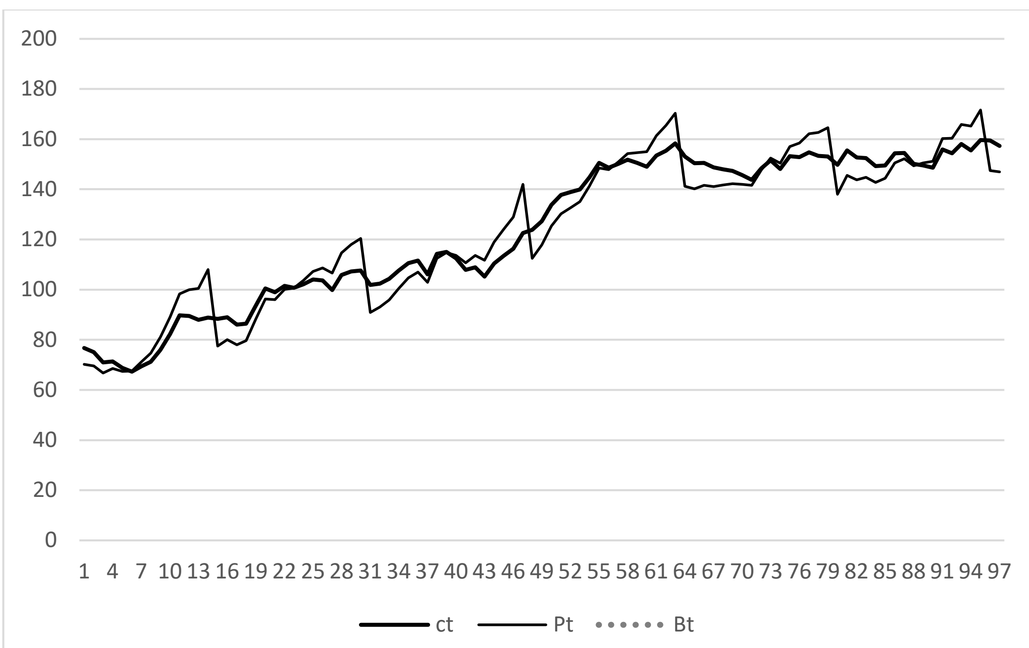
Table 2.1: Johansen Cointegration Test for Simulated series

Hypothesis	Eigenvalue	Trace Statistic	Max-Eigen Statistic
r = 0	0.079	30.07*	23.40*
r ≤ 1	0.016	6.66	4.59
	<u>*Normalized Cointegrating Coefficients*</u>		
D		*P*	
1.000		2.28 (0.76) *	

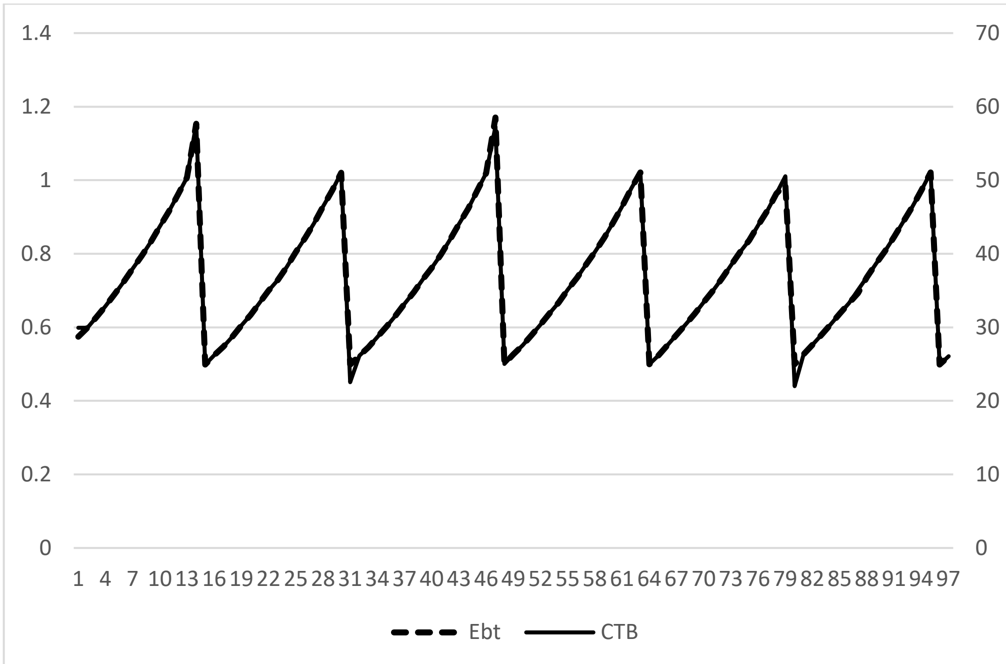
*Figures in (#) are standard errors; * indicates 5% level of significance.*

Figure 2.3: Dynamics of Price, fundamental and bubble process of periodically collapsing bubble process of Evans

Panel A: Actual and fundamental price series



Panel B: Estimated bubble process versus true bubble process



Following the method described in section 2.2, different periodically collapsing bubble processes are simulated with alternative parameters. This simulated data are then used in the Common Trend method, and the extracted transitory components are compared with the simulated bubble to understand the efficacy of the technique. The simulation has been carried out more than 100 times, all the times the common trend approach gave similar results, and we present the results from one simulated as a representative.

Fig. 2.3 provides an example of an Evans-bubble process and the stock-price process. In simulation, we set the parameter as follows: $\mu = 0.0373$, $\sigma2D = 0.0010$, $\alpha = 1.0$, $\rho = 0.985$, $b = 1$, $B0 = 0.50$, $\pi = 0.85$, $\zeta = 0.50$, $\tau = 0.05$. The dataset consists of 100 observations.

Based on the above parameters estimates of the Evans bubble process, we now derive the bubble process from the prices and dividends by using the common trend method. Figure 2.3 panel A displays the price and derived fundamental value. The fundamental value closely follows the dynamics of the price series. Obviously, the departure of the fundamental value from its price series is described as bubble portion. Panel B of figure 2.3 shows the comparison of the estimated common trend bubble process depicted in bold line and the simulated Evans bubble process as a dashed line. Comparing both the bubble trajectories, we find that the common trend method maps the bubble trajectories of Evans almost exactly with 99.8 percentage of correlation. The bubble derived estimated bubble process almost perfectly fits the simulated Evans bubble values.

2.4.2. Tracing the recurrently explosive and stochastically deflating bubble

Table 2.2: Johansen Cointegration Test for Simulated series

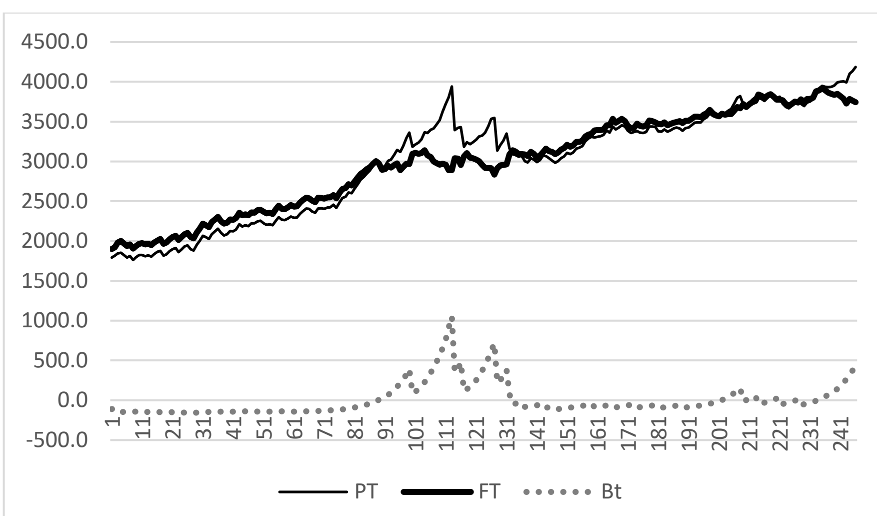
Hypothesis	Eigenvalue	Trace Statistic	Max-Eigen Statistic
r = 0	0.086	24.42*	21.82*
11r ≤ 1	0.010	2.59	2.59
	Normalized Cointegrating Coefficients		
D		*P*	
1.000		2.02 (0.73) *	

*Figures in (#) are standard errors; * indicates 5% level of significance.*

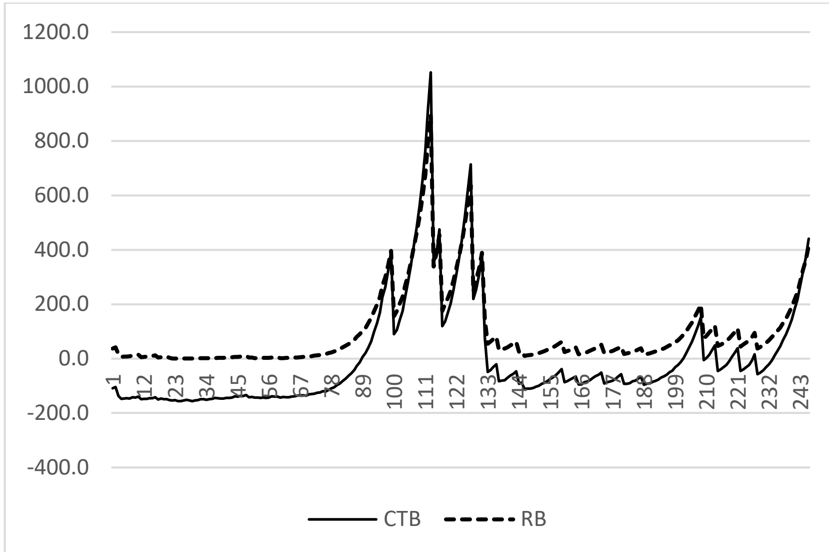
The study now analyses how well the common trend approach are suited to identify Rottermans' (2014) recurrently explosive and stochastically deflating bubble. As we disused earlier, we need to analyse the time series properties of the data. In order to employ our method, we have to make sure that the data series contains a permanent component, means all series are non-stationary in nature. The study employed the Augmented Dickey-Fuller (ADF) unit root test for the stationarity. At level we cannot reject the null of unit root. Later, we tested the first-differenced series and statistically rejected the unit root. Hence, the ADF results strongly exhibit that the simulated dividend and asset prices is non-stationary. Therefore, for every data series, we can obtain the permanent and transitory components. We used Johansen (1991) cointegration maximum likelihood approach to examine cointegration among these variables. The lag lengths are chosen based on the criteria of serially uncorrelated residuals. The finding based on the trace test statistics and reported in Table 2.2. indicate that the price and dividend series are cointegrated. Moreover, the tested values of the cointegrating coefficients are stable for all the cointegration techniques used.

Figure 2. 4: Dynamics of Price, fundamental and bubble process of recurrently explosive and stochastically deflating bubble

Panel A: Actual and fundamental price series



Panel B: Estimated bubble process versus true bubble process



Following the method described in section 2.3, different recurrently explosive and stochastically deflating bubble are simulated with alternative parameters. The fact about the recurrently explosive and stochastically deflating bubble never collapse periodically completely within one period as like periodically collapsing bubble. This simulated data are then used in the Common Trend method, and the extracted transitory components are compared with the simulated bubble to understand the efficacy of the technique. The simulation has been carried out more than 100 times, all the times the common trend approach gave similar results, and we present the results from one simulated as a representative.

Based on the parameter estimates of the Rotterman bubble process we now derive the bubble process from the prices and dividends by using the common trend method. figure 2.4 panel A displays the price and derived fundamental value. the fundamental value closely follows the dynamics of the price series. Obviously, the departure of the fundamental value from its price series is described as bubble portion. Panel B of the figure 2.4 shows the comparison of estimated common trend bubble process depicted in bold line and the simulated Rotterman bubble process as in dashed line. Comparing both the bubble trajectories, the result shows that the common trend method maps the simulated bubble process of Rotterman almost exactly with 99.7 percentage of correlation. Evidently, the common trend approach enables us to calculate the bubble process from the real data series nearly exactly. Moreover, the estimated bubble series, help us to understand the emergent phase the peak stage of the bubble and the bubble bursting dates.

2.5. Conclusion

This chapter analyses two theoretical bubbles, namely, periodically collapsing bubbles of Evans (1991) and recurrently explosive and stochastically deflating bubbles of Rotermann and Wilfling (2018). We use the Common Trend method of Warne (1993) and Blix (1995) to trace and extract the bubble path, and the results are validated with graphical comparison and correlation analysis. The empirical results from different data simulations establish that the Common Trend method is very useful and precisely identifies the bubble path. If an unobservable bubble drives the stock price, it can be precisely estimated using the Common Trend method. These findings support the recent claim by Monschang and Wilfling (2020) that the bubble identification tests using ADF type test, including Diba and Grossman (1998), to the latest Phillips et al. (2015), lacks power in identifying and date-stamping all the bubbles. The chapter shows that using the common trend approach, it is very easy to map the theoretical bubble and apply it in the real data. Due to the underlying present-value model of the asset prices, we can identify the emergent phase, the peak values, and the dates of bursting of the bubbles can be identified. A major limitation of this method is the non-identifiability of correct fundamental variables for estimating the bubble and non-possibility of implementing this method in stationary fundamental variables.

Chapter 3

FUNDAMENTAL AND BUBBLE SPILLOVERS IN STOCK MARKETS – A COMMON TREND APPROACH

3.1. Introduction

One of the major research questions in empirical finance is whether the stock prices follow market fundamentals? Since Shiller (1981) seminal work, it is well-documented in the empirical literature that the volatility in stock prices is not justified by the changes in the value of its fundamentals. The consequence of stock prices significantly deviating from their fundamentals amounts to inefficient allocation of investment resources in the economy. From an empirical standpoint, what constitutes the fair or fundamental value of the stock and how to extract the fundamental components from the price remains two important streams of research. The present value model of Gordon (1959) with discounted future dividends are extensively used to detect the fair value of a stock price. Still, LeRoy and Porter (1981) and Summers (1986) recognized that fundamentals are not explaining all of the stock price deviations, and they disregard the simple present value model of the discounted future dividends. Alternatively, Fama (1990), Barro (1990), and Schwert (1990) found a strong relationship between stock returns and macroeconomic variables. Theoretically, it makes sense since the expected future dividends are closely related to the projected macroeconomic conditions. A plethora of studies in the literature discusses the linkages between the macroeconomic variables and stock price movements.

Conversely, the idea of speculation in the markets and the deviation of prices from the theoretical prices termed as bubbles[1] gained prominence way back in literature when Samuelson (1957) questioned, *"Is there any other kind of price than speculative price?"* and evaluated the mathematics of speculation. In literature, speculative and rational bubbles are defined as the disposition of the investors to pay more than the discounted future dividends of stocks. The speculative bubble is due to the speculation in the market about the future price rather than its fundamental value, and as argued by Blanchard (1979), the speculative bubbles can take all kinds of shapes, so detecting and proving their existence or non-existence becomes harder.

In a rational expectation world, where the present price of an asset is positively affected by the expected rate of return, the subjective and self-fulfilling elements of expectations create price bubbles [Flood and Garber (1980)], since these rational bubbles ride on the expected rate of return, it grows much faster than the stock's fundamental value. As noted by Flood and Hodrick (1990), "Whether the actual volatility of equity return is due to time variation in the rational equity risk premium or to bubbles, fads and market inefficiencies is an open issue."

From an empirical perspective, Diba and Grossman (1988a, b) gave a theory of rational bubbles and implemented unit-root and cointegration tests to understand the presence of rational bubbles in the stock market, but provided mixed results in support of rational bubbles. Later, to decompose the fundamental and bubble components from the stock price, Lee (1995) implemented a structural Vector Autoregressive (SVAR) model for the returns

[1] The terms 'Bubble' and 'Non-fundamental' are used interchangeably in the literature, which defines the difference between the asset price from its theoretical fundamental price.

of US and Japan asset prices and concluded that a significant fraction of the United States and Japanese stock prices are accounted for by non-fundamental bubble components, and these stock prices overreact to non-fundamental bubble shocks.

Further, with the same method, Chung and Lee (1998) derived the fundamental and bubble components from the stock prices of Pacific-Rim countries. These studies used the changes in dividends, earnings, and gross national product as the fundamental variables to decompose the stock/asset prices. If there is cointegration among these variables, they used the spread between the price and the fundamental variables as one variable. The first difference of the rest of the variables is used in the SVAR framework. As an extension, this study uses the Common Trend approach of Warne (1993) by incorporating the cointegration relationship among the variables to derive the stock prices' fundamental and bubble component. Many studies applied the common trend method to understand the common trends and cycles across different stock markets [Narayan (2010), Narayan and Thuraisami (2013), Mehmeth (2016)]. To the best of our knowledge, this is the first study to use the common trend method for the decomposition of the stock price into fundamental and bubble components. As explained in the previous chapter, this method identifies and traces the bubble path with date precision. This study uses three variables common trend model with the stock price, economic output as a macroeconomic variable, and gold price as an alternative asset, which is exogenously determined but has a significant impact on the stock prices[2].

The very idea of decomposing these components for different markets is to understand the dynamic relationship of it across them. For the US, Louis and Eldomiaty (2010) analysed

[2] We can also use global oil prices as an exogenous foreign factor, since oil prices have differential sectoral effects on the stock market, this study uses gold prices in the model.

the properties of Dow Jones and NASDAQ indices and concluded that these markets are driven mostly by non-fundamental bubble shocks. In this context, this study examines the relationship across the markets of different countries using Diebold and Yilmaz (2012) return and volatility spillover method. Besides, it also implements continuous wavelet coherency of Aguiar-Conraria and Soares (2014) to explore the relationship among the returns from the stock price as well as fundamental and bubble components in the frequency-time domain. This study's main contribution is two-fold: first, it implements a common trend model to decompose the fundamental and bubble components of the stock price. Second, this study explores the dynamic spillover across return and volatility in a frequency-time domain to identify the connectedness among India, USA, and Japan's stock markets. The rest of the chapter proceeds as follows: Section 3.2 describes the data and the methodology used in this study. Section 3.3 explains the empirical analysis and the results, and the final section 3.4 concludes with implications.

3.2. Data and Methodology

3.2.1. Data

This study applies monthly data on BSE Sensex, S & P 500, and NIKKEI 225 as the stock prices for India, USA, and Japan respectively (P), Index of Industrial Production as a proxy for the dividend (Y), and World Gold Price (G) for the period from April 1994 to July 2018. The selection of these countries is mainly for understanding the fundamental and bubble relationship from both developed and emerging markets and covering the entire hemisphere of the world. The stock market data are collected from Yahoo Finance at www.finance.yahoo.com. The Index of Industrial Production of all these countries are compiled from www.data.oecd.org, and the world gold price is collected from www.gold.org. All the data are adjusted for seasonality, and logarithmic transformation of it are used in the analysis.

3.2.2. Common Trends Method

The Common Trend method explained in detail in Chapter 2, and section 2.4 is used to derive the permanent and transitory components of the model variables.

The Estimated Equation

$$\begin{pmatrix} G \\ Y \\ P \end{pmatrix}_t = \begin{pmatrix} G \\ Y \\ P \end{pmatrix}_0 + \begin{pmatrix} \kappa_{11} & 0 \\ \kappa_{21} & \kappa_{22} \end{pmatrix} \begin{pmatrix} \tau_f \\ \tau_r \end{pmatrix}_t + \Phi(L) \begin{pmatrix} \psi_f \\ \psi_r \\ \upsilon_1 \end{pmatrix}_t \tag{3.1}$$

Where the fundamental component is $P_t^f = P_0 + \widehat{\kappa}_{21}\widehat{\tau}_{f\,t} + \widehat{\kappa}_{22}\widehat{\tau}_{rt}$, and the bubble component is $P_t^b = P_t - P_t^f$

3.2.3. Spillover Index

The spillover index developed by Diebold and Yilmaz (2009, 2012) to measure the interdependence between markets is an extension of modeling a Vector Autoregression (VAR) system along with the variance decomposition to identify interconnectedness among the variables. This index is superior to other methods as it reveals both magnitude and direction of interdependence as well as it can be used to assess the dynamic connectedness by implementing the estimation over rolling windows. The Diebold and Yilmaz (2009) model had two limitations:

(a) as variance decomposition is based on Cholesky factorization, it is highly sensitive and vulnerable to the ordering of variables in the VAR system and

(b) it dealt with only total Spillover in the system and did not provide the direction or magnitude of spillovers between individual assets or markets.

Diebold and Yilmaz (2012), using a generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), developed a model to capture directional and total spillovers between assets.

A generalized form of VAR model, with p lags and N variables, can be represented as,

$$x_t = \sum_{t=1}^{n} \psi_i x_{t-i} + u_t \tag{3.2}$$

Where, the vector of i.i.d errors is given by u with $\sum$ as the variance-covariance matrix. The moving average representation of equation (4) is $x_t = \sum_{t=1}^{\infty} A_i \varepsilon_{t-i}$ where the coefficient matrix with dimension N × N can be written recursively, i.e. $A_i = \psi_1 A_{i-1} + \psi_2 A_{i-2} + \ldots\ldots\ldots\ldots + \psi_p A_{i-p}$ and $A_i = 0$ for $i < 0$.

The forecast error variances of each variable are decomposed via variance decomposition into parts that are attributed to various shocks in the system. The generalized VAR is used to obtain the h-step ahead forecast error variance decomposition (FEVD) as follows:

$$\theta_{ij}(H) = \frac{{\sigma_{ii}}^{-1} \sum_{h=0}^{H-1} \left(\mathrm{e}_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(\mathrm{e}_i' A_h \Sigma A_i' e_j\right)} \tag{3.3}$$

where σii is the ith element on the principal diagonal of $\sum$ where e is the selection vector with the ith element as 1 and 0 otherwise.

The share of own variance or spillover is the fraction of the h-step ahead error variances obtained by forecasting x_i with shocks to x_i, for $i = 1,2, \ldots N$. The share of cross variance representing cross spillover is the fraction of h-step-ahead error variances obtained by forecasting xi with shocks to x_j for i, j =1,2,….N, $i \neq j$ .Since the row summation of θ_{ij} (H) is not equal to 1, normalization is carried out by summing the row as $\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N}\left(\theta_{ij}(H)\right)}$. In doing so, the decomposition containing shocks in each market equals unity, i.e., $\sum_{j=1}^{N}(\theta_{ij}(H)) = 1$ and the total decomposition of all variables sums to N, i.e.,$\sum_{i,j=1}^{N}(\theta_{ij}(H)) = N$.

Now we can obtain the total connectedness measure or total spillover index as

$$S(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100 \qquad (3.4)$$

Using total spillover index, one can extract the contribution of shocks from all variables in the system to the total forecast error variance. As mentioned earlier, the advantage of the VAR-based method is that it enables us to quantify the direction of spillover among individual assets or markets.

3.2.4. Wavelet Coherency

The Continuous Wavelet Transform (CWT) proposed by Aguiar-Conraria and Soares (2011) is used to understand the dynamic relationship between the fundamental and bubble components of stock prices in a frequency-time domain. Aguiar-Conraria and Soares (2014) developed two measures, namely, Wavelet Coherency helps one in identifying the co-movement between two variables from a time-frequency perspective i.e. information across time and frequency can be extracted simultaneously. Similarly, Partial Wavelet Coherency calculates coherence between two variables by conditioning another variable with different time-frequency component. A detailed derivation and specification of the model are explained in Aguiar-Conraria and Soares (2011, 2014).

Wavelet coherency is related to the product of wavelet spectrum of individual series. In essence, wavelet is similar to the traditional correlation coefficient but captures the co-movement between two variables in both time and frequency simultaneously. Consider two-time series $x(t)$ and $y(t)$ their complex wavelet coherency is described as

$$C_{xy} = \frac{S(W_{xy})}{\sqrt{S(|W_x|^2)S(|W_y|^2)}} \tag{3.5}$$

The Wavelet Coherency is denoted as

$$R_{xy} = \frac{|S(W_{xy})|}{[S(|W_x|^2)\ S(|W_y|^2)]^{1/2}} \tag{3.6}$$

$$0 \leq R_{xy}(\tau, s) \leq 1$$

Where W_x and W_y are the continuous wavelet transforms of x and y respectively. The smoothing operator in the above equation denoted by S is used to smoothen both individual transform and cross-wavelet transform, so as to avoid the coherence being identical at varying time-scale.

The Partial Wavelet Coherency of x_1 and x_j $(2 \leq j \leq p)$ is given by:

$$C_{1j.qj} = -\frac{\varphi_{j1}^{d}}{\sqrt{\varphi_{11}^{d}\varphi_{jj}^{d}}} \tag{3.7}$$

Where r_{1jqj} is estimated in absolute value

$$r_{1\,j.qj} = \frac{\left|\varphi_{ji}^{d}\right|}{\sqrt{\varphi_{11}^{d}\varphi_{jj}^{d}}} \tag{3.8}$$

The partial wavelet coherency, of $x_{i,j}$ which is squared is given by

$$r_{1}^{2}\,_{j.qj} = \frac{\left|\varphi_{ji}^{d}\right|^{2}}{\sqrt{\varphi_{11}^{d}\varphi_{jj}^{d}}} \tag{3.9}$$

Where φ represents the *p x p* matrix the smoothed cross-wavelet spectrum S_{ij}.

Aguiar-Conraria and Soares (2014) defined the complex partial wavelet coherence between *x* and *y* by controlling z as

$$C_{xy/z} = \frac{C_{xy} - C_{xZ}C_{yz}^{*}}{\left|(1-R_{xz}^{2})(1-R_{yz}^{2}\right|^{1/2}} \tag{3.10}$$

Where C_{xy} and R_{xy} are derived from equations (3.5) and (3.6). The partial wavelet coherence between *x* and *y* given *z* can be specefied by taking the absolute value of the denominator in (3.6). Finally, the partial wavelet coherence is represented as:

$$R_{xy/z}(\tau,S) = \frac{\left|R_{xy}(\tau,S) - R_{xz}(\tau,S)R_{yz}^{*}(\tau,S)\right|}{\sqrt{(1-(R_{xz}(\tau,S))^{2})}(1-(R_{yz}(\tau,S))^{2})} \tag{3.11}$$

3.3. Empirical Results

First, we examined the stationarity properties of the variables used in this study with Augmented Dickey-Fuller and Philips-Perron tests. From these tests, it is clear that all the data series are integrated of order one and the results are given in Table 3.1.

Table 3.1: Unit Root Test

Stock Markets	ADF Test		Philips-Perron Test	
	Levels	First Difference	Levels	First Difference
S & P 500	-1.90 (0.65)	-16.06 (0.00)	-2.17 (0.50)	-16.40 (0.00)
BSE Sensex	-1.09 (0.92)	-15.23 (0.00)	-1.45 (0.84)	-15.36 (0.00)
NIKKEI 225	-2.29 (0.43)	-16.86 (0.00)	-2.58 (0.29)	-17.04 (0.00)
IIP USA	-2.01 (0.29)	-10.58 (0.00)	-1.43 (0.57)	-11.13 (0.00)
IIP India	-1.10 (0.93)	-17.17 (0.00)	-1.80 (0.70)	-28.12 (0.00)
IIP Japan	-0.75 (0.97)	-15.03 (0.00)	-1.06 (0.93)	-15.08 (0.00)
Gold	-1.37 (0.87)	-15.73 (0.00)	-1.50 (0.83)	-15.98 (0.00)

Figures in parenthesis are p-values, and the results are reported for the test with intercept

This study's methodological framework warrants that each variable contains a common trend and requires the variables to be non-stationary and have cointegration between them. So next, we examined the cointegration using Johansen's (1991) method with appropriate lag length among the logarithmic of the Gold price (G), Index of Industrial Production (Y), and Stock price (P) for all three markets, and the results are provided in Table 3.2. The results establish cointegration between the variables G, Y, and P with one cointegrating vector across all three markets.

3.3.1. Common Trend Decomposition

We implemented the Common Trend method and estimated the equation (3.1) in section 3.2.2 above, to retrieve the permanent component from the stock price for all three markets. The decomposed permanent and transitory components are graphed in Figures 3.1 to 3.3. Results of the historical decompositions of stock prices for USA, India, and Japan clearly shows that most of the stock price movements over the period from 1994 to 2018 are not fully explained by the fundamental shocks alone; this indicates that increases in the stock prices, especially after 2000, cannot be explained entirely by the market fundamental. The deviation of stock prices from there fundamentals corresponds to specific events in the financial markets and politics, especially during the financial crisis of 2007 to 2009 is evident for all markets. The price of S&P 500 is undervalued substantially for the periods spanning 1994–1999 and 2014–2018, whereas overvalued from 2000 to 2008, especially before the global financial crisis, it shows a higher level of overvalued series, and the deviations from the market fundamentals were substantial during these periods.

A similar pattern is observed for BSE Sensex, with overvaluation during the crisis period and flips to a prolonged undervaluation after the financial crisis. In the case of Nikkei 225, the stock index is overvalued from 1995 to 2000, but in the later periods, the fundamental is more or less follows the stock market movement except during the period of the global financial crisis.

Table 3.2: Johansen Cointegration Test

Stock Markets	Hypothesis	Eigenvalue	Trace Statistic	Max-Eigen Statistic
S & P 500	r = 0	0.091	38.35*	28.61*
	r ≤ 1	0.015	5.75	4.60
	r ≤ 2	0.003	1.14	1.14
		<u>Normalized Cointegrating Coefficients</u>		
5	*G*	*Y*	*P*	
	1.000	-138.12 (27.25)*	27.84 (6.99)*	
BSE Sensex	r = 0	0.079	30.07*	23.40*
	r ≤ 1	0.016	6.66	4.59
	r ≤ 2	0.007	2.07	2.07
		<u>Normalized Cointegrating Coefficients</u>		
	G	*Y*	*P*	
	1.000	-7.38 (1.56)*	2.38 (0.76)*	
NIKKEI 225	r = 0	0.061	29.88*	24.68*
	r ≤ 1	0.032	11.62	9.58
	r ≤ 2	0.007	2.04	2.04
		<u>Normalized Cointegrating Coefficients</u>		
	G	*Y*	*P*	
	1.000	-89.71 (40.28)*	8.33 (1.99)*	

*Figures in (#) are standard errors; * indicates 5% level of significance.*

Figure 3.1: Historical decomposition of USA stock prices

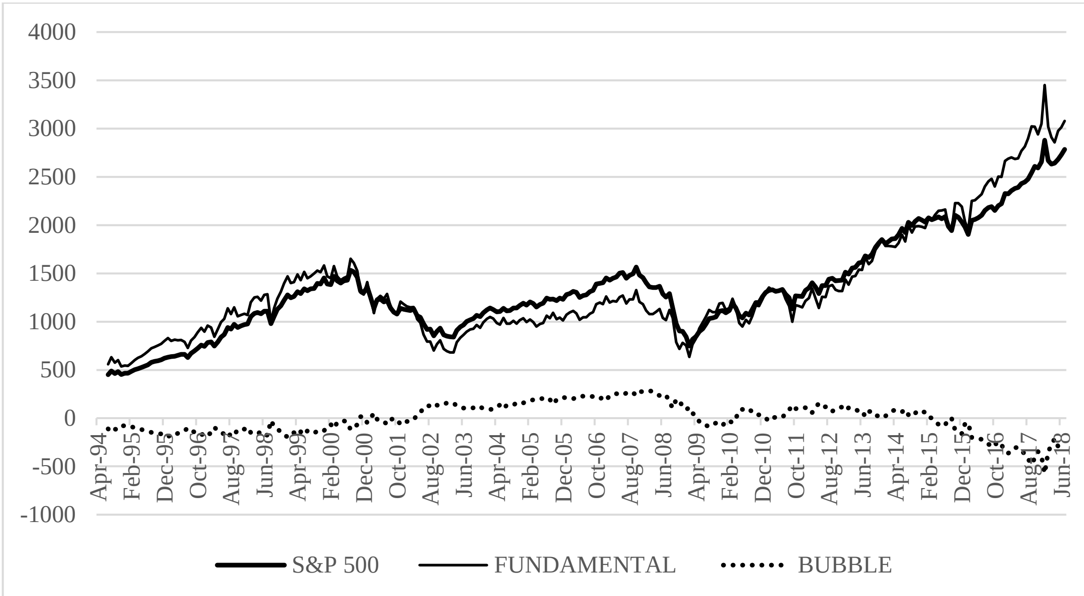


Figure 3.2: Historical decomposition of India stock prices

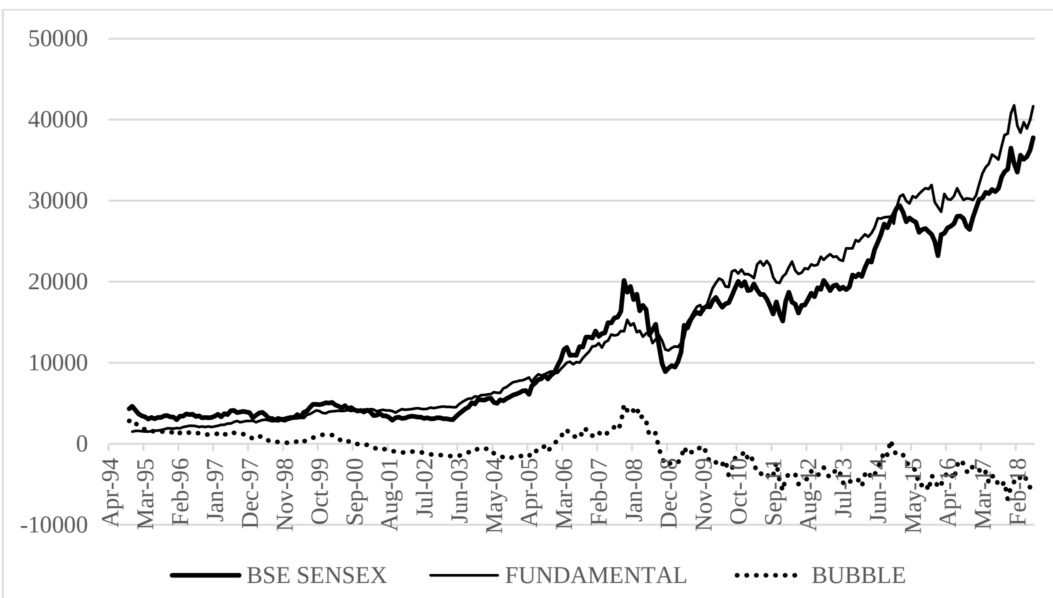
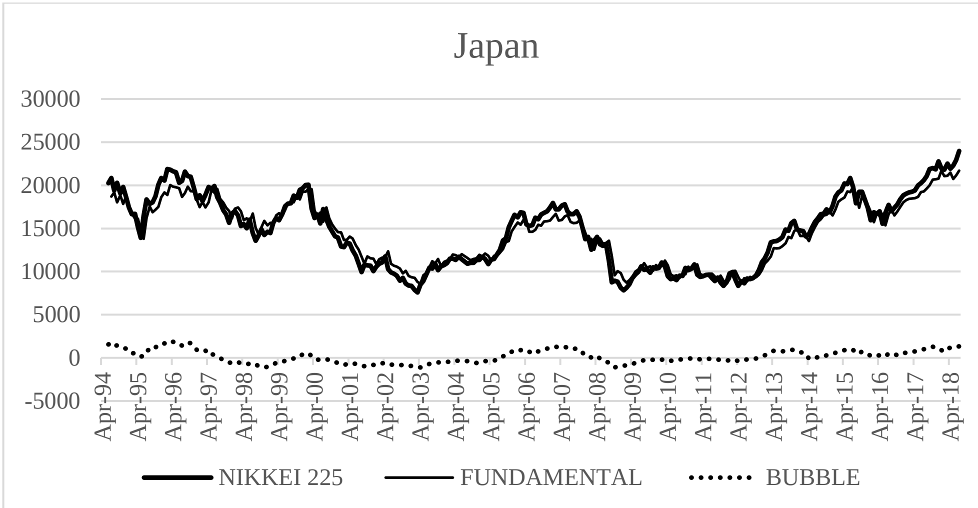


Figure 3.3: Historical decomposition of Japan stock prices



3.3.2. Return and Volatility Spillovers

After the stock price decomposition into fundamental and bubble components, we examine the relative importance of the actual, fundamental, and bubble components for the US, India, and Japan. Specifically, examine the degree of each component (actual, fundamental, and bubble) spillover from one market to another market. The return and volatility spillovers are estimated using the Diebold and Yilmaz (DY) (2012) method explained in section 3.2.3 above. The DY method is calculated using the 10-step-ahead procedure, and the results from the return series of actual, fundamental, and bubbles are presented in Tables 3.3 to 3.5. The tables highlight the variable's forecast error variance attributed to innovations in market. Elements in the diagonal represent own variance i.e. error variance of market *i* arising due to innovations or shock from market *i*. The column representing 'From' depicts total spillover to a market from other markets, whereas the row representing 'To' depicts the spillover from one market to other markets. Total spillover is represented in the lower corner towards the right of the spillover table.

Table 3.3: Estimates from Actual Return Spillover

	S & P 500	BSE Sensex	NIKKEI 225	From others
S & P 500	72.5	1	26.5	28
BSE Sensex	7.8	77	15.2	23
NIKKEI 225	1.3	2	96.7	3
Contribution to others	9	3	42	54
Contribution including own	82	80	139	17.90%

All the values are in percentages.

Table 3.4: Estimates from Fundamental Return Spillover

	S & P 500	BSE Sensex	NIKKEI 225	From others
S & P 500	71.1	5.7	23.2	29
BSE Sensex	6.5	86.5	6.9	13
NIKKEI 225	1.5	2.5	95.9	4
Contribution to others	8.0	8.0	30	46
Contribution including own	79	95	126	15.50%

All the values are in percentages.

Table 3.5: Estimates from Bubble Return Spillover

	S & P 500	BSE Sensex	NIKKEI 225	From others
S & P 500	99.4	0.1	0.5	1.0
BSE Sensex	0.1	99.6	0.3	0.0
NIKKEI 225	0.5	0.2	99.2	1.0
Contribution to others	1.0	0.0	1.0	2.0
Contribution including own	100	100	100	0.60%

All the values are in percentages.

Table 3.6: Estimates from Actual Volatility Spillover

	S & P 500	BSE Sensex	NIKKEI 225	From others
S & P 500	72.5	1	26.5	28
BSE Sensex	7.8	77	15.2	23
NIKKEI 225	1.3	2	96.7	3
Contribution to others	9	3	42	54
Contribution including own	82	80	139	17.90%

All the values are in percentages.

Table 3.7: Estimates from Fundamental Volatility Spillover

	S & P 500	BSE Sensex	NIKKEI 225	From others
S & P 500	71.9	4.6	23.4	28
BSE Sensex	7.5	91.6	0.9	8.0
NIKKEI 225	6.2	7.5	86.3	14
Contribution to others	14	12	24	50
Contribution including own	86	104	111	16.70%

All the values are in percentages.

Table 3.8: Estimates from Bubble Volatility Spillover

	S & P 500	BSE Sensex	NIKKEI 225	From others
S & P 500	99.4	0.4	0.1	1.0
BSE Sensex	1.6	98.3	0.1	2.0
NIKKEI 225	0.0	0.9	99.1	1.0
Contribution to others	2.0	1.0	0.0	3.0
Contribution including own	101	100	99	1.10%

All the values are in percentages.

Tables 3.6 to .8 presents the results of volatility spillover across these markets. Volatility is calculated as the 12-month standard deviation of the actual, fundamental, and bubbles returns.

The results for actual returns reveal that 17.90 percent of the market return is explained by other markets, which means, on average, 18 percentage of the market price movements are coming from other equity markets. The fundamental returns spillover analysis shows that 15.50 percent of spillover are explained by other market shares, whereas in the case of bubble return spillover, it is only 0.60 percent, very less compared to fundamental return spillover, indicating that the overall spillover is coming from the fundamental component of the returns than the bubble components. The dynamics of these countries' stock market mostly depends on the real changes in the economy. This is true in volatility spillovers, where more spillover comes from the fundamental component of the return than the bubble component.

Interestingly, the actual and fundamental return and volatility spillover results indicate that NIKKEI 225 is significantly contributing to the US S&P 500. Whereas for BSE Sensex, the actual return and volatility spillover are more from NIKKEI 225, but the influence is much less in the case of the fundamental component. It indicates that the fundamentals of BSE Sensex are mainly depended on their own market movement rather than outside. Overall the spillover analysis shows that NIKKEI 225 is the highest contributor to the other market, followed by the S&P 500, and the contribution from BSE Sensex to the other two markets is relatively less.

3.3.3. Continuous Wavelet Coherence

Further, to understand the interdependence among the USA, India, and Japan's stock markets in a frequency-time domain, we implemented the continuous wavelet coherence for actual and decomposed fundamentals and bubbles of each pair of countries separately. The estimated continuous wavelet coherence are plotted in figures 3.4, 3.5, and 3.6. The scale depicted in the graphs' right-hand side indicates the colour red at the top and blue colour at the bottom, scaling the highest and lowest level of wavelet coherence. The y-axis is frequency scale with the numbers denoting the months, and the x-axis is the time scale indicating years. As shown in Figures 3.4, 3.5, and 3.6, for the total return, the red colour at the bottom of the wavelet coherence figure shows the strongly positive coherence at a longer time horizon (more than 64 months) while at the shorter time horizon (less than 16 months), represents a weak coherence between each pair of the stock markets. The fundamental component also gives a consistent result similar to the total return dependence of the stock markets.

In the long-run, at 32–64-month frequency, the fundamental return coherence constantly remains high for the period analysed. Further, this indicates that the short-run horizon investors can benefit from diversification to mitigate market risk, whereas in the long-term investment gives no diversification benefit among the US, India, and Japan. The coherence between each pair of countries' bubble component shows an insignificant relationship, specifically in the long horizon. Whereas in the short run or high frequency, it is evident for some coherence that exists, mainly during the high turbulent crisis period across the globe. These results give some policy implications for international investors, and they provide new evidence to the optimization of financial investment strategies. Similar results are obtained for the volatility of wavelet coherence analysis, and the results are shown in figures 3.7, 3.8, and 3.9. In summary, the fundamental return and volatility have long-run effects across these three stock markets and not the bubble return and volatility.

Figure 3.4: Continuous Wavelet Coherence from Actual Return

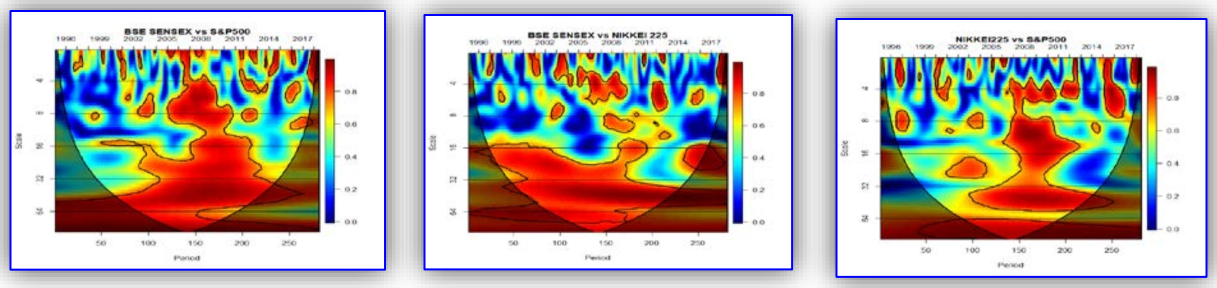


Figure 3.5: Continuous Wavelet Coherence from Fundamental Return

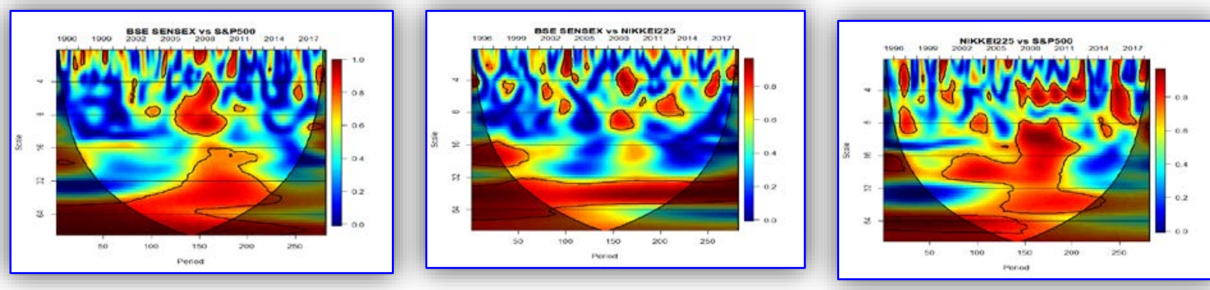


Figure 3.6: Continuous Wavelet Coherence from Bubble Return

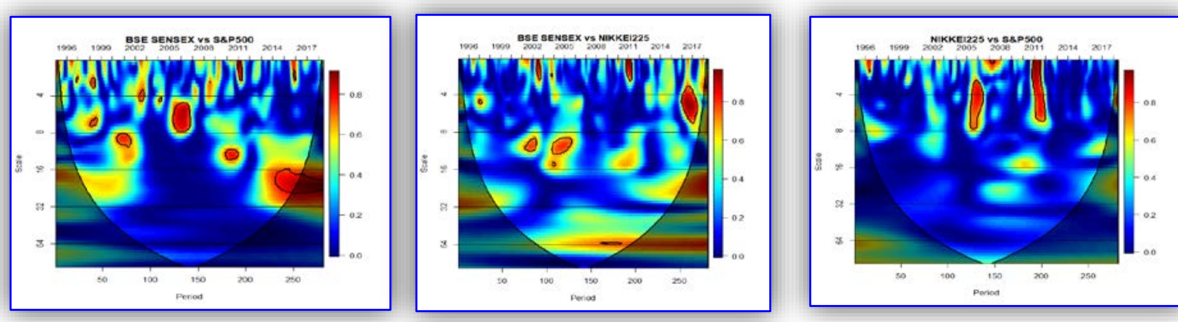


Figure 3.7: Continuous Wavelet Coherence from Actual Return Volatility

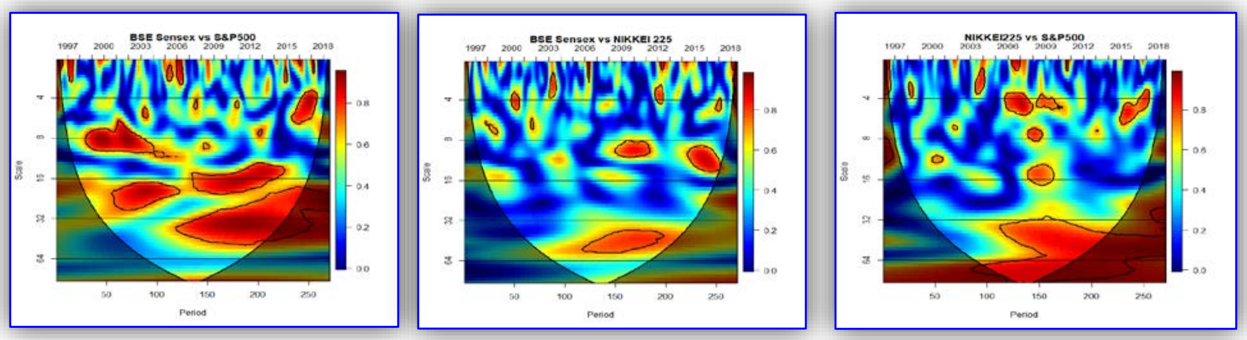


Figure 3.8: Continuous Wavelet Coherence from Fundamental Return Volatility

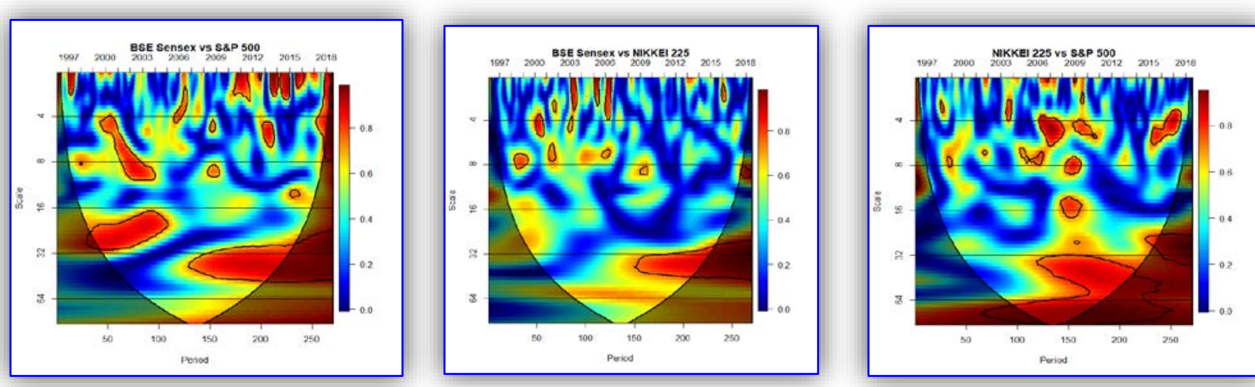
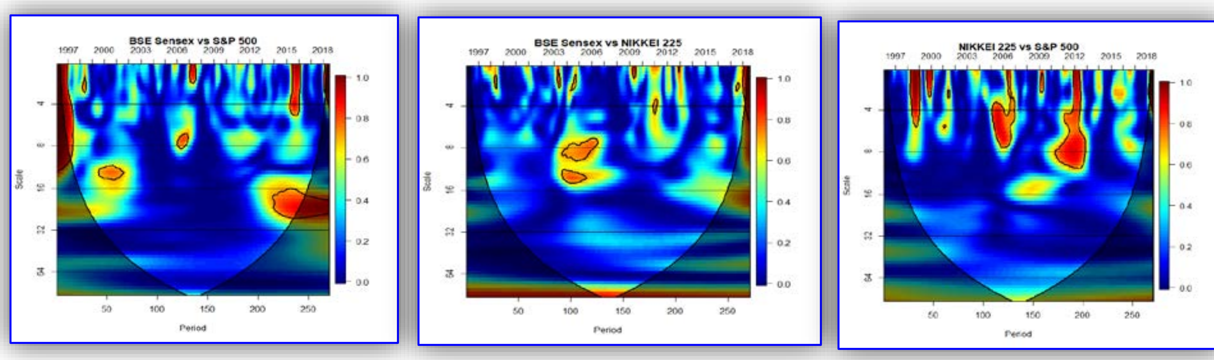


Figure 3.9: Continuous Wavelet Coherence from Bubble Return Volatility



3.4. Conclusion

The study decomposed the asset prices from the US, India, and Japan into fundamental (permanent) and bubble (transitory) components. This study uses real economic activity as fundamental for these markets and estimates a common trend method of Warne (1993) and Blix (1995) to identify fundamental and bubble components of stock prices from April 1994 to July 2018. The study identified that all three stock markets are cointegrated with the Index of Industrial Production as a proxy of output and global Gold prices. The results from the common trend method identify that the long-term trend in the stock price variability is due to fundamental components; at the same time, some part of stock price movements is explained by the bubble component as well during the period of the global financial crisis of 2007. Further, to understand the dynamic relationship between the actual, fundamental, and bubble components of return and volatility of these stocks are connected, first we employed Diebold and Yilmaz (2012) return and volatility spillovers along with the continuous wavelet coherence analysis of Aguiar-Conraria and Soares (2014) to find out the origin and their relationship in a frequency-time domain. The return and volatility spillover, as well as the wavelet coherence results, clearly say an overwhelming predominance in the fundamental component of the stock market than the bubble component, indicating that in the long term, the markets are driven by the fundamentals rather than the bubbles.

Chapter 4

AN ALTERNATIVE APPROACH TOWARDS BUBBLE IDENTIFICATION

4.1. Introduction

This chapter proposes a new alternative method, which is unexplored in the present literature, to detect asset price bubbles. The popular definition of bubble refers to a persistent deviation of asset price from their fundamental values. The existing methodologies in the literature mostly talk about detecting asset price bubbles based on the fundamental value and then mapping that with the market price. Fama (1965) proposed the efficient market hypothesis and prescribed that persistent profit-making is not possible in an efficient market. An enormous increase in the stock price during the 1980s questioned the validity of an efficient market in the financial literature and started checking the presence of speculative bubbles. Studies by Shiller (1981), LeRoy and Porter (1981), West (1987), Froot and Obstfeld (1991), Frommel and Kruse (2011), Phillips, et al. (2011), and later Phillips, Shi, Yu (2015) are some of the examples in bubble detection literature.

Moreover, the strong and unexpected stock price rise since the nineties led economist to challenge the determinants of stock price valuations and examine whether this growth is due mainly to fundamentals or the result of a bubble. Therefore, the prime hindrance for identifying an adequate test to detect bubbles lies in observing the true fundamental value for stocks. With the possibility of observing the fundamentals unambiguously, it would be easy to understand bubbles in the market. However, we estimate fundamental values based on certain assumptions or anomalies on the expectations and representations in literature.

Therefore, the deviation of asset price from there fundamentals to extract the bubbles has these assumptions or anomalies [Jawadi and Prat, 2017]. This chapter's main objective is to explore an alternative approach in identifying a correct fundamental based on a simple idea of minimizing the stock market's cross-sectional irregularities.

Cornelli and Yilmaz (2015) argued that prices converge to their fundamental values if the traders do not face short-selling constraints. On the contrary, Bekjarovski (2017) argued that high short-selling cost might cause the price to remain away from fundamental values.

To identify a correct fundamental for a stock is a complicated task; most of the existing studies use dividends, price-earnings ratio, or real economic activities as fundamental of the stock price. The previous chapter of this thesis also used the economic activity as the fundamental determinant of the three countries' stock prices.

These fundamentals, which are generally used in the existing literature, do not fully represent the correct fundamental values of stocks. Therefore, this study tries to find a new way to assess the fundamental value of stocks' market price and its moments without any external variables. The chapter attempts to understand whether minimizing the cross-sectional variance and skewness of the components that constitute an index in identifying the bubbles from its market value. The method follows the basic idea of decomposing the stock price into two components, the price changes due to the fundamental movement, and the remaining as a bubble. This study's contribution comes from the fact that it uses the cross-sectional information of a stock index in identifying the bubbles. In contrast, most of the other studies are limited only to time-series analysis.

Very few studies talk about the importance of cross-sectional information in understanding the asset price movements [McEnally and Todd, 1992] and its relationship with speculative bubbles [Anderson and Brooks, 2014]. The proposed method's basis is backed by the theoretical framework to understand the transitory deviation of inflation from the underlying trend emanated from firms' cross-sectional behavior to the price change specified in Ball and Mankiw (1995) (BM hereafter). Deriving similar parlance, the component stocks that constitute the market index react to their fundamentals, like firms' reaction to a price change in the BM model. If skewness of the price change of individual firms/return component stocks is considered an aggregate shock, minimizing the skewness will get us the fundamental return of the market index. Following the model explained in the next section, it involves three steps: the first step is to have the time series of the market index and its component stock prices with weights, aggregating to market index over time. Second, the skewness of the distribution of the cross-sectional return of component stocks is minimized every period to derive the fundamental return of the market return. Third, convert this identified fundamental return to derive fundamental market price and the term remaining as bubbles.

This study's main contribution is manifold as follows: To our knowledge, no other research employs the information on the cross-sectional moments of the component stock returns that constitute market index to derive fundamental and bubble values. It addresses the main problem faced by the usual present value model of rational asset pricing, which requires an appropriate variable to determine the fundamental value. Most emerging economies do not have a valid and reasonable data on these financial variables. Most importantly, merely mapping the price dividend ratio or any other ratios to stock price will not give much insight into the market movements, as many markets do not regularly distribute the dividends. Further, in a market with two kinds of investors, one who invests based on the underlying benefits of the stocks such as dividend or future pay-outs from the stocks, another invests based on the price movements alone in the market. Using present value models fails to map all the trends in the prices, and this new approach provides a valid alternative to understand it.

This chapter organizes as follows: section 4.2 explains the methodology of the proposed alternative approach. Section 4.3 describes the data used and its construction to make it suitable to implement this model. Section 4.4 provides the empirical analysis results with a discussion and comparison with other bubble identification models. The final section concludes with a summary and implications of this model.

4.2. An Alternative Method

The new approach follows Ball and Mankiw's (1995) theoretical framework and the empirical framework of Rather et al. (2016). In a traditional present value model, the price of an asset $\boldsymbol{P_t}$ contains the fundamental component $\boldsymbol{D_t}$ and a bubble component $\boldsymbol{B_t}$ as $P_t = D_t + B_t$. A stock price's fair or fundamental value can be identified by subtracting the transitory or bubble part from the actual price. To derive the fundamental value, we modified the model of Ball and Mankiw (1995) in the stock market context.

Consider a market that contains several sectors, each with a set of imperfectly competitive firms, and their stocks are traded in the market. The expected price change (return) of a firm's stock equals $\Delta P^f + \theta$, where ΔP^f is the fundamental price change common across all the stocks in the sector and θ a non-fundamental idiosyncratic shock that follows skewed normal distribution *f(θ)* with 0 mean probability density function. In the presence of asymmetric information and the investors' behavior, not all the firms in the sector and not all sectors in the market get equal attention. With a transaction cost, C that follows a cumulative distribution function G(.), the actual price changes of a sector is $\Delta P^f + \{\theta G(|\theta|)\}$ and the realized aggregate return of the market is as follows:

$$\Delta P^m = \Delta P^f + \int_{-\infty}^{\infty} \theta G(|\theta|)\ f(\theta) d(\theta) \tag{4.1}$$

Hence, if the density of the transitory shock *f(θ)* is symmetric $\{f(\theta) = f(-\theta)\}$ then the actual price change is the same as ΔP^f. Whereas if *f(θ)* is asymmetric and skewed $\{f(\theta) \neq f(-\theta)\}$ then the actual price change ΔP^m differs from ΔP^f based on this argument, we minimize the skewness of the actual price to reduce the influence of θ on ΔP^m and uncover ΔP^f a common component of price change, which is the same across all the stocks that we term the market's fundamental return. To minimize the skewness, we adopt the method introduced by Rather et al. (2016) as follows:

1. Calculate the change in the price ($\boldsymbol{\Delta P_{it}}$) of the i^th stock for period $\boldsymbol{t}$ as ln($\boldsymbol{P_{it}/P_{it-1}}$); hence the market return is defined as

   $$\Delta P_t = \sum_{i=1}^{N} w_i \Delta P_{it} \tag{4.2}$$

   where N represents the total number of stocks and w_i represents the weight assigned for ith stock.

2. organize each stock price change $\boldsymbol{\Delta P_{it}}$ in ascending or descending order with their concerned weights for each time period.

3. A grid-search method is applied to determine the range of stock price changes {i^*, j^*} which minimizes the absolute skewness $|S_h|$. The search method can be written as follows:

$$S_h = \frac{\left(\sum_{h=i}^{j} w_h (\Delta P_h - \Delta P)^3\right) \times \left(\sum_{h=i}^{j} w_h\right)^{1/2}}{\left(\sum_{h=i}^{j} w_h (\Delta P_h - \Delta P)^2\right)^{3/2}} \tag{4.3}$$

For all $j = \{n, n\text{-}1, n\text{-}2 \ldots .T\}$, $i = \{1, 2, 3, \ldots .j\text{-}T\text{+}1\}$, where T is the upper limit that leaves minimum required data for the estimation of skewness and $\boldsymbol{\Delta P}$ is the sample mean of price change in each period. For each period, this produces T(T-1)/2 estimate of skewness for every time period.

4. The fundamental return of the market (ΔP_t^f) for period t, specified as the weighted average of stock price changes within the optimal range i^* to j^*, is calculated as:

$$P_t^f = \sum_{h=i^*}^{j^*} w_h P_h \,/\, \sum_{h=i^*}^{j^*} w_h \tag{4.4}$$

This method's advantage is that the trimming range, which could be symmetric or asymmetric for each time period, is endogenously and uniquely determined based on the size and sign of skewness.

4.3. Data

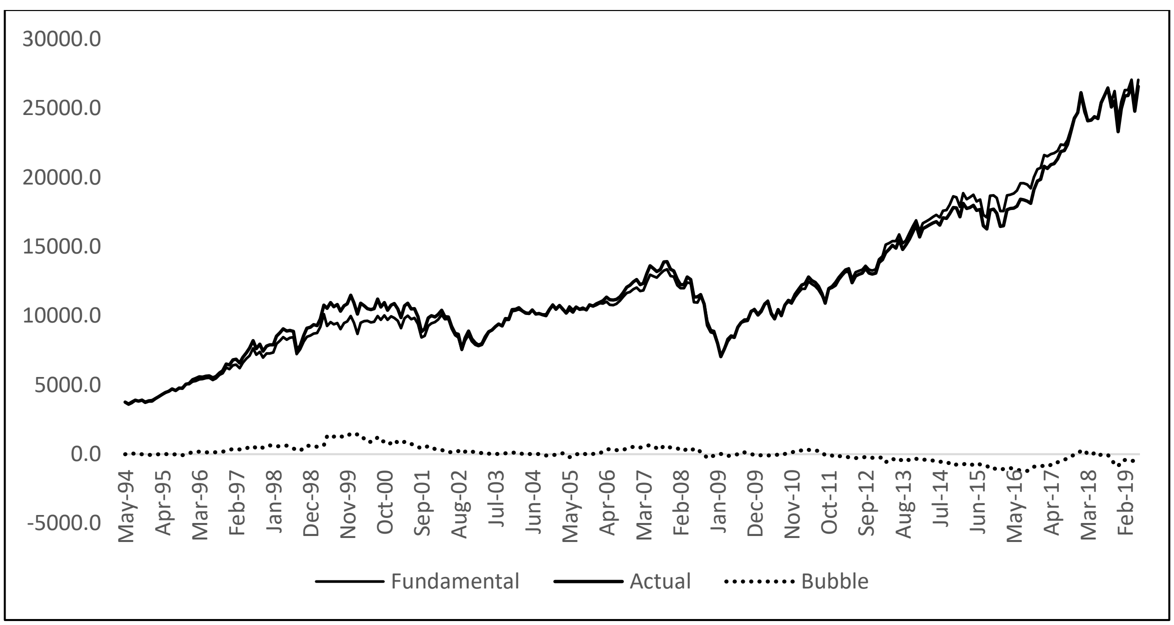
The data used to implement this new approach are monthly data of all the 30 stocks comprised in the Dow Jones Industrial Average (DJIA) Index of the US from May 1994 to May 2019. Since the DJIA Index is an equally weighted index with a base divisor, the study provides equal weights to all stocks with an appropriate base divisor. The data on all the 30 individual stocks comprised in Dow Jones Index and the market index is obtained from the

Yahoo Finance website at www.finance.yahoo.com. The detailed methodology on the construction of the index and the base divisor information is collected from DJIA's official website[3].

4.4. Empirical Results and Discussion

The study develops an approach to detect bubbles by minimizing the skewness of the stocks' cross-sectional returns in the DJIA index. The extracted minimum skewness range and its weighted value for each period are considered the fundamental return of the market, and remainin g is viewed as the bubble component. We can derive the fundamental part of the DJIA index from the resultant fundamental returns by calculating forward from the index's initial value.

Figure 4.1: Actual, Fundamental, and Bubble Components of DJIA

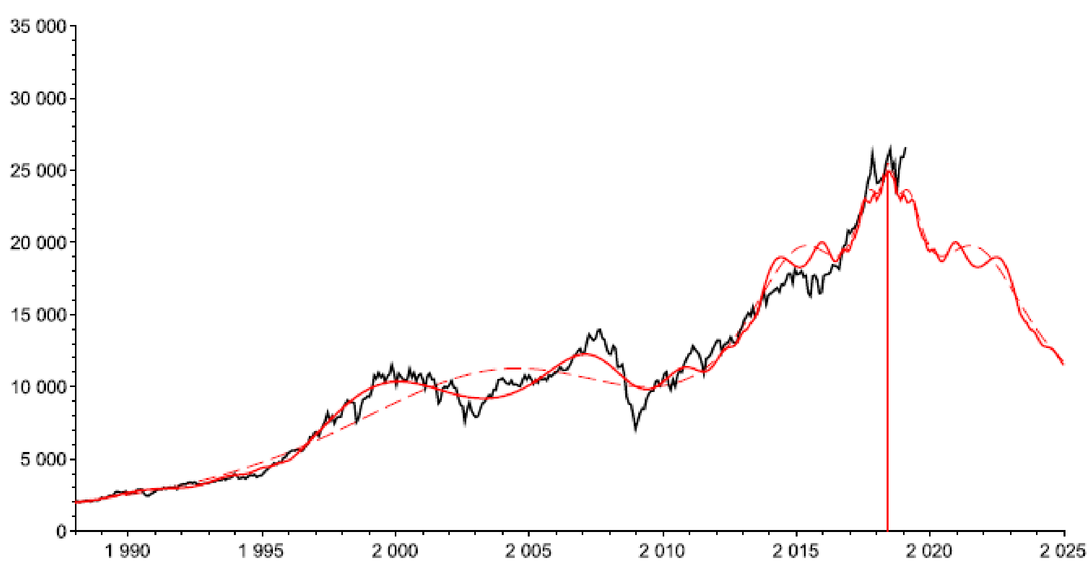


[3] https://www.spglobal.com/spdji/en/indices/equity/dow-jones-industrial-average

Figure 4.1 depicts the actual, along with the derived fundamental and bubble components.

From the figure, we can infer that the fundamental follows the actual price most of the time period except in some periods. During the 1998-2002 period, it shows that the actual price deviates from the fundamental value indicating the bubble's presence during that period. During this period, the bubble can be explained by the now-famous Dotcom bubble of IT companies in the US, indicating the Dotcom bubble is connected with the NASDAQ market and its consequences spread across the DJIA index too. Another major deviation of actual price from its fundamental was during the period from 2006 onwards, demonstrating the existence of bubbles in the market. The projected fundamental value using our method during this period is remarkably lower than the actual price and corresponds to the global financial crisis. The new alternate approach identifies the bubbles consistent with the US economy's specific events and the market.

Figure 4.2: Detection of a speculative bubble in the Dow Jones index of two-scale LPPL law.



To evaluate this model's validity, we compare the results with the recent study by Siess (2019), which is based on the two-scale LPPL method. The result produced in this study is precisely similar to that of Siess (2019) that involves complex computation. Figure 4.2 illustrates the two stage LPPM model of the DJIA index. The figure depicts that the black line represents as the actual DJIA index and the continuous red line corresponds to the two-scale LPPL formula, while the red dashed line corresponds to its main macroscopic component. He studied the DJIA index from1988 to 2019 and clearly identified the Dotcom bubble of 1998-2000 and the Global Financial Crisis of 2006-2008, same as what we found in our approach. Calibrating two stage LPPM formula with respect to a given time series is not as easy as it may seem. Even Though the number of parameters is small, the function to optimize may exhibit a great number of local minima, thus rendering the optimization a little risky.

The log periodic power model (LPPL) identifies the existence of asset price behaviour converging to a crash (Sornette, 2003). Using the notion of positive feedback, a faster than exponential rise in price is defined as a bubble. However, statistical estimates of the above model bounded within specified ranges, which determines market crashes. Due to a given range for statistical estimation, the above model constraints the LPPL model fit within the specified range and therefore cannot capture information outside the given range. Moreover, for the sake of statistical consistency of the LPPL process, prices must continuously increase during the entirety of the bubble phase. This is consistent with literature encompassing rational bubble models but contradicts early empirical studies.

The advantage of the proposed new methodology over his approach is that it distinguishes the price into a fundamental component and bubble component and extracts it over the sample period. Further, the decomposed components can be used to understand its usefulness in various financial applications, including portfolio optimization discussed in the next chapter.

4.5. Conclusion

The empirical literature on speculative bubbles aims to develop quantitative techniques and mechanisms to detect the origination, termination, and level of explosiveness in asset prices. These mechanisms must empirically distinguish the contribution of bubbles and market fundamentals to exuberance detected in the data. The exuberance identified should only be ascribed to bubbles when all other issues that affect asset prices have been ruled out as possible explanations. Even though empirical bubble detection studies have made significant steps over the past decades, it is still a big challenging task to design appropriate for identifying bubble episodes. The prime reason for this lies in the fact that the fundamental value is generally not observable, and it is therefore challenging to determine an asset's fundamental value.

This chapter proposes and examines a new alternative approach to detecting the fundamental value of a market. The approach is built on the cross-sectional skewness of component stock returns by minimizing it to derive the fundamental return theoretically explained by Ball and Mankiw (1995). An empirical application using the method similar to Rather et al. (2016), the derived fundamental and bubble components of the Dow Jones Industrial Average index, precisely identifies bubbles equivalent to the study by Siess (2019) LPPL model. The simplicity of our method identifies the bubble periods and provides an opportunity to extract the time series of the fundamental and bubbles values to the investors for their use in investment strategies.

Chapter 5

FUNDAMENTAL BETA AND PORTFOLIO PERFORMANCE: EVIDENCE FROM AN EMERGING MARKET

5.1. Introduction

The mean-variance portfolio analysis of Markowitz (1952) remains the gold standard of portfolio selection even today with all its limitations[4]. In a situation with a large number of securities available for the construction of the portfolio, Markowitz model turns complex owing to the size of calculating the expected return and variance-covariance matrix involving all the securities along with solving the quadratic programming problem to derive the optimal portfolio. Sharpe (1963) simplified this process by relating the return of a security to a single Market index; by this, all the information is narrowed only to the market beta of each security and the expected market return and variance[5]. Further, Elton et al. (1976) proposed a simple ranking model to construct the optimal portfolio that absolves the problem of solving quadratic programming, with the advent of ever-increasing computing capabilities, this is no longer a more significant constraint; still, the model performs equivalently well. The empirical literature has extensively adopted both these methods and extended it to substantiate improvements in the performance of the portfolio [Zhang et al. 2018].

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[4] Important limitations highlighted in the literature include, mean-variance preferences fails to be monotone and using variance as risk measure have disadvantage as it treats both profit and loss equally, while the risk is associated only with the loss. Refer to Maccheroni et al. (2009) and Ahmadi-Javid and Fallah-Tafti (2019).

[5] Subsequently, the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), Lintner (1965) and Mossin (1966) became the benchmark in evaluating the price and risk premium of any security.

In literature, the static market beta estimation, as well as the usage of it in portfolio management, received much criticism. Blume (1971) emphasized that no economic variable is constant over time, including the market beta. In portfolio evaluation, he argued that if time variation in the beta is stationary, the static beta can be an unbiased estimate of the future values. With the data from the common stocks listed in NewYork Stock Exchange, he identified that the beta for a portfolio is relatively stable and showing regression tendencies towards unity as the number of stocks in the portfolio increases, while the beta of individual securities is not. Afterward, many studies established that the beta coefficients of individual stocks move randomly over time and not remain static [Fabozzi and Francis (1978); Sundar (1980); Bos and Newbold (1984)] and studies explained possible reasons for this regression tendencies of the portfolio betas (Goldberg, 1981). Abdymomunov and Morley (2011) investigated the time variation in CAPM betas for Book-to-Market and momentum portfolios across different regimes of stock market volatility. They find that betas vary significantly across changing volatility regimes, and the time-varying character of the beta coefficient is more when financial market volatility is high.

The time-varying betas of individual securities are estimated predominantly through rolling regression, multivariate GARCH, and Kalman filter techniques [Fama and MacBeth (1973); Giannopoulos (1995); Gonzalez-Rivera (1996); Brooks *et al*. (1998); Marshall *et al*. (2009)]. Recently, Engle (2016) renewed the interest in the estimation of time-varying beta by extending it to the Fama-French 3 factor model with a dynamic conditional beta method. Most of these studies are addressing either the forecasting performances of the future betas or the relationship between this dynamic betas on the cross-section of stock returns and only a few studies like Ghysels and Jacquier (2006) and Nieto et al. (2014) uses it in understanding the portfolio performances. Recently, Borup (2019) employed time-varying beta analysis to quantify uncertainties and abnormal returns from the market and found that the abnormal returns are closely connected to the uncertainties in the market. He argues that the usual CAPM beta cannot identify this, and using time-varying beta is the better way forward. For an emerging market, the literature on this time-varying beta estimation is very sparse, and particularly for India, studies like Shah and Moonis (2003), Dubey (2014), Das and Barai (2015) are few exceptions.

On the other hand, understanding the fair value of a stock price in the prevalence of speculative bubbles and deriving the fundamental component in stock returns is an important stream of research in empirical finance. Starting from Gordon (1959), the present value models using discounted future dividends are widely used to identify the fair value of a stock price. Later on, Lee (1995) implemented a structural VAR model to decompose the fundamental and bubble components from US and Japan asset prices. Bramante and Gabbi (2012) decomposed the beta as bull beta and bear beta in a time-varying framework using state-space models to assess the performances of the portfolios with the decomposed betas. The results are different for bull and bear betas than the usual passive beta portfolios with new information for designing active strategies to enhance portfolio performance. Anderson and Brooks (2014) identified that the common variation in stock returns are better explained by the co-movement of bubbles present in an individual stock and the market rather than the fundamentals for UK stocks. They introduced the bubble CAPM model that decomposes the market beta into fundamental and bubble beta[6].

[6] In another stream of research, fundamental beta is derived as the estimated value from a cross-sectional regression of historical betas of stocks with fundamental ratios. [See Rosenberg and Marathe (1975)]

Further, in recent times, combining the fundamental analysis with portfolio optimization for a better performing portfolio is gaining focus. Cosemans *et al*. (2016) estimated security betas using firm fundamental priors and found that the method provides superior forecasts of the beta. Lyle and Yohn (2018) combined the expected returns derived from the fundamental ratios to construct the portfolio that offers a substantial gain in the performance.

Although it is well established in the literature on the usefulness of time-varying beta and the inclusion of fundamental factors in the construction of a portfolio, these two remain as two distinct sets of empirical analysis and forms the scope of this study. The main focus of this study is to evaluate the portfolio performance by combining time-varying beta and the fundamental factors from an emerging market perspective using both static and dynamic time-varying framework. This study modifies the bubble CAPM model in a time-varying framework by deriving the conditional covariances and variances from a multivariate GARCH model to assess the efficacy of this decomposition in the improvement of portfolio performance.

This study contributes to the literature in three ways: first, it adapts Anderson and Brooks (2014) bubble CAPM in a static and dynamic time-varying framework and uses it in evaluating the portfolio performance. Second, examining the relative effectiveness of the portfolio for the data from an emerging market, India, with this time-varying market, fundamental and bubble beta is first of its kind from an emerging market perspective, and finally, it provides a simple, parsimonious alternative towards combining portfolio optimization with fundamental and bubble factors. The rest of the paper is organized as follows: Section 2 briefly introduces the methodology and the data used, while section 3 provides the results from the empirical analysis, and the final section concludes with implications for investment analysis.

5.2. Methodology and Data

5.2.1. Portfolio Optimization

Considering the market model of Sharpe (1963) as $R_{it} = \propto_i + \beta_i R_{mt} + \varepsilon_{it};\ \varepsilon_{it} \sim N(0, \sigma^2_{\varepsilon_i})$ where R_{it} and R_{mt} are the returns of i^{th} stock and the market at time t with β_i as market risk measures the sensitivity of changes in i^{th} stock to the changes in the market. Using this Elton et al. (1976) derived the optimal portfolio shares Z_i of each stock by maximizing the ratio of portfolio excess return to portfolio risk as

$$Z_i = \frac{\beta_i}{\sigma^2_{\varepsilon_i}}\left[\frac{E(R_i)-R_f}{\beta_i} - C\right];\ C = \sigma^2_m \frac{\sum_{j=1}^{n}\left[\frac{E(R_j)-R_f}{\sigma^2_{\varepsilon_j}}\beta_j\right]}{1+\sigma^2_m \sum_{j=1}^{n}\frac{\beta^2_j}{\sigma^2_{\varepsilon_j}}} \tag{5.1}$$

where $E(R_i)$ is the expected return of the i^{th} stock, and R_f is the risk-free rate. In an environment where short sales are not allowed, Z_i should be positive and for that $\frac{E(R_i)-R_f}{\beta_i}$ should be greater than C; eventually, C act as a criterion for including the stocks in the portfolio. Finally, Z_i is scaled to summation equals 1.

Alternatively, following Nieto et al. (2014), we can also implement the portfolio optimization with a static market beta as follows: the variance of a portfolio with n stocks can be derived as $\vartheta = \sigma^2_m BB' + R$; where σ^2_m is the variance of the market return; $\boldsymbol{B}$ is an n-vector of individual betas, and $\boldsymbol{R}$ is an n-vector of the idiosyncratic residuals from the market model. With this, the minimum variance portfolio is derived by choosing the n-vector portfolio shares ($\boldsymbol{z}$) by solving the equation $\boldsymbol{min\ z'\vartheta z}$ subject to $\boldsymbol{z'1 = 1}$.

5.2.2. The Bubble CAPM

Anderson and Brooks (2014) derived the total return on *i*th stock and the market as the sum of fundamental and bubble return as $R_i = R_i^f + R_i^b$ and $R_m = R_m^f + R_m^b$ along with β_i expressed as $\beta_i = \frac{Cov(R_i, R_m)}{Var\,(R_m)} = \frac{Cov(R_i^f + R_i^b, R_m^f + R_m^b)}{Var\,(R_m^f + R_m^b)}$. Further, they assumed that the covariance between bubble and fundamental components in both i^{th} stock and the market returns are equal to zero. With this restriction, they decomposed the market beta into fundamental and bubble beta as

$$\beta_i = \frac{Cov\left(R_i^f, R_m^f\right) + Cov\left(R_i^b, R_m^b\right)}{Var\left(R_m^f\right) + Var\,(R_m^b)} = \frac{Cov\left(R_i^f, R_m^f\right) + Cov\left(R_i^b, R_m^b\right)}{Var\,(R_m)} = \beta_i^f + \beta_i^b \qquad (5.2)$$

where $\beta_i^f = \frac{Cov\left(R_i^f, R_m^f\right)}{Var\,(R_m)}$ and $\beta_i^b = \frac{Cov\left(R_i^b, R_m^b\right)}{Var\,(R_m)}$.

To implement this fundamental and bubble beta in the portfolio optimization, we need to calculate the residual variance $\sigma_{\varepsilon_i}^2$ separately. To derive that we first calculated α_i^f and α_i^b as follows: $\alpha_i^f = \bar{R}_i - \beta_i^f * \bar{R}_m$ and $\alpha_i^b = \bar{R}_i - \beta_i^b * \bar{R}_m$. The derived β_i^f, $\sigma_{\varepsilon_i}^{2^f}$ and β_i^b, $\sigma_{\varepsilon_i}^{2^b}$ are then substituted in equation (1) to derive the fundamental and bubble beta optimal portfolio shares.

To decompose the stock price into fundamental and bubble component, they followed Van Norden and Schaller (1999) model in which the fundamental component is derived as a multiple of current dividend if the dividends follow a geometric random walk and a constant discount rate and represented as $p_{it}^f = \rho d_{it}$. Anderson and Brooks (2014) approximated ρ as the trailing average of price-dividend ratio, and this study uses the same procedure in deriving the fundamental and bubble component.

5.2.3. Time-varying Beta

A range of Generalized Autoregressive Conditional Heteroscedastic (GARCH) models is used in the empirical literature to derive the time-varying conditional betas starting with Bollerslev et al. (1988), Engle and Rodrigues (1989) and Ng (1991). This study considers the widely used MGARCH-BEKK model of Engle and Kroner (1995), which has the advantage of a positive-definite constraint of the conditional covariance matrix by construction for estimating the conditional covariance and variance between an i^{th} stock return and the market return[7]. This model constructs conditional variance-covariance matrix H as follows:

$$H_{it} = C_i{}'C_i + A_i{}'\varepsilon_{it-1}\varepsilon_{it-1}{}'A_i + B_i{}'H_{it-1}B_i \tag{5.3}$$

where $\boldsymbol{C_i}$ is a 2 × 2 lower triangular coefficient matrix, and $\boldsymbol{A_i}$ and $\boldsymbol{B_i}$ are 2 × 2 coefficient matrices and maximizes the following log-likelihood function

$$\ln L\,(\theta_i) = -\frac{1}{2}\sum_{t=1}^{T} \ln|H_{it}| - \frac{1}{2}\sum_{t=1}^{T} y_{it}{}'H_{it}^{-1}\, y_{it} \tag{5.4}$$

where $\boldsymbol{\theta_i}$ is the parameters to be estimated, and $\boldsymbol{y_{it}}$ consists of i^{th} stock return and market return in the mean equation expressed as $y_{it} = \mu_i + \nu_{it}$, and $\nu_{it} = \varepsilon_{it} \sqrt{H_{it}}$ in which μ_i is a constant and $\varepsilon_{it} \sim N(0,1)$. From this, the time-varying conditional beta is estimated as

$$\beta_{it} = \frac{H_{imt}}{H_{mmt}} \tag{5.5}$$

[7] This model is preferred over the Kalman filter, for a similar exposition of the bubble CAPM of Anderson and Brooks (2014) in a time-varying framework.

where H_{imt} is conditional covariance between ith stock and the market return, and H_{mmt} is the conditional variance of the market return.

To adapt the bubble CAPM of Anderson and Brooks (2014) in a time-varying framework with the assumption that the covariance between bubble and fundamental components in both i^{th} stock and the market returns are equal to zero, we charted the following procedure. First, we decomposed the stock price into the fundamental and bubble component using Van Norden and Schaller (1999) model explained in section 2.2 for both the i^{th} stock and the market return. Second, a univariate GARCH model is run separately for the fundamental and bubble component of the market return to estimate the conditional variances H_{mt}^{f} and H_{mt}^{b}. Finally, the conditional covariances for the fundamental and bubble component of i^{th} stock and market return H_{imt}^{f} and H_{imt}^{b} are estimated separately through the MGARCH-BEKK model explained in equations (3) and (4). With that, the dynamic conditional time-varying market beta is estimated as

$$\beta_{it}^{m} = \frac{H_{imt}^{f}+H_{imt}^{b}}{H_{mt}^{f}+H_{mt}^{b}} = \beta_{it}^{f} + \beta_{it}^{b} \qquad (5.6)$$

where $\beta_{it}^{f} = \frac{H_{imt}^{f}}{H_{mt}^{f}+H_{mt}^{b}}$ and $\beta_{it}^{b} = \frac{H_{imt}^{b}}{H_{mt}^{f}+H_{mt}^{b}}$.

Subsequently α_{it}^{f} and α_{it}^{b} is derived as follows: $\alpha_{it}^{f} = \bar{R}_i - \beta_{it}^{f} * \bar{R}_m$ and $\alpha_{it}^{b} = \bar{R}_i - \beta_{it}^{b} * \bar{R}_m$. The derived β_{it}^{f}, α_{it}^{f} and β_{it}^{b}, α_{it}^{b} are used for each period t to calculate the residual variance $\sigma_{\varepsilon_{it}}^{2f}$ and $\sigma_{\varepsilon_{it}}^{2b}$. With a dynamic time-varying beta for the period $t = 1, 2, \ldots T$; the portfolio optimization is implemented for every period t. In this case, the variance of the portfolio with *n* stocks become *n x T*-matrix $\vartheta = \sigma_m^2 BB' + R$; where σ_m^2 is the variance of the market return while $\boldsymbol{B}$ is an *n x T*-matrix of individual betas for the period 1 to T and $\boldsymbol{R}$ is an *n x T*-matrix of the idiosyncratic residuals from the market model. The portfolio is optimized for every period t by solving $\boldsymbol{min\ z_t{}'\vartheta_t z_t}$ subject to $\boldsymbol{z_t{}'1 = 1}$, to derive the optimal portfolio shares z_t. The optimal shares are used to evaluate portfolio performances.

5.2.4. Evaluating the Portfolio Performance

The relative performances of the portfolios are assessed with a simple Markowitz mean-variance portfolio return and risk derived as $R_p = \sum_{i=1}^{n} \bar{R}_i Z_i\,; \sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_{ij} Z_i Z_j$. Along with the three optimal portfolio shares of the market, fundamental and bubble beta from equation (1), an equal weight naïve portfolio share as well as Markowitz portfolio share by minimizing the variance σ_p^2 for a positive return are also calculated. For all these five portfolio shares Sharpe ratio is calculated as $\theta = \frac{R_p - R_f}{\sigma_p}$ and compare it using the equality test proposed by Jobson and Korkie (1981) and improved by Memmel (2003) (JK-M test hereafter). As argued by Ledoit and Wolf (2008), this test is not appropriate when there are autocorrelated and non-normal fat-tailed returns, and proposed robust alternative inference methods in which HAC inference uses kernel estimators to cone up with consistent standard errors. So first, we construct the portfolio return series $R_{pt} = \sum_{i=1}^{n} R_{it} Z_i$ and check for autocorrelation and normality before implementing the JK-M test.

In JK-M test, the null hypothesis of equality of Sharpe ratios from two different portfolio shares is rejected at α level of significance if zero lies outside the confidence interval derived from the standard normal distribution Z as $\hat{d} \pm Z_{1-\frac{\alpha}{2}}\, \hat{\delta}(\hat{d})$; where $\hat{d} = \hat{\theta}_p - \hat{\theta}_q$ and

$$\hat{\delta}(\hat{d}) = \sqrt{[\left(\frac{1}{T}\right)\left\{2 - 2\hat{\rho}_{pq} + 0.5 * \left(\hat{\theta}_p{}^2 + \hat{\theta}_q{}^2 - 2\hat{\theta}_p\hat{\theta}_q\hat{\rho}_{pq}{}^2\right)\right\}]} \tag{5.7}$$

Where $\hat{\theta}_p, \hat{\theta}_q$ and $\hat{\rho}_{pq}$are estimates of Sharpe ratios and correlation between portfolio return series with *p* and *q* portfolio shares. A similar procedure is used in the case of dynamic time-varying beta as well in analyzing the relative performances of the portfolios. The portfolio return series is constructed with time-varying optimal portfolio shares z_t, as $R_{pt} = \sum_{i=1}^{n} R_{it} Z_{it}$ and check for autocorrelation and normality before choosing the JK-M test or the one proposed by Ledoit and Wolf (2008).

5.2.5. Data

This study uses monthly data on eight sectoral and four thematic indices of the National Stock Exchange of India and NIFTY 500 index along with their dividend data for the period from January 2012 to December 2018. The selection of these indices is based on the availability of consistent dividend data for the sample period. The eight sectoral indices include Bank, Auto, Financial Services, FMCG, IT, Media Metal, and Pharma, while four thematic indices are Service Sector, Energy, MNC, and Infra and the data for all these indices are collected from www.nseindia.com.

5.3. Empirical Results

For the 12 indices and NIFTY 500 index, the fundamental and bubble components are derived, and their returns are calculated as the first difference of its natural logarithm. The estimated market, fundamental, and bubble beta from the static model, as well as the median of the time-varying betas, is given in Table 5.1. It is evident that for all the indices, bubble beta explains a major portion of the market beta than the fundamental beta in both the static and time-varying estimation. For the infrastructure sector, the negative bubble beta indicates the discordance with the market bubble component. The market beta for Auto, FMCG, IT, Media, Metal, and MNC indices shows a higher beta in the median of the time-varying beta than the static beta. In contrast, it is reverse for Bank, Financial Services, Pharma, Service sector, Energy, and Infra indices indicate the variations between the static and time-varying framework and have heightened implications in the portfolio construction.

Since Elton et al. (1976) derived optimal portfolio shares by maximizing excess return, we used three different risk-free rates, namely 4, 6, and 8 percent[8], to calculate excess return and derived the optimal portfolio shares for the market, fundamental and bubble beta. The optimal portfolio share is substituted in a Markowitz mean-variance framework, and corresponding portfolio excess return and risk are estimated along with the Sharpe ratio. The results are presented in Table 5.2 for the static model. The results are very similar to all the risk-free rates used where the fundamental beta proportion has a higher Sharpe ratio compared to others.

The results from the time-varying model are provided in Table 5.3, with the average excess return and risk of the portfolio along with the Sharpe ratio

[8] This is the range of risk-free rate in India during the sample period and the same risk-free rates are used for equal weight and Markowitz mean-variance portfolios as well.

Table 5.1: Estimated Betas

Indices	Static Betas			Median Time-varying Betas		
	Market	Fundamental	Bubble	Market	Fundamental	Bubble
Bank	2.452	0.839	1.613	1.963	0.592	1.277
Auto	0.660	0.144	0.517	0.694	0.090	0.578
Financial Services	1.858	0.612	1.246	1.282	0.246	0.962
FMCG	0.365	0.039	0.326	0.420	0.005	0.356
IT	0.510	0.240	0.269	0.621	0.230	0.338
Media	0.645	0.105	0.539	0.669	0.118	0.546
Metal	0.353	0.015	0.338	0.493	0.169	0.331
Pharma	1.056	0.317	0.739	0.217	0.063	0.186
Service Sector	1.528	0.487	1.041	0.944	0.267	0.659
Energy	1.303	0.415	0.888	1.019	0.305	0.682
MNC	0.847	0.120	0.727	1.045	0.201	0.787
Infra	0.486	0.175	0.311	0.048	0.132	-0.109

We report the results only for a 6 percent risk-free rate for validation hereafter. From the results, we can see that the Sharpe ratio is relatively higher with the fundamental beta model compared to other models[9].

[9] The results remain similar for the risk-free rate at 4 and 8 percent as well, which is not reported here but can be obtained upon request.

Table 5.2: Excess Return, Risk and Sharpe Ratio from Static model

Model	Excess Return $(R_p - R_f)$	Risk (σ_p)	Sharpe Ratio $(\theta = \frac{R_p - R_f}{\sigma_p})$
Risk-free rate at 4%			
Naïve	0.0049	0.0033	1.481
Markowitz	0.0045	0.0027	1.677
Market Beta	0.0061	0.0033	1.867
Fundamental Beta	0.0067	0.0032	2.062
Bubble Beta	0.0066	0.0032	2.041
Risk-free rate at 6%			
Naïve	0.0032	0.0033	0.967
Markowitz	0.0028	0.0027	1.043
Market Beta	0.0053	0.0035	1.496
Fundamental Beta	0.0058	0.0034	1.731
Bubble Beta	0.0056	0.0034	1.655
Risk-free rate at 8%			
Naïve	0.0015	0.0033	0.453
Markowitz	0.0012	0.0027	0.447
Market Beta	0.0040	0.0036	1.109
Fundamental Beta	0.0044	0.0034	1.304
Bubble Beta	0.0042	0.0034	1.235

Table 5.3: Excess Return, Risk and Sharpe Ratio from Time-varying model

Model	**Excess Return** $(R_p - R_f)$	**Risk** (σ_p)	**Sharpe Ratio** $(\theta = \frac{R_p - R_f}{\sigma_p})$
Risk-free rate at 6%			
Market Beta	0.0054	0.0019	2.806
Fundamental Beta	0.0120	0.0034	3.540
Bubble Beta	0.0064	0.0024	2.656

Before evaluating the difference in Sharpe ratios statistically using the JK-M test, we examined the autocorrelation and normality of the portfolio return series derived from different model optimal shares. Table 5.4 provides the Q-statistics of first-order autocorrelation and Jarque-Bera statistics of normality test for portfolio returns with a 6 percent risk-free rate. The results show that for all the model portfolios, return series are normal and having no first-order autocorrelation except the time-varying market beta model, which is significant at the 10 percent level[10].

We implement the JK-M test for all these portfolios returns to validate the difference in the Sharpe ratio in comparison to the static and time-varying fundamental beta. First, the JK-M test for the static model with a 6 percent risk-free rate is carried out. The results reported in Table 5.5 shows that the equality of fundamental beta Sharpe ratio in comparison with all the other models Sharpe ratios are statistically rejected, indicating the supremacy of fundamental beta in portfolio optimization. Further, an elaborate JK-M test is conducted with

[10] It shows only first-order autocorrelation and subsequent orders show no autocorrelation

the time-varying fundamental beta as the benchmark as it gives the highest Sharpe ratio, and the results in Table 5.6 establish the fact that the time-varying fundamental beta provides a far superior portfolio performance over all the other models.

Table 5.4: Test of Autocorrelation and Normality of Portfolio Returns

Model	Q-Statistics	Jarque-Bera
Naïve	0.072 (0.789)	0.428 (0.807)
Markowitz	0.818 (0.366)	0.123 (0.940)
Market Beta – Static	0.082 (0.775)	0.741 (0.690)
Fundamental Beta - Static	0.335 (0.563)	0.760 (0.683)
Bubble Beta – Static	0.283 (0.595)	0.878 (0.645)
Market Beta – Time-varying	3.155* (0.076)	0.729 (0.694)
Fundamental Beta– Time-varying	0.143 (0.706)	0.201 (0.904)
Bubble Beta– Time-varying	1.749 (0.186)	1.308 (0.520)

*In the parentheses are p-values and * denotes significance at 10 percent level*

Table 5.5: Results of JK-M Test – Static Model

Model	Static Fundamental beta with risk-free rate at 6%		
	$\widehat{d} = \widehat{\theta}_{f.beta} - \widehat{\theta}_q$	$\widehat{\rho}_{f.beta\,q}$	Confidence Interval at 5% level
Naïve	0.764	0.953	[0.548, 0.980]
Markowitz	0.688	0.861	[0.419, 0.957]
Market Beta	0.235	0.977	[0.009, 0.371]
Bubble Beta	0.076	0.999	[0.006, 0.146]

Table 5.6: Results of JK-M Test – Time-varying Model

Model	Time-varying Fundamental beta with risk-free rate at 6%		
	$\widehat{d} = \widehat{\theta}_{f.beta} - \widehat{\theta}_q$	$\widehat{\rho}_{f.beta\,q}$	Confidence Interval at 5% level
Naïve	2.573	0.783	[2.053, 3.093]
Markowitz	2.497	0.738	[1.964, 3.030]
Market Beta – Static	2.044	0.772	[1.544, 2.544]
Fundamental Beta – Static	1.809	0.738	[1.295, 2.323]
Bubble Beta – Static	1.885	0.746	[1.374, 2.396]
Market Beta – Time-varying	0.734	0.701	[0.172, 1.296]
Bubble Beta– Time-varying	0.884	0.606	[0.267, 1.501]

As a robustness check, Ledoit and Wolf (2008) test[11] is carried out to evaluate the equality of Sharpe ratios of the portfolio constructed using the optimal shares from the time-varying

[11] We used ‘sharpeTesting’ package in R for the estimation.

market, fundamental, and bubble betas. The results in Table 5.7 state that the equality of the Sharpe ratio is rejected in favor of time-varying fundamental beta.

Table 5.7: Results of Ledoit and Wolf Test on equality of Sharpe Ratio

Test	χ^2 Statistic
Fundamental Beta Vs. Market Beta	6.683 (0.009)**
Fundamental Beta Vs. Bubble Beta	26.556 (0.000)**
Bubble Beta Vs. Market Beta	25.838 (0.000)**

*In the parentheses are p-values and ** denotes significance at 1 percent level*

The consistent performance of fundamental beta both in static as well as the time-varying framework has far-reaching implications for portfolio analysis and risk management, in creating compelling investment strategies for a better outcome.

5.4. Conclusion

This study combines two distinct but highly researched aspects of empirical finance in portfolio analysis; first, the growing importance of the time-varying beta in financial analysis and second, the usefulness of fundamental factors in portfolio analysis. In doing so, it provides a simple strategy that has a considerable stake in investment analysis. This study examines portfolio optimization using Sharpe single index model in both static and dynamic time-varying framework by combining the bubble CAPM model of Anderson and Brooks (2014) that decomposes the market beta into fundamental and bubble beta from an emerging market perspective. The empirical results suggest that the portfolio constructed using the fundamental beta portfolio shares performs better than the naïve, mean-variance, bubble, and market beta portfolio shares with a larger Sharpe ratio in both the static and dynamic models.

The dynamic time-varying model with fundamental beta outperforms even the static model with fundamental beta in the portfolio performances. These results have far-reaching implications for investment analysis by providing evidence in favour of using the dynamic time-varying model for better portfolio performance and contribute to the recent literature that combines fundamental analysis with portfolio optimization.

Chapter 6

SUMMARY AND CONCLUSION

6.1. Introduction

The concept of bubbles has attracted considerable attention over time, particularly after the recent global financial crisis. In simple terms, the bubble can be defined as a deviation from the asset prices' fair value. Identifying bubbles in an asset market is an important research question as the bubble impacts on the real economy are enormous. Post financial crisis of 2008, bubbles and crashes in the financial market have become policymakers, financial regulators, investment risk managers, and financial institutions' immediate attention as the financial markets directly or indirectly linked with the economy and society. The channel through which a burst in the asset prices impacts the people who are not only directly related, but it also spreads to other parts of the economy. It induces bankruptcy, increases unemployment, decreases business activities, and diminishes the level of consumption leading to an economic recession. Contrastingly, speculative activities in the stock markets could give substantial benefits as well in risk-reward pursuit. Therefore, not only economists are interested with bubbles and crashes, but almost everyone is concerned in these financial market phenomena. So, the study of financial market bubbles and crashes are getting much attention in economic research and the real world.

This thesis contributes to the literature on asset price bubbles by evaluating the usage of Common Trend methodology in identifying the bubble path, proposing a new skewness based alternative method in doing the same thing, and assessing the efficacy of these identified bubbles and fundamental values in portfolio optimization. This chapter summarizes the thesis with section 6.1, highlighting the major findings. Section 6.2 provides the policy implications derived from the thesis and, finally, section 6.3. gives the limitations and scope for future research.

6.2. Summary and Major Findings

The thesis's introduction provides the theoretical and empirical overview of the importance of asset price bubbles and their impact on the economy. The first empirical chapter, Chapter 2, investigated the theoretical models of asset price bubbles, particularly the asset's fundamental value and the bubble component explained by the famous periodically collapsing bubble model by Evans (1991) and the modified version of recurringly explosive and stochastically deflating bubble of Rotterman and Wilfling (2018). The existing popular empirical methodologies are constructed based on the Unit-root tests, particularly an extended version of Augmented Dickey-Fuller tests that date-stamps bubble period, but none traced the bubble path. To deal with this issue, we employed the Common Trend framework of Warne (1995) to map and trace the theoretical bubble path. The Common Trend method decomposes the asset price into the fundamental (permanent) and bubble (transitory) component from the actual asset price series. The empirical analysis from the simulated series demonstrates that the Common Trend estimation procedure can identify the bubble process well and captures the characteristics of periodically collapsing bubbles and stochastically deflating bubbles exactly.

Chapter 3 attempted to identify fundamental and bubble components of stock prices for India, the USA, and Japan. The identified fundamental and bubble components of these stock markets are further evaluated with the Diebold and Yilmaz (2012) return and volatility spillovers along with the wavelet coherency analysis to find out the origin and their relationship in a frequency-time domain. The empirical results for the period from April 1994 to July 2018 indicate that during the global financial crisis of 2007 – 2009, all these stock markets are invariably driven by bubbles of different sizes. The result from the spillover analysis across these stock markets indicates that the spillover's significant part is coming from the fundamentals than the bubble components. Further, the wavelet coherency analysis results also show that the fundamental components have consistent longer horizon coherency, while there is none among the bubble components. These results imply that these markets' bubble components are purely transitory and have no impact across them, so focusing on fundamentals is a better strategy for longer horizon investments.

Chapter 4 attempted to propose an alternative way to understand market movements from the higher moments of cross-sectional asset price changes in identifying the presence of bubbles. The proposed method mainly followed from the Ball and Mankiw (1995) arguments on extracting the impact of relative price variability and skewness on the general price change. We used the method from cross-sectional returns of the stocks that are part of a market index to extract the core returns by minimizing the skewness that is proved to be transitory shocks. The extracted series are considered the fundamental or core of the stock return, and the remaining from the actual are the bubble. To our knowledge, this is the first study that uses the cross-sectional information in extracting the fundamental and bubble components. This proposed method applied to the Dow Jones Industrial Average index and identified the fundamental and bubble components. The newly proposed mechanism produces the same result as identified by Siess (2019) using the Log-periodic Power Law

(LPPL) model. Instead of using complex LPPL type models, this new alternative is handy in extracting the bubble component. Furthermore, our new alternative method precisely identified the dotcom bubble and the financial crisis of 2007-08. Our method's simplicity allows investors to clearly understand the market movements and take advantage of market movements and invest accordingly.

Chapter 5 explores the benefits of fundamental and bubble information in portfolio optimization analysis. Using the method proposed by Anderson and Brooks (2014), Sharpe’s Single Index Model’s market beta is decomposed into fundamental and bubble beta, to evaluate their usefulness in the portfolio analysis in static and dynamic time-varying method. This empirical analysis is being carried out for India, an emerging market. The period over which the analysis is being done is between January 2012 and December 2018 on 12 nifty sectoral indices, NIFTY 500 as the market index. The results of this analysis show that the fundamental beta portfolio performs better and gives higher sharp ratio than the Markowitz mean-variance, naïve, market and bubble beta portfolios in both the static and dynamic time-varying analysis. These findings provide extensive implications for investment analysis and support to the recent study that include fundamental analysis in the creation of portfolios.

6.3. Policy Implications

Insights from these analyses provide investors and regulators with significant policy implications. Analysing the stock price movements and bubble behaviour serves to understand and improve the financial markets' functioning. Furthermore, a bubble can cause investors' overtrading due to speculation and expectation of higher return; these behaviours warrants to test whether the market has deviated from its fundamental value. Understanding the impact of this speculation and how it affects the other asset markets are important aspects for all. In this situation, the market participants and policymakers should closely monitor the market to keep the financial market's stability and the economy. Therefore, timely identification of the asset price bubble is very relevant to policymakers and financial professionals alike, which helps to prevent losses from the investment and the economy. Proper bubble detection helps identify the critical points in asset prices, which prevents market crashes. Therefore, we need to concentrate more on identifying the bubbles and their path on its origin to prevent a crisis.

Another significant implication drawn from this thesis's results is that the international diversification effect still stands during the financial crisis. Contagion and spillover analysis provide considerable evidence for investors, portfolio managers, and policymakers. It is helping them understand the extent of integration and vulnerability of equity markets to financial shocks from the other markets. Moreover, the study helps the investors and fund managers can make a correct decision regarding portfolio diversification. Based on the findings of this study, policymakers of these countries can develop strategies to protect their own markets from financial market crashes while simultaneously focusing on developments in other financial markets. Contagion and spillover analysis clearly says an overwhelming predominance in the stock market's fundamental component than the bubble component, indicating that the markets are driven by the fundamentals rather than the bubbles in the long term.

The important inference coming out of this research is that investors, fund managers, and financial professionals should concentrate more on fundamental components than the bubble component while preparing portfolios, particularly long-term market players. Understanding market movements have a more significant impact on portfolio optimization during the turbulence period. It will give an idea of which stocks we should include in the basket and how much weight we should give each asset while making a portfolio. The empirical results from this thesis work help policymakers and market regulators with a handy tool to trace the bubble path and provide information regarding the predominance of fundamental components in the spillovers and contagion and its usefulness in portfolio construction.

6.4. Scope for Future Research

Two new methods proposed in this study to trace the bubble paths are not without any limitations. The Common Trend methodology is a better method in identifying the bubble path only in the presence of cointegration between the variables. With more than one fundamental variable and more than one cointegrating vectors, identifying permanent shock from the Common Trend methodology would be more complex. Still, we cannot deny the possibility of deriving the expected results.

The empirical validation of the new Common Trend method is only focused on evaluating the impact of the contagion and volatility spillover effects using the decomposed fundamental and bubble components between India, the USA, and Japan. In contrast, a comprehensive study can be carried out to understand the transmission mechanism of how the crisis spread to these economies and how the fundamentals are adequate in preventing or transmitting the crisis. This study adopts a new direction in financial research by taking the alternate cross-sectional approach. It is unique in its approach, and yet, just as with any idea in its infancy, but more empirical validation is required to make it a more robust bubble identification model. It would be a definite addition to have a detailed study to validate the alternative mechanism.

For future work, portfolio optimization could be tested the proposed method in individual stocks and other assets with different trends and volatility levels, ensuring the robustness of the idea in the most adverse environment of the market. Moreover, the decomposed portfolio approach can be improved by using different risk measures and performance indicators. This approach can be extended to multi-objective portfolio optimization models.

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Fundamental beta and portfolio performance: evidence from an emerging market

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ABSTRACT

The market beta is decomposed into fundamental and bubble beta to assess their effectiveness in the portfolio performance in both static and dynamic time-varying frameworks. The empirical results from India on 12 sectoral indices with NIFTY 500 as the market index establish that the portfolio constructed using the fundamental beta proportions performs better than the naïve, Markowitz mean-variance, market, and bubble beta portfolios with larger Sharpe ratio in both the static and dynamic time-varying estimates. These results open up far-reaching implications for investment analysis and contribute to the recent literature that combines fundamental analysis in the construction of portfolios.

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1. Introduction

The mean-variance portfolio analysis of Markowitz (1952) remains the gold standard of portfolio selection even today with all its limitations.[1] In a situation with a large number of securities available for the construction of the portfolio, Markowitz model turns complex owing to the size of calculating the expected return and variance-covariance matrix involving all the securities along with solving the quadratic programming problem to derive the optimal portfolio. Sharpe (1963) simplified this process by relating the return of a security to a single Market index; by this, all the information is narrowed only to the market beta of each security and the expected market return and variance.[2] Further, Elton, Gruber, and Padberg (1976) proposed a simple ranking model to construct the optimal portfolio that absolves the problem of solving quadratic programming, with the advent of ever-increasing computing capabilities, this is no longer a more significant constraint; still, the model performs equivalently well. The empirical literature has extensively adopted both these methods and extended it to substantiate improvements in the performance of the portfolio (Zhang, Li, and Guo 2018).

In literature, the static market beta estimation, as well as the usage of it in portfolio management, received much criticism. Blume (1971) emphasized that no economic variable is constant over time, including the market beta. In portfolio evaluation, he argued that if time variation in the beta is stationary, the static beta can be an unbiased estimate of the future values. With the data from the common stocks listed in NewYork Stock Exchange, he identified that the beta for a portfolio is relatively stable and showing

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regression tendencies towards unity as the number of stocks in the portfolio increases, while the beta of individual securities is not. Afterwards, many studies established that the beta coefficients of individual stocks move randomly over time and not remain static (Fabozzi and Francis 1978; Sunder 1980; Bos and Newbold 1984) and studies explained possible reasons for this regression tendencies of the portfolio betas (Goldberg 1981). Abdymomunov and Morley (2011) investigated the time variation in CAPM betas for Book-to-Market and momentum portfolios across different regimes of stock market volatility. They find that betas vary significantly across changing volatility regimes, and the time-varying character of the beta coefficient is more when financial market volatility is high.

The time-varying betas of individual securities are estimated predominantly through rolling regression, multivariate GARCH, and Kalman filter techniques (Fama and MacBeth 1973; Giannopoulos 1995; Gonzalez-Rivera 1996; Brooks, Faff, and McKenzie 1998; Marshall, Maulana, and Tang 2009). Recently, Engle (2016) renewed the interest in the estimation of time-varying beta by extending it to the Fama-French 3 factor model with a dynamic conditional beta method. Most of these studies are addressing either the forecasting performances of the future betas or the relationship between this dynamic betas on the cross-section of stock returns and only a few studies like Ghysels and Jacquier (2006) and Nieto, Orbe., and Zarraga (2014) uses it in understanding the portfolio performances. Recently, Borup (2019) employed time-varying beta analysis to quantify uncertainties and abnormal returns from the market and found that the abnormal returns are closely connected to the uncertainties in the market. He argues that the usual CAPM beta cannot identify this, and using time-varying beta is the better way forward. For an emerging market, the literature on this time-varying beta estimation is very sparse, and particularly for India, studies like Shah and Moonis (2003), Dubey (2014), Das and Barai (2015) are few exceptions.

On the other hand, understanding the fair value of a stock price in the prevalence of speculative bubbles and deriving the fundamental component in stock returns is an important stream of research in empirical finance. Starting from Gordon (1959), the present value models using discounted future dividends are widely used to identify the fair value of a stock price. Later on, Lee (1995) implemented a structural VAR model to decompose the fundamental and bubble components from US and Japan asset prices. Bramante and Gabbi (2006) decomposed the beta as bull beta and bear beta in a time-varying framework using state-space models to assess the performances of the portfolios with the decomposed betas. The results are different for bull and bear betas than the usual passive beta portfolios with new information for designing active strategies to enhance portfolio performance. Anderson and Brooks (2014) identified that the common variation in stock returns are better explained by the co-movement of bubbles present in an individual stock and the market rather than the fundamentals for UK stocks. They introduced the bubble CAPM model that decomposes the market beta into fundamental and bubble beta.[3]

Further, in recent times, combining the fundamental analysis with portfolio optimization for a better performing portfolio is gaining focus. Cosemans et al. (2016) estimated security betas using firm fundamental priors and found that the method provides superior forecasts of the beta. Lyle and Yohn (2018) combined the expected returns derived from the fundamental ratios to construct the portfolio that offers a substantial gain in the performance.

Although it is well established in the literature on the usefulness of time-varying beta and the inclusion of fundamental factors in the construction of a portfolio, these two remain as two distinct sets of empirical analysis and forms the scope of this study. The main focus of this study is to evaluate the portfolio performance by combining time-varying beta and the fundamental factors from an emerging market perspective using both static and dynamic time-varying framework. This study modifies the bubble CAPM model in a time-varying framework by deriving the conditional covariances and variances from a multivariate GARCH model to assess the efficacy of this decomposition in the improvement of portfolio performance.

This study contributes to the literature in three ways: first, it adapts Anderson and Brooks (2014) bubble CAPM in a static and dynamic time-varying framework and uses it in evaluating the portfolio performance. Second, examining the relative effectiveness of the portfolio for the data from an emerging market, India, with this time-varying market, fundamental and bubble beta is first of its kind from an emerging market perspective, and finally, it provides a simple, parsimonious alternative towards combining portfolio optimization with fundamental and bubble factors. The rest of the paper is organized as follows: Section 2 briefly introduces the methodology and the data used, while Section 3 provides the results from the empirical analysis, and the final section concludes with implications for investment analysis.

2. Methodology and data

2.1. Portfolio optimization

Considering the market model of Sharpe (1963) as$R_{it} = \propto_i + \beta_i R_{mt} + \varepsilon_{it};\ \varepsilon_{it}\tilde{N}\left(0, \sigma^2_{\varepsilon_i}\right)$ where R_{it} and R_{mt} are the returns of i^{th} stock and the market at time t with β_i as market risk measures the sensitivity of changes in i^{th} stock to the changes in the market. Using this Elton, Gruber, and Padberg (1976) derived the optimal portfolio shares Z_i of each stock by maximizing the ratio of portfolio excess return to portfolio risk as

$$Z_i = \frac{\beta_i}{\sigma^2_{\varepsilon_i}}\left[\frac{E(R_i) - R_f}{\beta_i} - C\right]; C = \sigma^2_m \frac{\sum_{j=1}^{n}\left[\frac{E\left(R_j\right) - R_f}{\sigma^2_{\varepsilon_j}}\beta_j\right]}{1 + \sigma^2_m \sum_{j=1}^{n}\frac{\beta^2_j}{\sigma^2_{\varepsilon_j}}} \tag{1}$$

where $E(R_i)$ is the expected return of the i^{th} stock, and R_f is the risk-free rate. In an environment where short sales are not allowed, Z_i should be positive and for that $\frac{E(R_i) - R_f}{\beta_i}$ should be greater than C; eventually, C act as a criterion for including the stocks in the portfolio. Finally, Z_i is scaled to summation equals 1.

Alternatively, following Nieto, Orbe, and Zarraga (2014), we can implement the portfolio optimization with a static market beta as follows: the variance of a portfolio with n stocks can be derived as $\vartheta = \sigma^2_m BB' + R$; where σ^2_m is the variance of the market return; $\boldsymbol{B}$ is an n-vector of individual betas, and $\boldsymbol{R}$ is an n-vector of the idiosyncratic residuals from the market model. With this, the minimum variance portfolio is derived by choosing the n-vector portfolio shares ($\boldsymbol{z}$) by solving the equation $min z' \vartheta z$ subject to $z' 1 = 1$.

2.2. The bubble CAPM

Anderson and Brooks (2014) derived the total return on i^{th} stock and the market as the sum of fundamental and bubble return as $R_i = R_i^f + R_i^b$ and $R_m = R_m^f + R_m^b$ along with β_i expressed as $\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)} = \frac{Cov\left(R_i^f + R_i^b, R_m^f + R_m^b\right)}{Var\left(R_m^f + R_m^b\right)}$. Further, they assumed that the covariance between bubble and fundamental components in both i^{th} stock and the market returns are equal to zero. With this restriction, they decomposed the market beta into fundamental and bubble beta as

$$\begin{aligned}\beta_i &= \frac{Cov\left(R_i^f, R_m^f\right) + Cov\left(R_i^b, R_m^b\right)}{Var\left(R_m^f\right) + Var\left(R_m^b\right)} = \frac{Cov\left(R_i^f, R_m^f\right) + Cov\left(R_i^b, R_m^b\right)}{Var(R_m)} \\ &= \beta_i^f + \beta_i^b\end{aligned} \tag{2}$$

where $\beta_i^f = \frac{Cov\left(R_i^f, R_m^f\right)}{Var(R_m)}$ and $\beta_i^b = \frac{Cov\left(R_i^b, R_m^b\right)}{Var(R_m)}$.

To implement this fundamental and bubble beta in the portfolio optimization, we need to calculate the residual variance $\sigma_{\varepsilon_i}^2$ separately. To derive that we first calculated α_i^f and α_i^b as follows: $\alpha_i^f = \bar{R}_i - \beta_i^f * \bar{R}_m$ and $\alpha_i^b = \bar{R}_i - \beta_i^b * \bar{R}_m$. The derived$\beta_i^f$, $\sigma_{\varepsilon_i}^{2^f}$and β_i^b, $\sigma_{\varepsilon_i}^{2^b}$are then substituted in equation (1) to derive the fundamental and bubble beta optimal portfolio shares.

To decompose the stock price into fundamental and bubble component, they followed Van Norden and Schaller (1999) model in which the fundamental component is derived as a multiple of current dividend if the dividends follow a geometric random walk and a constant discount rate and represented as $p_{it}^f = \rho d_{it}$. Anderson and Brooks (2014) approximated ρ as the trailing average of price-dividend ratio, and this study uses the same procedure in deriving the fundamental and bubble component.

2.3. Time-varying beta

A range of Generalized Autoregressive Conditional Heteroscedastic (GARCH) models is used in the empirical literature to derive the time-varying conditional betas starting with Bollerslev, Engle., and Wooldridg. (1988), Engle and Rodrigues (1989) and Ng (1991). This study considers the widely used MGARCH-BEKK model of Engle and Kroner (1995), which has the advantage of a positive-definite constraint of the conditional covariance matrix by construction for estimating the conditional covariance and variance between an i^{th} stock return and the market return.[4] This model constructs conditional variance-covariance matrix H as follows:

$$H_{it} = C_i'C_i + A_i'\varepsilon_{it-1}\varepsilon_{it-1}'A_i + B_i'H_{it-1}B_i \tag{3}$$

where $\boldsymbol{C_i}$ is a 2 × 2 lower triangular coefficient matrix, and $\boldsymbol{A_i}$ and $\boldsymbol{B_i}$ are 2 × 2 coefficient matrices and maximizes the following log-likelihood function

$$\ln L(\theta_i) = -\frac{1}{2}\sum_{t=1}^{T} \ln|H_{it}| - \frac{1}{2}\sum_{t=1}^{T} y_{it}'H_{it}^{-1}y_{it} \tag{4}$$

where $\boldsymbol{\theta_i}$ is the parameters to be estimated, and $\boldsymbol{y_{it}}$ consists of ith stock return and market return in the mean equation expressed as $y_{it} = \mu_i + v_{it}$, and $v_{it} = \varepsilon_{it}\sqrt{H_{it}}$ in which μ_i is a constant and $\varepsilon_{it} \sim N(0,1)$. From this, the time-varying conditional beta is estimated as

$$\beta_{it} = \frac{H_{imt}}{H_{mmt}} \tag{5}$$

where H_{imt} is conditional covariance between ith stock and the market return, and H_{mmt} is the conditional variance of the market return.

To adapt the bubble CAPM of Anderson and Brooks (2014) in a time-varying framework with the assumption that the covariance between bubble and fundamental components in both i^{th} stock and the market returns are equal to zero, we charted the following procedure. First, we decomposed the stock price into the fundamental and bubble component using Van Norden and Schaller (1999) model explained in Section 2.2 for both the ith stock and the market return. Second, a univariate GARCH model is run separately for the fundamental and bubble component of the market return to estimate the conditional variances H^f_{mt} and H^b_{mt}. Finally, the conditional covariances for the fundamental and bubble component of ith stock and market return $H^f_{imt}$and H^b_{imt} are estimated separately through the MGARCH-BEKK model explained in equations (3) and (4). With that, the dynamic conditional time-varying market beta is estimated as

$$\beta^m_{it} = \frac{H^f_{imt} + H^b_{imt}}{H^f_{mt} + H^b_{mt}} = \beta^f_{it} + \beta^b_{it} \tag{6}$$

where $\beta^f_{it} = \frac{H^f_{imt}}{H^f_{mt} + H^b_{mt}}$ and $\beta^b_{it} = \frac{H^b_{imt}}{H^f_{mt} + H^b_{mt}}$.

Subsequently α^f_{it} and α^b_{it} is derived as follows: $\alpha^f_{it} = \bar{R}_i - \beta^f_{it} * \bar{R}_m$ and $\alpha^b_{it} = \bar{R}_i - \beta^b_{it} * \bar{R}_m$. The derived$\beta^f_{it}$, $\alpha^f_{it}$and β^b_{it}, $\alpha^b_{it}$are used for each period t to calculate the residual variance $\sigma^{2^f}_{\varepsilon_{it}}$and $\sigma^{2^b}_{\varepsilon_{it}}$. With a dynamic time-varying beta for the period t = *1, 2, ….T*; the portfolio optimization is implemented for every period t. In this case, the variance of the portfolio with n stocks become n x T-matrix $\vartheta = \sigma^2_m BB' + R$; where σ^2_m is the variance of the market return while $\boldsymbol{B}$ is an n x T-matrix of individual betas for the period 1 to T and $\boldsymbol{R}$ is an n x T-matrix of the idiosyncratic residuals from the market model. The portfolio is optimized for every period t by solving $min z_t{}' \vartheta_t z_t$ subject to$z_t{}' 1 = 1$, to derive the optimal portfolio shares z_t. The optimal shares are used to evaluate portfolio performances.

2.4. Evaluating the portfolio performance

The relative performances of the portfolios are assessed with a simple Markowitz mean-variance portfolio return and risk derived as$R_p = \sum_{i=1}^{n} \bar{R}_i Z_i$;$\sigma^2_p = \sum_{i=1}^{n}\sum_{j=1}^{n} \sigma_{ij} Z_i Z_j$. Along with the three optimal portfolio shares of the market, fundamental and bubble beta from equation (1), an equal weight naïve portfolio share as well as Markowitz portfolio share by minimizing the variance σ^2_p for a positive return are also calculated. For all these five portfolio shares Sharpe ratio is calculated as $\theta = \frac{R_p - R_f}{\sigma_p}$ and compare it using the equality test proposed by Jobson and Korkie (1981) and improved by Memmel (2003) (JK-M test hereafter). As argued by Ledoit and Wolf (2008), this test is not appropriate when there are autocorrelated and non-normal fat-tailed returns, and proposed robust alternative inference methods in which HAC inference uses kernel estimators to cone up with consistent standard errors. So first, we construct the portfolio return series $R_{pt} = \sum_{i=1}^{n} R_{it} Z_i$ and check for autocorrelation and normality before implementing the JK-M test.

In JK-M test, the null hypothesis of equality of Sharpe ratios from two different portfolio shares is rejected at α level of significance if zero lies outside the confidence interval derived from the standard normal distribution Z as $\hat{d} \pm Z_{1-\frac{\alpha}{2}} \hat{\delta}\left(\hat{d}\right)$; where $\hat{d} = \hat{\theta}_p - \hat{\theta}_q$ and

$$\hat{\delta}\left(\hat{d}\right) = \sqrt{\left[\left(\frac{1}{T}\right)\left\{2 - 2\hat{\rho}_{pq} + 0.5 * \left(\hat{\theta}_p{}^2 + \hat{\theta}_q{}^2 - 2\hat{\theta}_p\hat{\theta}_q\hat{\rho}_{pq}{}^2\right)\right\}\right]} \tag{7}$$

Where $\hat{\theta}_p, \hat{\theta}_q$ and $\hat{\rho}_{pq}$ are estimates of Sharpe ratios and correlation between portfolio return series with p and q portfolio shares. A similar procedure is used in the case of dynamic time-varying beta as well in analysing the relative performances of the portfolios. The portfolio return series is constructed with time-varying optimal portfolio shares z_t, as $R_{pt} = \sum_{i=1}^{n} R_{it} Z_{it}$ and check for autocorrelation and normality before choosing the JK-M test or the one proposed by Ledoit and Wolf (2008).

2.5. Data

This study uses monthly data on eight sectoral and four thematic indices of the National Stock Exchange of India and NIFTY 500 index along with their dividend data for the period from January 2012 to December 2018. The selection of these indices is based on the availability of consistent dividend data for the sample period. The eight sectoral indices include Bank, Auto, Financial Services, FMCG, IT, Media Metal, and Pharma, while four thematic indices are Service Sector, Energy, MNC, and Infra and the data for all these indices are collected from www.nseindia.com.

3. Empirical results

For the 12 indices and NIFTY 500 index, the fundamental and bubble components are derived, and their returns are calculated as the first difference of its natural logarithm. The estimated market, fundamental, and bubble beta from the static model, as well as the median of the time-varying betas, is given in Table 1. It is evident that for all the indices, bubble beta explains a major portion of the market beta than the fundamental beta in both the static and time-varying estimation. For the infrastructure sector, the negative bubble beta indicates the discordance with the market bubble component. The market beta for Auto, FMCG, IT, Media, Metal, and MNC indices shows a higher beta in the median of the time-varying beta than the static beta. In contrast, it is reverse for Bank, Financial Services, Pharma, Service sector, Energy, and Infra indices indicate the variations between the static and time-varying framework and have heightened implications in the portfolio construction.

Since Elton, Gruber, and Padberg (1976) derived optimal portfolio shares by maximizing excess return, we used three different risk-free rates, namely 4, 6, and 8 percent,[5] to calculate excess return and derived the optimal portfolio shares for the market,

Table 1. Estimated betas.

	Static Betas			Median Time-varying Betas		
Indices	Market	Fundamental	Bubble	Market	Fundamental	Bubble
Bank	2.452	0.839	1.613	1.963	0.592	1.277
Auto	0.660	0.144	0.517	0.694	0.090	0.578
Financial Services	1.858	0.612	1.246	1.282	0.246	0.962
FMCG	0.365	0.039	0.326	0.420	0.005	0.356
IT	0.510	0.240	0.269	0.621	0.230	0.338
Media	0.645	0.105	0.539	0.669	0.118	0.546
Metal	0.353	0.015	0.338	0.493	0.169	0.331
Pharma	1.056	0.317	0.739	0.217	0.063	0.186
Service Sector	1.528	0.487	1.041	0.944	0.267	0.659
Energy	1.303	0.415	0.888	1.019	0.305	0.682
MNC	0.847	0.120	0.727	1.045	0.201	0.787
Infra	0.486	0.175	0.311	0.048	0.132	−0.109

Table 2. Excess return, risk and sharpe ratio from static model.

Model	Excess Return $(R_p - R_f)$	Risk (σ_p)	Sharpe Ratio $\left(\theta = \frac{R_p - R_f}{\sigma_p}\right)$
		Risk-free rate at 4%	
Naïve	0.0049	0.0033	1.481
Markowitz	0.0045	0.0027	1.677
Market Beta	0.0061	0.0033	1.867
Fundamental Beta	0.0067	0.0032	2.062
Bubble Beta	0.0066	0.0032	2.041
		Risk-free rate at 6%	
Naïve	0.0032	0.0033	0.967
Markowitz	0.0028	0.0027	1.043
Market Beta	0.0053	0.0035	1.496
Fundamental Beta	0.0058	0.0034	1.731
Bubble Beta	0.0056	0.0034	1.655
		Risk-free rate at 8%	
Naïve	0.0015	0.0033	0.453
Markowitz	0.0012	0.0027	0.447
Market Beta	0.0040	0.0036	1.109
Fundamental Beta	0.0044	0.0034	1.304
Bubble Beta	0.0042	0.0034	1.235

fundamental and bubble beta. The optimal portfolio share is substituted in a Markowitz mean-variance framework, and corresponding portfolio excess return and risk are estimated along with the Sharpe ratio. The results are presented in Table 2 for the static model. The results are very similar to all the risk-free rates used where the fundamental beta proportion has a higher Sharpe ratio compared to others.

The results from the time-varying model are provided in Table 3, with the average excess return and risk of the portfolio along with the Sharpe ratio. We report the results only for

Table 3. Excess return, risk and sharpe ratio from time-varying model.

Model	Excess Return $(R_p - R_f)$	Risk $(_p)$	Sharpe Ratio $\left(\theta = \frac{R_p - R_f}{_p}\right)$
Risk-free rate at 6%			
Market Beta	0.0054	0.0019	2.806
Fundamental Beta	0.0120	0.0034	3.540
Bubble Beta	0.0064	0.0024	2.656

a 6 percent risk-free rate for validation hereafter. From the results, we can see that the Sharpe ratio is relatively higher with the fundamental beta model compared to other models.[6]

Before evaluating the difference in Sharpe ratios statistically using the JK-M test, we examined the autocorrelation and normality of the portfolio return series derived from different model optimal shares. Table 4 provides the Q-statistics of first-order autocorrelation and Jarque-Bera statistics of normality test for portfolio returns with a 6 percent risk-free rate. The results show that for all the model portfolios, return series are normal and having no first-order autocorrelation except the time-varying market beta model, which is significant at the 10 percent level.[7]

We implement the JK-M test for all these portfolios returns to validate the difference in the Sharpe ratio in comparison to the static and time-varying fundamental beta. First, the JK-M test for the static model with a 6 percent risk-free rate is carried out. The results reported in Table 5 shows that the equality of fundamental beta Sharpe ratio in comparison with all the other models Sharpe ratios are statistically rejected, indicating the supremacy of fundamental beta in portfolio optimization. Further, an elaborate JK-M test is conducted with the time-varying fundamental beta as the benchmark as it gives the highest Sharpe ratio, and the results in Table 6 establish the fact that the time-varying fundamental beta provides a far superior portfolio performance over all the other models.

As a robustness check, Ledoit and Wolf (2008) test[8] is carried out to evaluate the equality of Sharpe ratios of the portfolio constructed using the optimal shares from the time-varying market, fundamental, and bubble betas. The results in Table 7 state that the equality of the Sharpe ratio is rejected in favour of time-varying fundamental beta.

Table 4. Test of autocorrelation and normality of portfolio returns.

Model	Q-Statistics	Jarque-Bera
Naïve	0.072	0.428
	(0.789)	(0.807)
Markowitz	0.818	0.123
	(0.366)	(0.940)
Market Beta – Static	0.082	0.741
	(0.775)	(0.690)
Fundamental Beta – Static	0.335	0.760
	(0.563)	(0.683)
Bubble Beta – Static	0.283	0.878
	(0.595)	(0.645)
Market Beta – Time-varying	3.155*	0.729
	(0.076)	(0.694)
Fundamental Beta – Time-varying	0.143	0.201
	(0.706)	(0.904)
Bubble Beta – Time-varying	1.749	1.308
	(0.186)	(0.520)

In the parentheses are p-values and * denotes significance at 10 percent level

Table 5. Results of JK-M test – static model.

	Static Fundamental beta with risk-free rate at 6%		
Model	$\widehat{d} = \widehat{\theta}_{f.beta} - \widehat{\theta}_q$	$\widehat{\rho}_{f.betaq}$	Confidence Interval at 5% level
Naïve	0.764	0.953	[0.548, 0.980]
Markowitz	0.688	0.861	[0.419, 0.957]
Market Beta	0.235	0.977	[0.009, 0.371]
Bubble Beta	0.076	0.999	[0.006, 0.146]

Table 6. Results of JK-M test – time-varying model.

	Time-varying Fundamental beta with risk-free rate at 6%		
Model	$\hat{d} = \hat{\theta}_{f.beta} - \hat{\theta}_q$	$\hat{\rho}_{f.betaq}$	Confidence Interval at 5% level
Naïve	2.573	0.783	[2.053, 3.093]
Markowitz	2.497	0.738	[1.964, 3.030]
Market Beta – Static	2.044	0.772	[1.544, 2.544]
Fundamental Beta – Static	1.809	0.738	[1.295, 2.323]
Bubble Beta – Static	1.885	0.746	[1.374, 2.396]
Market Beta – Time-varying	0.734	0.701	[0.172, 1.296]
Bubble Beta – Time-varying	0.884	0.606	[0.267, 1.501]

Table 7. Results of ledoit and Wolf test on equality of sharpe ratio.

Test	χ^2Statistic
Fundamental Beta Vs. Market Beta	6.683 (0.009)**
Fundamental Beta Vs. Bubble Beta	26.556 (0.000)**
Bubble Beta Vs. Market Beta	25.838 (0.000)**

In the parentheses are p-values and ** denotes significance at 1 percent level

The consistent performance of fundamental beta both in static as well as the time-varying framework has far-reaching implications for portfolio analysis and risk management, in creating compelling investment strategies for a better outcome.

4. Conclusion

This study combines two distinct but highly researched aspects of empirical finance in portfolio analysis; first, the growing importance of the time-varying beta in financial analysis and second, the usefulness of fundamental factors in portfolio analysis. In doing so, it provides a simple strategy that has a considerable stake in investment analysis. This study examines portfolio optimization using Sharpe single index model in both static and dynamic time-varying framework by combining the bubble CAPM model of Anderson and Brooks (2014) that decomposes the market beta into fundamental and bubble beta from an emerging market perspective. The empirical results suggest that the portfolio constructed using the fundamental beta portfolio shares performs better than the naïve, mean-variance, bubble, and market beta portfolio shares with a larger Sharpe ratio in both the static and dynamic models. The dynamic time-varying model with fundamental beta outperforms even the static model with fundamental beta in the portfolio performances. These results have far-reaching implications for investment analysis by providing evidence in favour of using the dynamic time-varying model for better portfolio performance and contribute to the recent literature that combines fundamental analysis with portfolio optimization.

Notes

1. Important limitations highlighted in the literature include, mean-variance preferences fails to be monotone and using variance as risk measure have disadvantage as it treats both profit and loss equally, while the risk is associated only with the loss. Refer to Maccheroni et al. (2009) and Ahmadi-Javid and Fallah-Taft (2019).

2. Subsequently, the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), Lintner (1965) and Mossin (1966) became the benchmark in evaluating the price and risk premium of any security.
3. In another stream of research, fundamental beta is derived as the estimated value from a cross-sectional regression of historical betas of stocks with fundamental ratios (see Rosenberg and Marathe 1975).
4. This model is preferred over the Kalman filter, for a similar exposition of the bubble CAPM of Anderson and Brooks (2014) in a time-varying framework.
5. This is the range of risk-free rate in India during the sample period and the same risk-free rates are used for equal weight and Markowitz mean-variance portfolios as well.
6. The results remain similar for the risk-free rate at 4 and 8 percent as well, which is not reported here but can be obtained upon request.
7. It shows only first-order autocorrelation and subsequent orders show no autocorrelation.
8. We used 'sharpeTesting' package in R for the estimation.

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