Market Efficiency, Behavioural Finance, and Anomalies

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Biographical Notes

Professor WONG, Wing-Keung obtained his Ph.D. from the University of Wisconsin-Madison, the USA with a major in Business Statistics (Statistics and Finance) and obtained his Bachelor degree from the Chinese University of Hong Kong, Hong Kong, with a major in Mathematics and a double minor in Economics and Statistics. Currently, he is a Chair Professor at the Department of Finance, Asia University. He was a Full Professor at the Department of Economics, Hong Kong Baptist University, and Deputy Director at Risk Management Institute, National University of Singapore.

He appears in “Who's Who in the World” and gets Albert Nelson Marquis Lifetime Achievement Award. 2017, Marquis Who's Who. His Erdos number is 3. He is ranked top 1% by Social Science Research Network and in the list of top Taiwan economists and Asian economists and top economists by RePEc. He has published more than three hundred papers including papers published in some top journals. He has more than 11500 citations in Google Scholar, more than 9800 citations in Researchgate, and more than 4500 citations in Scopus. His h-index is 59, (40 since 2017) and i10-index is 230, (209 since 2017) by Google Scholar citation in December 2021.

He is in the list of top (2nd, 0.8%) Taiwan economists (counted publications last 10 years), top (3rd, 1.2%) Taiwan economists, (39th, 0.5) Asian economists (counted publications last 10 years), (44th, 0.6%) Asian economists, (459th, 0.7%) [World] authors [in Economics in last 10 years] and (1011th, 1.6%) [World] authors [in Economics], top (211st, 0.33%) in Number of Works, top (162nd, 0.25%) in Number of Distinct Works, top (759th, 1.2%) in Number of Distinct Works, Weighted by Number of Authors, top (37th, 0.06%) in Number of Journal Pages, top (229th, 0.36%) in Number of Journal Pages, Weighted by Number of Authors, top (515th, 0.80%) in Number of Abstract Views in RePEc Services over the past 12 months, top (852th, 1.3%) in Record of graduates, top (110th, 0.2%) in Closeness measure in co-authorship network, top (15th, 0.02%) in Betweenness measure in co-authorship network by RePEc in Feb 2022. I have 37 items ranked within 15%, 31 items ranked within 10%, 19 items ranked within 5%, 17 items ranked within 3%, 17 items ranked within 2%, and 11 items are within 1% among all Economists registered in RePEc in February 2022.

He has been serving international academies, Government, society, and universities, providing consultancy to several Government departments and corporations, and giving lectures and seminars to several universities. For example, he has been serving as editor, guest leading editor, advisor, associate editor for some international journals, appointed as an advisor/member of various international associations/institutes, serving as a referee for many journals/conferences, supervising solely or jointly several overseas graduate students, appointed as an external reviewer and external examiner by other universities, and invited by many universities/institutions to present papers or conduct seminars.

He has published more than four hundred papers including papers published in journals ranked as A* in ABDC, Q1 in SJR Quartile, Q1 in JCR, and 4 in AJG and including papers published in Contemporary Accounting Research, Annals of Applied Probability, Scientific Report, Mathematical Finance, European Journal of Operational Research, Journal of Business and Economic Statistics, Economic Theory, Journal of Empirical Finance, Journal of Financial Markets, Journal of Economic Behavior and Organization, Economics Letters, Econometrics Journal, Quantitative Finance, Economic Inquiry, Energy Economics, Statistics and Probability Letters, Journal of Risk, Journal of Operational Research Society, Journal of Financial Econometrics, Journal of Forecasting, Journal of International Financial Markets, Institutions & Money, Transport Policy, Personality and Individual Differences, Journal of Time Series Analysis, Applied Economics, Journal of Multinational Financial Management, Journal of Behavioral Finance, Pacific-Basin Finance Journal, Annals of Finance, IMA Journal of Management Mathematics, Accounting & Finance, Economic Modelling, Energy Policy, Applied Mathematics Letters, Journal of International Consumer Marketing, Statistical Papers, International Review of Financial Analysis, Current Issues in Method and Practice, International Review of Economics & Finance, Studies in Nonlinear Dynamics and Econometrics, Current Issues in Tourism, Finance Research Letters, PLOS ONE, Physica A: Statistical Mechanics and its Applications, International Journal of Production Research, Resources Policy, World Economy, Emerging Markets Review, Econometrics and Statistics, Fractals, etc.

Kai-Yin Woo is working at the Department of Economics and Finance of Hong Kong Shue Yan University. His research interests include economics of finance and applied econometrics. He has published papers in Economics Letters, Applied Economics, Economic Modelling, Journal of Macroeconomics, Journal of Housing Research, Applied Economics Letters, The Chinese Economy, etc.

Wing-Kwong Au has been working at the Department of Social Work of Hong Kong Shue Yan University since 1990s. He is an Associate Professor / Director of China Liaison Office of the University; the Fellow of the University of Liverpool and the Registered Social Worker of Social Workers Registration Board, Hong Kong. He obtained his MPhil and Ph.D from the University of Liverpool and Master of Arts in Social Work from the University of Wales,. Bangor in the United Kingdom. His research interests include elderly services; community development; employment; social services in China (PRC); children and marginal youth; finance and youth. He has published the reports on Hidden Youth Drug Abusers; Die in Exhaustion and the Labour Compensation in Hong Kong; the Interventions of the Marginal Youth Behavioural Pattern; Positive Life of Young People in Eastern District of Hong Kong, and a conference paper in Young Night Drifters' Social Workers and Health. He has also published two books "Eastern District Positive Life project 15th Anniversary: A Book of Reflections" and "The Interventions of the Marginal Youth Behavioural Pattern".

A survey report on "Children's life in COVID19" is forthcoming. His current project is a book chapter in "Finance and Youth".

Tai-Yuen Hon was an Academic Assistant/Lecturer/Senior Lecturer/Assistant Professor in the Department of Economics and Finance (formerly known as the Department of Economics) of Hong Kong Shue Yan University from 1993 to 2016 and is a Research Affiliate at the Business, Economic and Public Policy Research Centre of this University. He obtained his PhD in Business Administration from the Bulacan State University, and Master of Arts in Money, Banking and Finance from the University of Sheffield. He has published papers in Asian Profile, International Journal of Financial Management, International Journal of Humanities and Social Science, Journal of Emerging Issues in Economics, Finance and Banking, International Journal of Banking, Risk and Insurance, Journal of Risk and Financial Management, Journal of Economics Bibliography, Journal of Economics Library, Journal of Economics and Political Economy, Journal of Social and Administrative Sciences, Journal of Economic and Social Thought, Turkish Economic Review, Journal of Family and Economic Issues, International Journal of Revenue Management, Advances in Decision Sciences. He has also published a book 'Monetarism and Behavioural Finance'.

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Wing-Keung Wong

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Kai-Yin Woo

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Wing-Kwong Au

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Michael McAleer

is one of our coauthors. He has agreed to work with us and had been working on our book from time to time, and thus, we would like to include him in our book though he passed away in July 2021. The authors would like to thank the co-authors Massoud Moslehpour for completing the article “Review on Behavioral Finance with Empirical Evidence”; Hok-Fu Wu for completing the article ‘Volatility between commodity and stock sectors: evidence in Hong Kong and the implication of hedging effectiveness’; Leong-Kwan Chan for completing the article ‘Study on the Performance of Initial Public Offerings in Hong Kong’; Boon-Kiat Chew, Douglas Sikorski for completing the article ‘Can the Forecasts Generated from E/P Ratio and Bond Yield be Used to Beat Stock Markets?’; the authors would also like to thank the supports from the editor-in-chief Michael McAleer of Advances in Decision Sciences; the editor of Economies; the editor of Asian Profile; the editor of International

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Preface

This book has complied with five Journals papers and two working papers, a total of seven papers. For all the journal papers, we have obtained permission from the Editors/Editors-in-Chief to include all the journal papers in our book and we have all the rights for our working papers. Thus, we do not have any copyright issue in our book. In this book, we first write two papers (Chapters 1 and 2) to review the theory and literature on market efficiency, behavioural finance and market anomalies. Then, the readers can find it easy to understand the key concepts of this book. One of co-authors, Wing-Kwong Au, revises two papers (Chapters 3 and 4) which were written by Tai-Yuen Hon about the behaviour and investment decision of small investors in the Hong Kong Stock Market, with the empirical results basically consistent with the predictions of behavioural finance theory. Kai-Yin Woo guides two students to complete two working papers (Chapters 5 and 6) about hedging effectiveness and the performance of Initial Public Offerings (IPO) in Hong Kong. The results in these studies provide important implications for portfolio diversification and also suggest that IPOs in Hong Kong may underperform the market in the long run. Wing-Keung Wong and his research partners make the forecast generated from E/P Ratio and bond yield in order to beat stock markets (Chapter 7) and can conclude that Standardized Yield Differential (SYD) indicator is indeed a useful technical analysis tool for stock market investment. Five of the authors spend three years to complete this book “Market Efficiency, Behavioural Finance, and Anomalies”. However, one of our co-authors, Michael McAleer, passed away in July 2021. We are still eager to publish this book in KSP Library to commemorate his contributions and guidance.

Contents

Introduction

C*hapter 1* "Review on Market Efficiency and Anomalies": Efficient-market hypothesis (EMH) is one of the most important hypotheses to be tested in the past century. Due to many abnormal phenomena and conflicting evidence called anomaly against EMH, some academics question whether EMH is valid. They point out that financial literature is full of evidence of anomalies and many theories have been developed to explain some anomalies. To address the issue, this paper reviews the theory and literature on market efficiency and market anomalies. We first give a brief review on market efficiency and define clearly the concept of EMH. We discuss some efforts that challenge EMH. We then review different market anomalies. Our review is useful to academics for their studies in EMH and anomalies useful to investors for their decisions on their investment, and useful to policy makers in reviewing their policies in stock markets.

Chapter 2 "Review on Behavioral Finance with Empirical Evidence": When many anomalies challenge efficiency market hypothesis and rationality, behavioral finance theories are developed to investigate the psychological effects on human behaviors and how their cognitive biases explain why the market is inefficient and anomalies exist. Behavioral finance is a fast-growing branch of financial economics, making this review paper beneficial to academics for developing leading-edge usages of financial theory that behavioral finance underlies and undertaking empirical studies on behavioral finance models. This review paper indoctrinates readers into the introductory concepts of behavioral finance with their prominent literature and empirical evidence. In this review paper, we swiftly familiarize readers with the introductory concepts of behavioral finance and their salient readings with some empirical evidence. This paper lays the solid foundation of behavioral finance theory and is the centerpiece of modern financial economics, which is useful to academics for developing cutting-edge treatments of financial theory that EMH and behavioral finance underpin and for undertaking empirical studies on the behavioral bias in the financial markets. This paper is furthermore helpful to investors in making investment products and strategy choices that suit their risk preferences and behavioral traits predicted from behavioral models. This paper also provides the recent empirical evidence of behavioral finance in literature. The readers can then follow the research methods to undertake empirical studies on this field.

Chapter 3 "The Behaviour of Small Investors in the Hong Kong Stock Market" examines the key factors and the decision-making processes that affect the behaviour of small investors in the Hong Kong stock market. Informed by behavioural finance, we develop several hypotheses regarding the changes in the opinions and investment behaviour of small investors during and immediately after the buoyant stock market. These hypotheses are then tested with the data collected from 1,199 small investors via a questionnaire survey. The empirical results are basically consistent with the predictions of behavioural finance, particularly prospect theory. The study provides new insight regarding the investment behaviour of smaller investors in the stock market.

Chapter 4 "The Dilemma of Investment Decision for Small Investors in the Hong Kong Stock Market" examines the dilemma of investment decision for small investors in the Hong Kong stock market. The survey was conducted between October and November 2008.The data were collected from 1,199 respondents via a questionnaire survey. The objective of this study is to examine the key factors (determinants) and the dilemma of investment decision that affect local small investors. This paper addresses the determinants of possible ways to measure the level of investment decision.

Chapter 5 "Volatility between commodity and stock sectors: evidence in Hong Kong and the implication of hedging effectiveness" employs the multivariate threshold GARCH approach to estimate the conditional covariances between returns on global commodity indexes, measured by the CRB and CCI, and the Hong Kong Hang Seng Composite Industry Indexes over the sample period from 2004 to 2014. We find asymmetry in the volatilities. Moreover, the optimal hedge ratios are calculated, and it is suggested that in order to hedge against the long stock position in the energy and material sectors, the largest weight of the global commodity contract needs to be short sold. Again, the hedging effectiveness ratios for the energy and material sector indexes are the highest among the eleven industry sectors. Unanimously, the CCI is more effective than the CRB in hedging the stock positions in all sectors. The results in this study shed light on the dynamic relationship between the global commodity market and the Hong Kong equity sectors. This provides important implications for portfolio diversification and management.

Chapter 6 "Study on the Performance of Initial Public Offerings in Hong Kong" analyzes the long-run return of initial public offerings (IPOs) on the Stock Exchange of Hong Kong (SEHK). We use a sample of 253 IPOs listed on the SEHK between 2008 and 2012. The initial return is 8.38%. The two-year raw and market-adjusted returns are -4.83% and -3.78%, respectively. The study is mainly consistent with most of the previous studies linked to the long-run IPO performance in the US and Hong Kong. The results are sensitive to outliers. After elimination of outliers from cross-sectional analysis, the results suggest that IPOs in Hong Kong may underperform the market in the long run.

Chapter 7 "Can the Forecasts Generated from E/P Ratio and Bond Yield be Used to Beat Stock Markets?" tests the performance of stock market forecasts derived from technical analysis by means of a specific indicator. The indicator is computed from E/P ratios and bond yields. Several stock markets are studied over a 20-year period. Two test statistics are introduced to utilize the indicator. The results show that the forecasts generated from the indicator would enable investors to escape most of the crashes and catch most of the bull runs. The trading signals provided by the indicator can generate profits that are significantly better than the buy-and-hold strategy.

Wong, Woo, Au, Hon & McAleer
June, 2022

1 Review on market efficiency and anomalies

By
Wing-Keung ***Wong***
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Introduction

Efficient-market hypothesis (EMH) is one of the most important hypotheses that has been tested over the past decades. Traditional finance theory supporting EMH is based on important financial theories such as portfolio theory, asset pricing models and corporate finance theory. We know that the rational economic man will chase after maximum profit. When a rational economic man comes to stock markets, s/he becomes a rational investor who aims to maximize his/her profits. However, an investor's rationality requires some strict assumptions. When not every investor in the stock market looks rational enough, the assumptions could be loosened to include some irrational investors who could trade randomly and independently, resulting in an offsetting effect on each other so there is no impact on asset prices (Fama, 1965a). If those irrational investors do not trade randomly and independently, Fama (1965a) and others comment that rational arbitrageurs will buy low and sell high to eliminate the effect on asset prices caused by irrational investors.

In this paper, we review the theory and literature on market efficiency in addition to market anomalies. We first give a brief review on market efficiency and define the concept of market efficiency and efficient-market hypothesis (EMH). We then review different market anomalies that challenge EMH and discuss the defense of EMH. When market efficiency and anomalies are are used to explain the impacts on price movements, policy makers can factor in these impacts in reviewing their policies in the development of stock markets.

The paper is organized as follows. In Section 2, we will define the concept of Market Efficiency, review the literature of Market Efficiency, and discuss several factor models to explain Market Efficiency. We will review some market anomalies and discuss the defense of Market Efficiency in Section 3. The final section concludes.

Market efficiency

The idea of market efficiency is used to describe a market in which relevant information is rapidly incorporated into the asset prices so that investors cannot expect to earn abnormal profits from their investment strategies.

Early developments

In 1900, French mathematician Louis Bachelier published his PhD thesis, Théorie de la Spéculation (Theory of Speculation) (Bachelier, 1900). He recognized that "*past, present and even discounted future events are reflected in market price, but often show no apparent relation to price changes*". Hence, the market does not predict changes in asset prices. Moreover, he deduced that *'The mathematical expectation of the speculator is zero'*, which is consistent with Samuelson (1965) in explaining efficient markets in terms of a martingale. The implication is that asset prices fluctuate randomly, and then their movements are not predictable.

Pearson (1905) introduced the term 'random walk' to describe the path taken by a drunk with the drunk staggering in an unpredictable and random pattern. If prices follow a random walk, then it is difficult to predict the future path of asset prices. Kendall (1953), in examining weekly data on stock prices finds that they essentially move in a random walk pattern with near-zero autocorrelation of price changes. Working (1934) and Roberts (1959) find that the movements of stock prices look like a random walk. Cowles (1933 and 1944) and Working (1949) document that market participants cannot successfully forecast, and investors cannot beat the market.

Recent developments

Eugene Fama, the Nobel laureate in 2013, made influential contributions to theoretical and empirical investigation for the recent development of market efficiency. Fama (1965a) defines an efficient market as a market in which there are a lot of rational, profit-maximizing, actively competing traders, who try to predict future asset values with current available information. In an efficient market, competition among many sophisticated traders leads to a situation where actual asset prices, at any point in time, already reflect the effects of all available information and therefore, they will be good estimates of their intrinsic values. The intrinsic value of an asset depends upon the earnings prospects of the company under study, which is not known exactly in an uncertain world, so that its actual price is expected to be above or below its intrinsic value. If the number of the competing traders is large enough, their actions should cause the actual asset price to wander randomly about its intrinsic value through offsetting mechanisms in the markets, and the resulting successive price changes will be independent. A market in which the prices of securities change independently of each other is defined as a random-walk market (Fama, 1965a). Fama (1965b) links the random walk theory to the empirical study on market efficiency. The theory of random walk requires successive prices changes to be independent and to follow some probability distribution.

When the flow of news coming into the market is random and unpredictable, current price changes will reflect only current news and will be independent of past price changes. Hence, independence of successive price changes implies that the history of an asset price cannot help in predicting its future prices and profits. It is then consistent with the existence of an efficient market. Using serial correlation tests, run tests and Alexander's (1961) filter technique, Fama (1965b) cannot reject the independence of successive price changes and concludes that history of price changes would not help make the expected profits of market traders more than buy-and-hold.

The random-walk theory does not specify the shape of the probability distribution of price changes. Fama (1965b) finds that a Paretian distribution with characteristic exponents less than 2 fit the stock market data better than the Gaussian distribution, which is in line with the findings of Mandelbrot (1963). Hence, the empirical distributions have more relative frequency in their extreme tails than would be expected under a Gaussian distribution while the intrinsic values change by large amounts during very short periods of time.

Efficient-market hypothesis (EMH)

A comprehensive review of theory and evidence on market efficiency was first provided by Fama (1970). He defines an efficient market in which asset prices at any time fully reflect all available information, and then further introduces three kinds of tests of EMH that are concerned with different sets of relevant information.

Weak form tests

Weak-form tests are used to examine whether investors can earn abnormal profits from the past data on asset prices. If successive price changes are independent and then unpredictable, it is impossible for investors to earn more than buy-and-hold. In literature, there is evidence of random walk and independence in the successive price changes in support of weak-form market efficiency (e.g., Alexander, 1961; Fama, 1965a, b; Fama & Blume, 1966). Nevertheless, Fama (1970) recognizes that rejection of the random walk model does not imply market inefficiency. Market efficiency does not require the independence assumption, which is too restrictive, but only requires the martingale process of asset returns (Samuelson, 1965) with zero expected profits to the investors.

Furthermore, if investors can make significant abnormal profits using any tools in technical analysis based on past data, the weak-form efficiency is also violated. For instance, Wong, Chew, & Sikorski (2001), Wong, Manzur, & Chew (2003), Lam, Chong, & Wong (2007), McAleer, Suen, & Wong (2016) and Chong, Cao, & Wong (2017) propose new trading rules or indicators to earn abnormal profits in the markets. However, Kung & Wong (2009 a, b) find that the use of trading rule in technical analysis may have been useful in the past but may not be able to generate significant profit currently.

Semi-strong form tests

Semi-strong form tests involve an event study which is used to test the adjustment speed of asset prices in response to an event announcement released to the public. An event study averages the cumulative abnormal return of assets under investigation over time, from a specified number of pre-event time periods to a specified number of post-event periods. Fama, Fisher, Jensen, & Roll (1969) provide evidence on the reaction of share prices to stock split in support of semi-strong form market efficiency. Other event studies on earnings announcements (Ball & Brown, 1968), announcements of discount rate changes (Waud, 1970) and secondary offerings of common stocks (Scholes, 1972) generally provide supportive evidence for semi-strong forms of market efficiency.

Strong-form tests

Strong-form tests are used to assess whether professional investors have monopolistic access to all private as well as public information so that they can outperform the market. Jensen (1968) indicates that professional investors of mutual funds cannot beat the market in favor of the strong-form market efficiency. Malkiel (2005) also finds that the performance of professional investment managers in domestic and foreign capital markets does not exceed the corresponding index benchmark so that market prices already reflect all available public and inside information.

Evolution of EMH

The EMH is developing in several aspects that arouse attention. The first is to consider the information and trading costs. The stock prices in an efficient market should reflect all available information. A precondition for the market efficiency is that information and trading costs are always zero in the markets. If, for instance, information is costly, there must be a financial incentive to obtain it. But there would be no financial incentive if the information is already fully reflected in asset prices (Grossman & Stiglitz, 1980). A weaker but economically more sensible version of the market efficiency is that prices reflect information to the point where the marginal benefits of acting on information (the expected profits to be made) equal to the marginal costs of collecting it. Further, since information and trading costs are surely positive, the empirical studies are to test whether EMH is a good approximation, i.e., the deviations of the EMH are within information and trading costs.

The second is to abandon the rational assumptions of market participants. Rubinstein (2001) acknowledges that irrational behaviors are observed in behavioral psychology experiments among investors in the market. He has re-examined some historical evidence against market rationality and concluded that although markets are not perfectly rational, they are at least minimally rational: although prices are not set as if all investors are rational, there are still no abnormal profit opportunities for the investors that are rational.

The third is to deal with the joint-hypothesis problem. Empirical testing of EMH is necessarily a joint test of market efficiency and a particular asset pricing model. This joint-hypothesis problem makes empirical work on market efficiency not testable. Rejection of the joint hypothesis may be due to market inefficiency and/or a bad model of market equilibrium (Fama, 1991). The asset pricing models or market models that ignore the cross-section of expected returns, such as size, leverage, and E/P effects, may possibly lead to results of spurious market inefficiencies. Factor models are proposed to solve the bad-model problem.

Factor models

Beside market risk that exists in tradition asset pricing models, some propose additional risk factors in factor models to explain cross-section expected returns of securities so the excess returns are considered as compensations for additional sources of risk (Beard & Sias, 1997; Fama & French, 2008).

Fama-French Three-Factor model

Fama & French (1993) provide evidence that a three-factor model can explain stock returns. The three-factor model considers that the excess returns of a stock portfolio can be explained by its exposure to three factors: market risk premium (*RMRF*), market value factor (*SMB*, Small market capitalization Minus Big market capitalization), and book-to-market ratio factor (*HML*, High book-to-market ratio Minus Low book-to-market ratio).

Carhart Four-Factor Model

Some factors, like short-term reversal, medium-term momentum, volatility, skewness, gambling, and others are not considered or included in the three-factor model. Carhart (1997) develops a four-factor model which includes the momentum factor (*PRIYR*, the return for the one-year momentum in stock returns) in addition to RMRF, SMB and HML. Carhart (1997) provides evidence that it can explain large cross-sectional variation of the average returns stock portfolios.

Fama-French Five-Factor Asset Pricing Model

Fama & French (2015) further examine profitability and investment factors, as well as RMRF, SMB and HML, which is called a five-factor asset pricing model, to absorb the patterns in average returns and explain more anomalies. Fama & French (2017) tested the five-factor model. They found that average stock returns for markets of North America, Europe, and Asia Pacific increase with HML and profitability factor and are negatively related to the investment factor. The relation between average returns for the market of Japan and HML is strong but there is little relation between average returns and profitability or investment factor.

Liu-Stambaugh-Yuan Factor Models

Liu, Stambaugh & Yuan (2019) propose a Chinese version of the three-factor model which consists of EP (earning-price ratio) as well as RMRF and SMB, of the four-factor model which consists of turnover factor PMO (Pessimistic minus Optimistic) as well as EP, RMRF and SMB, and of the seven-factor model which consists of trading volume and turnover rate factors in addition to RMRF, SMB, HML, profitability and investment factors. These Chinese versions of factor models can empirically explain the returns on China's A-share market.

Market anomalies

There are many studies full of evidence of abnormal behaviors that seem inconsistent with market efficiency (e.g., Lehmann, 1990; Dimson & Mussavian, 1998; Chordia *et al.*, 2008). In the following, we summarize some well-known anomalies that prevail in stock markets.

Contrarian Effect / Reversal Effect

De Bondt & Thaler (1985, 1987) found that investors are too pessimistic about the past loser portfolio and too optimistic about the past winner portfolio. Consequently, past losers (stocks with low returns in the past three to five years) will win positive excess returns than past winners (stocks with high returns in the past three to five years) which will have negative excess returns, when the market is finally adjusted to the fundamental value. This is known as the Contrarian Effect (or the Winner-Loser Effect). This market anomaly can be used to predict stock returns and use the reversal strategy to buy the loser portfolios in the past and sell the winner portfolios in the future.

The representative heuristic (Tversky & Kahneman, 1974), for example, shows that people tend to rely too heavily on small samples and too little on large samples. Then, it inadequately discounts both for the regression phenomenon, and for selection bias in the generation or reporting of evidence (Hirshleifer, 2001). Due to the existence of representative heuristic, investors signify excessive pessimism about the past loser portfolios and excessive optimism about the past winner portfolios. Consequently, investors overreact to both good and bad news. This leads to the underestimation of the loser portfolio prices and the overestimation of the winner portfolio prices, leading to deviations from their fundamental values.

Momentum effect

Jegadeesh & Titman (1993) found that recent past winners (portfolios formed on the last year of past returns) outperform recent past losers, known as the Momentum Effect. If stock returns are examined over a period of 6 months, the average return of the winner portfolio is about 9% higher than that of the loser portfolio. Chan, Jegadeesh & Lakonishok (1996) enlarged upon the research samples of Jegadeesh & Titman (1993) and obtained the same results. Schwert (2003) found that the Momentum Effect seems quite large and reliable using both CAPM and the three-factor model.

Asness, Frazzini, Israel & Moskowitz (2014) however challenge the existence of the Momentum Effect. They prove that momentum return is small, fragmentary, in danger of disappearing and only applicable in short positions. Also, there is no theory to support the Momentum Effect. Moreover, the Momentum Effect may not exist or may be limited by taxes or other transaction costs, and it may provide various results depending on different momentum measures in any given period.

Calendar anomalies

January Effect

The January Effect was first discovered by Wachtel (l942). Rozeff & Kinney (1976) found that the return of NYSE's stock index in January from 1904 to 1974 was significantly higher than that of the other 11 months. The studies of Gultekin & Gultekin (1983) and Nippani & Arize (2008) found similar evidence of the January effect. However, according to Riepe (1998), the January effect is weakening. Moller & Zilca (2008) investigated the evolution of the daily pattern of the January effect across size deciles and confirmed its existence. However, from Zhang & Jacobsen (2013), well-known monthly seasonals in returns such as January effect, are sample specific revealed by over 300 years of UK stock returns so that monthly seasonals might be in the eye of the beholder.

Two most important explanations for the January Effect include the Tax-Loss Selling Hypothesis (Gultekin & Gultekin, 1983) and the Window Effect Hypothesis (Haugen & Lakonishok, 1988). The tax-loss selling hypothesis suggests that people will sell down stocks at the end of the year, offsetting the appreciation of other stocks in that year, in order to pay less in taxes. After the end of the year, people buy back these stocks. This collective buying and selling leads to a year-end decline in the stock market and a January rise in the stock market the following year. The window effect hypothesis argues that institutional investors want to sell losing stocks and buy profitable stocks to enhance year-end statements. This kind of trading exerts positive price pressure on profitable stocks at the end of the year and negative pressure on losing stocks. When the selling behavior of institutional investors stops at the end of the year, the losing stocks that were depressed in the previous year will rebound substantially in January, leading to a larger positive trend of price movements. Some such as Chen & Singal (2004), and Starks, Yong, & Zheng (2006) favor the explanation of the tax-loss selling hypothesis.

Weekend effect and reverse weekend effect

French (1980) analyzed the 1953-1977 US daily stock returns and found that the gain on Monday has a negative trend, while the gains on other days are positive. When one gets higher returns on Friday than on Monday, it is known as the Weekend Effect, whereas when one gets higher returns on Monday as opposed to Friday, it is called the Reverse Weekend Effect. Schwert (2003) found that the weekend effect seems to have disappeared or at least substantially attenuated since French (1980). Nevertheless, other evidence of the Weekend Effect can be found in Bampinas, Fountas & Panagiotidis (2015). There exist various explanations for stock market behaviors on weekends. For example, the regular Weekend Effect has been attributed to payment and check-clearing settlement lags. On the other hand, Brusa, Liu & Schulman (2000, 2003, 2005) and Brusa, Hernández & Liu (2011) found the Reverse Weekend Effect, which can be explained by the reward for higher volatility on Mondays than on Fridays (Chan & Woo, 2012).

Turn-of-the-month effect

Ariel (1987) first pointed out that on the last day of the month, stock returns are generally higher. Specifically, Turn-of-the-Month is defined as beginning with the last trading day of the month and ending with the third trading day of the following month. Studying CRSP daily returns over the 109-year interval of 1897-2005, all returns to equities on the average were found to be positive during the turn-of-the-month interval (McConnell & Xu, 2008).

Holiday effect

Lakonishok & Smidt (1988) and Ariel (1990) have shown that average returns are higher the day before a holiday than other trading days, which is the so-called Holiday Effect.

Keim (1988) argues that seasonals in returns are anomalies in the sense that asset-pricing models do not predict them, but they may not imply market inefficiency. These seasonals can be explained in terms of market microstructure (Lakonishok & Maberly, 1990, Ritter, 1988 and Keim, 1989).

Empirical tests

Lean, Smyth, & Wong (2007) use the stochastic dominance (SD) test to examine the existence of day-of-the-week and January effects for several Asian markets. Their empirical results support the existence of weekday and monthly seasonality effects in some Asian markets but suggest that first-order SD for the January effect has largely disappeared. Wong, Agarwal, & Wong (2004) investigate the Day-of-the-Week Effects in the Asian Markets and find the Day-of-the-Week Effects in the Asian Markets. However, Wong, Agarwal, & Wong (2004) investigate the January effect, the day-of-the-week effect, the turn-of-the-month effect, and the pre-holiday effect in the Singapore stock market reveal that these anomalies have largely disappeared from the Singapore stock market from 2000 onwards. Wong & McAleer (2009) show that in the almost four decades from January 1965 through to December 2003, US stock prices closely followed the 4-year Presidential Election Cycle. In general, stock prices fell during the first half of a Presidency, reached a trough in the second year, rose during the second half of a Presidency, and reached a peak in the third or fourth year. This cyclical trend is found to hold for the greater part of the last ten administrations, starting from President Lyndon Johnson to the administration of President George W. Bush, particularly when the incumbent is a Republican. The empirical results suggest that the Republican Party may have greater cause to engage in active policy manipulation to win re-election than their Democratic counterparts. There is irony in that bullish runs in the stock market have tended to coincide with sub-periods under Democratic administrations. The existence of the Presidential Election Cycle shown in the paper may constitute an anomaly in the US stock market, which could be useful for investors.

Book-to-market effect/value anomaly

Many studies have investigated the Book-to-Market (BM). For example, Fama & French (1992) found the BM effect in the US market; Wang & Xu (2004), and Lam, Dong & Yu (2019) confirmed the existence of the BM effect in the Chinese stock markets. Kothari, Shanken, & Sloan (1995) however consider that it is the selection bias. Chan, Hamao, & Lakonishok (1991), Davis (1994), and Fama & French (1998) tested the stock markets outside the US or during an extended test period, and they still found the BM effect.

Fama & French (1992, 1993, and 1996) believe that BM represents a risk factor, i.e., financial distress risk. Firms with high BM generally have poor performance in profitability, sales and other fundamental aspects, and their financial situation is more fragile, making their risk higher than that of firms with low BM. Also considered is that a high return obtained by firms with high BM is only the compensation for their own high risk. BM can then be explained by Fama-French in the three-factor model and is not an unexplained anomaly. Furthermore, Fama & French (1998) confirm that a two-factor model with a relative distress risk factor added could explain the BM effect on the international level.

Size effect

Banz (1981) showed that the stock market value decreased with the increase of company size. The phenomenon that small-cap stocks earn higher returns than those calculated by CAPM (Reinganum, 1981), and large-cap stocks (Siegel, 1998), clearly contradicts EMH, as the firm size is regarded as public information. Lakonishok, Shleifer, & Vishny (1994) demonstrated that since the stock with high P/E ratio is riskier, if P/E ratio is taken as known information, then this negative relationship between P/E ratio and return rate provides a considerable prediction on the latter, and then challenges EMH.

On the contrary, Daniel & Titman (1997) claimed that BM and firm size only represent the preference of investors, not the determinants of returns. Due to the poor fundamentals of high BM companies, and good fundamentals of low BM companies, while investors currently prefer to hold value stocks with good fundamentals rather than those with poor fundamentals, the long-term investment returns on companies with high BM are expected to be higher. Moreover, Schwert (2003) closely mimicked the strategy described by Banz (1981) and re-estimated the abnormal returns with updated sample periods. It is found that the small-firm anomaly has disappeared since it was discovered.

Disposition effect

From Shefrin & Statman (1985), the Disposition Effect refers to two phenomena of the stock market. In the first, investors tend to have a strong propensity to hold onto losing stocks and avoid the regret associated with the sale of a losing investment and, in the second, investors tend to sell stocks in order to lock in profits. In these cases, two kinds of psychology describe investors whose regret and embarrassment cause the first phenomenon and whose arrogance leads to the second. Hence, investors have a disposition effect which leads them to sell winners and hold losers. The Disposition Effect is one implication of extending Kahneman & Tversky's prospect theory (1979) to investments.

Barber, Lee, Liu & Odean (2008), Odean (1998a, 1999) and Zhao & Wang (2001) found the Disposition Effect in Taiwanese, US, and Chinese stock markets, respectively. They conclude that investors tend to sell profitable stocks and continue to hold losing stocks. On the other hand, Odean (1998a, 1999) also found that US stock investors sell more loss-making shares in December, making the Disposition Effect less pronounced because of tax avoidance.

Herd effect and Ostrich effect

Herd behavior refers to behavior patterns that are correlated across individuals but could also be caused by correlated prevailing information in independently acting investors. The people with herd behavior will do what others are doing rather than what is optimal based on their own information. Herding is closely linked to expectations, fickle changes without new information, bubbles, fads, and frenzies. Barber, Heath, & Odean (2003) compared the investment decisions of groups (stock clubs) and individuals. Both individuals and clubs are more likely to purchase stocks that are associated with good reasons (e.g., a company that is featured on a list of most-admired companies). However, stock clubs favor such stocks more than individuals, even though such reasons do not improve performance. The previously mentioned seven-factor model by Li, Hu, & Tang (2019) also indicates that herd behavior of the Chinese A-share market is more prevalent in times of market turmoil, especially when the market falls.

Another market anomaly is the Ostrich Effect. Ostriches deal with obvious risk situations by pretending that risk does not exist, so the ostrich effect is used to describe some investors' decisions as shown in Galai & Sade (2006). Karlsson, Loewenstein & Seppi (2009) present a theoretical model in which investors collect additional information conditional on favorable news and avoid information following bad news under this effect They also provide empirical evidence to support the existence of the Ostrich Effect in financial markets.

Bubbles

Bubbles feature large and rapid price increases which result in share prices rising to unrealistically high levels sustained largely by investors' enthusiasm rather than by consistent estimations of real value, but bubbles finally collapse. Shiller (2000) explored changes in bubble expectations and investor confidence among institutional investors in the U.S. stock market. Experiments are useful to isolate, distinguish and test the validity of different mechanisms that can lead to or rule out bubbles (Abreu & Brunnermeier, 2003).

West (1987) suggests a specification test to examine the existence of speculative bubbles or fads by comparing two sets of parameters: one assumes that there are bubbles, or fads; another assumes no bubbles or fads. The specification tests can be applied to a wide class of linear rational expectations models. Chan & Woo (2008) employ a new non-stationary test to detect the existence of stochastic explosive root bubbles in stock markets with high statistical power. Phillips, Shi, & Yu (2014) propose a right-tail unit root test to examine the explosive properties of asset price.

Some reasons for bubbles existence in asset markets include the use of internet (Barber & Odean, 2002), exercise of stock-options as compensation (Heath, Huddart & Lang, 1999), feedback pattern (Shiller, 2002; 2003), existence of smart money (Shiller, 2003), influence of media (Shiller, 2002; Diacon, 2004), and investor sentiments and emotions (e.g. Barberis, Shleifer, & Vishny, 1998; Peterson, 2002; Barberis & Thaler, 2003; Guo, McAleer, Wong & Zhu, 2017).

In defence of EMH

The above phenomena are called "anomalies" because their common feature is that not only information leads to price changes, but other factors make stock prices predictable to some extent, so the EMH is questioned. EMH supporters have been trying to explain the ‘anomalies’ within the EMH framework. They defended against the critiques of EMH from the following aspects.

First, the existence of anomalies may be caused by the choice of measurement methods and models used to estimate abnormal returns. Many EMH supporters believe that anomalies are only the result of data snooping, data mining, inappropriate data collection or bad-model problems. Fama (1998) also supports this view that most long-term return anomalies are very sensitive to the methodology used. If different measurement methods are adopted, the long-term abnormal returns may become smaller or even disappear. Likewise, different asset-pricing models will produce different estimates of long-term abnormal returns. The anomalous returns, due to for example the size effect and the book-to-value effect, may be explained by different factor models introduced in Section 2.5 as additional risk factors (Beard & Sias, 1997; Schwert, 2003; Fama & French, 2008) consistent with the EMH. The 'findings' of anomalies may be caused by a bad-model problem (Fama, 1991). As emphasized by Fama (1998), a reasonable change of models often causes an anomaly to disappear.

Moreover, the anomalies are considered as occasional events and chance results. From Fama (1998), there are various events in markets, and the prices will be overreacted or underreacted to the event, but the frequency of apparent overreaction is equal to the frequency of underreaction. If the phenomenon of anomaly is randomly spread over the periods of overreaction and underreaction, it is just in line with the market efficiency. Similarly, the post-event continuation of pre-event abnormal returns before an event is about as frequent as the post-event reversal. In addition, price overreaction and long-term reversal can also be considered as a kind of price fluctuation around its fundamental value, that is, the expected value of abnormal return is still zero. Long-term revenue continuation and long-term returns can also be chance results (Fama, 1998).

Furthermore, in the long run, the anomalies may disappear consistent with EMH. Some argue that there is a systematic bias in stock price movements when investors are irrational, and their irrational behaviors are not random. However, EMH proponents believe that the bias will disappear if only there are hedgers undertaking rational hedging buy-low and sell-high transactions. Malkiel (2003) acknowledges that psychological factors and the Internet "bubble" can indeed affect the price of securities, but the true value will ultimately be reflected in the price. Schwert (2003) argues that many models or strategies generated to produce anomalous profits seem to disappear after they are published in financial journals. It is because even if the anomalies existed in the sample period in which they were first identified, the activities of practitioners who implement strategies to take advantage of the market anomalies can cause the anomalies to disappear. Ironically, research findings of anomalies cause the market to become more efficient.

Hence, the existence of anomalies does not completely overthrow the EMH. The discovery of anomalies does not prove that the market is ineffective. The research on EMH and anomalies will therefore continue.

Conclusion

Many studies have attempted to detect the existence of EMH and anomalies using the data from stock markets all over the world. In literature, more and more empirical results favor the evidence of anomalies that challenge EMH. Some try to explain the anomalies and defend that the phenomena of 'anomalies' are consistent with EMH (Fama, 1998; Fama & French, 2008). On the other hand, some explain the anomalies by using concepts of Behavioral Finance that apply psychology to explain behavioral bias (Frankfurter & Mcgoun, 2000). The arguments for and against EMH continue in the literature.

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2 Review on behavioral finance with empirical evidence

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Introduction

In the traditional finance framework, where market participants are rational and frictionless, an asset price is equal to its intrinsic value. The intrinsic value is the present value of all expected future cash flows from the asset, where rational expectations are formed with all available information and where the discount rate is consistent with a normatively acceptable preference specification (Barberis & Thaler, 2003). The hypothesis that actual prices, at any point in time, already reflect the effects of all available information and, therefore, will be good estimates of their intrinsic values is known as the Efficient Markets Hypothesis (EMH). Under the EMH, investors cannot adopt any investment strategies to make abnormal risk-adjusted returns on the average or make the expected returns more than buy-and-hold (Fama, 1970). Moreover, EMH is important for understanding asset pricing theory (Jarrow, 2012) and option pricing theory (Jarrow, 2013; Bhattacharya, 2019). However, many studies are full of evidence of anomalous behaviors in the market that challenge market efficiency

(Woo *et al.,* 2020). Fama (1998) defends against the critiques of EMH and argues that the anomalies are occasional events and chance results, that apparent overreaction to information is about as common as underreaction, that post-event continuation of pre-event abnormal returns is about as frequent as post-event reversal, and that the existence of anomalies depends upon the choice of the methodology used to estimate excess returns. The anomalies, in the long run, are then predicted to disappear.

There is a vast amount of literature on empirical testing of EMH. For example, Kung & Wong (2009) use two technical trading rules to assess whether the efficiency of Taiwan's securities market has improved due to the gradual liberalization measures implemented over the last decades. Their results favor the evidence of market efficiency. Vieito *et al.* (2013) are amongst the first to test for weak-form efficiency of the G-20 countries, with serial correlation test, ADF unit root test and multiple variance ratio tests employed for the empirical study. It is concluded that most of the individual markets are weak-form efficient.

On the other hand, stochastic dominance tests have been developed recently for testing EMH. Bai *et al.* (2011), Bai *et al.* (2015), Ng *et al.* (2017) and others have developed stochastic dominance tests used to examine whether the market is efficient. Lean *et al.* (2010) apply the stochastic dominance test to examine the EMH of oil spot and futures prices and conclude that the spot and futures oil markets are efficient and rational. Chan *et al.* (2012) apply the stochastic dominance approach to examine the efficiency of the UK covered warrants market and do not reject market efficiency. Clark *et al.* (2016) cannot reject EMH using the stochastic dominance test. Zhu *et al.* (2019) apply the stochastic dominance test to analyze the impacts of the most recent global financial crisis on the seven most important Latin American stock markets and conclude that the markets are efficient.

Moreover, Fong *et al.* (2005) apply a stochastic dominance test to distinguish between two hypotheses that there exist general asset pricing models explaining the momentum effect versus the alternative hypothesis that no asset pricing models are consistent with risk-averse investors rationalizing that momentum effect. They find that the search for rational asset pricing explanations for the momentum effect may be unsuccessful and then reject the existence of an efficient market. Wong *et al.* (2008) and others have claimed that if the first-order stochastic dominance exists statistically, there could be arbitrage opportunity, and investors can increase their expected wealth and expected utility if they switch from holding the dominant to the dominant assets. Tsang *et al.* (2016) use the stochastic dominance method for analysis and find an arbitrage opportunity in the real estate market of Hong Kong by considering rental yield in this market. Finally, Guo *et al.* (2017a) adopt stochastic dominance and Omega ratio to examine market efficiency. They find that the real estate market in Hong Kong is not efficient with expected arbitrage opportunities and anomalies. Many approaches can be used to examine market efficiency. Readers may refer to Wong (2020, 2021), Woo *et al.* (2020), and others for more information.

The arguments for and against the EMH continue in the literature. The skeptics of EMH integrate the effects of psychological, cognitive, emotional and economic factors on the decisions of investors, financial analysts and financial institutions, which are different from the predictions of traditional finance theory. The new branch of financial economics, known as behavioral finance, is increasingly important in the literature and questions the EMH (Thaler, 2015). Unlike the EMH, behavioral finance argues that asset prices are likely to deviate from their fundamental values, and these deviations are caused by the presence of traders whose rationality is bounded by behavioral bias (Barberis & Thaler, 2003). Understanding behavioral finance concepts are essential for developing cutting-edge treatments of financial economics. In this paper, we review brief behavioral finance concepts with their salient readings so that readers can grasp the basic ideas quickly, which are needed to go further in their studies on behavioral finance at a more advanced level (Venezia, 2018). We also provide the recent empirical evidence of behavioral finance in the literature. The readers can then follow the research methods to undertake empirical studies on this field.

The rest of the paper is organized as follows: Section 2 illustrates behavioral finance concepts with empirical evidence in the literature. Finally, section 3 presents the concluding remarks.

Behavioral finance

Behavioral finance studies the effect of psychological factors on human behavior, which further affects asset price movements. Standard financial models assume that individuals are rational and risk-averse. In reality, individuals may be however irrational and risk-seeking. For example, Li & Wong (1999), Wong & Li (1999), Wong (2006, 2007), Wong & Ma (2008), Guo & Wong (2016), Chan *et al.* (2020), and many others consider that investors could be risk-averse or risk-seeking. Behavioral finance models do not adhere to the traditional assumptions of rationality and risk aversion but investigate how irrationality and behavioral bias affect our decisions. Well-known concepts with some selected empirical evidence in the literature are briefly reviewed below to enhance the understanding of behavioral finance.

The prospect theory

Tversky & Kahneman (1981) consider that individuals could be judged irrational either because their preferences are contradictory or because their desires and aversions do not reflect their pleasures and pains. Prospect theory developed by Kahneman & Tversky (1979) is used to explain irrational behavior under risk and uncertainty due to cognitive bias. The theory tries to model real-life choices among risky prospects that are inconsistent with the basic tenets of expected utility theory rather than an optimal decision.

The prospect theory begins with the value function from which people react differently when faced with potential gains and losses. The value function is concave for gains, convex for losses, and is generally steeper for losses than for gains indicating that losses outweigh gains. Under the prospect theory, people make decisions based on the potential gains or losses relative to their reference point rather than absolute wealth values. The status quo is usually taken as the reference point as it is found that investors use the purchase price as a reference point, but there are situations in which gains and losses are coded relative to an expectation level that is different from the status quo. For example, when faced with a risky prospect leading to gains, people are risk-averse with a concave value function. Hence, they prefer choices with a higher certainty. In contrast, when faced with a risky choice leading to losses, people become risk-seeking with a convex value function. Accordingly, they prefer the outcomes to avoid the sure losses. These concepts are contractionary to the rational theory of expected utility maximization.

According to the prospect theory, the value is assigned to gains and losses rather than final wealth. The value function that passes through the reference point is then S-shaped and asymmetrical. Also, the value function is steeper for losses than gains indicating that losses outweigh gains due to loss aversion, which is considered a main behavioral bias under the prospect theory (Selim *et al.,* 2015). This theory differs from the expected utility theory, in which a rational agent is indifferent to the reference point, and people do not care how the outcome of losses and gains is framed. Furthermore, unlike the expected utility theory, the probabilities are replaced by probability weighting functions when the expected utility is estimated. However, the model is based on observations that low probabilities are usually overweighted, and high probabilities are usually underweighted. It is consistent with the observation that people tend to overreact to low probability and underreact to high probability. It is observed that overweighting of low probabilities may also contribute to the attractiveness of both the insurance and gambling industries. Prospect theory has laid solid foundations of behavioral finance and has led to the influential development of financial theory in the literature. For example, Levy & Levy (2002), Wong & Chan (2008), Levy & Orkan (2012), and others extend the stochastic dominance theory to fit into the prospect theory. Barberis (2013) provides more insights on the prospect theory.

Zhang & Semmler (2009) explore evidence on the prospect theory for stock markets with time-series data, and they find that gains and losses may have asymmetric effects on investment behavior under the prospect theory. Gasbarro *et al.* (2012) adopt ascending and descending stochastic dominance procedures to test for risk-averse and risk-seeking behavior. They find evidence of all four utility functions: concave, convex, S-shaped, and reverse S-shaped. Abdellaoui *et al.* (2013) undertake an experimental study in which a sample of private bankers and fund managers behave according to prospect theory and violate expected utility maximization. Finally, Liu *et al.* (2014) test the prospect theory by analyzing over 28.5 million trades made by 81.3 thousand traders of an online financial trading community over 28 months. The results support the unprecedentedly large-scale evidence of prospect theory in online financial trading. The finance professionals are suggested to develop trading strategies to reduce the impacts of loss aversion and disposition under the prospect theory.

Mental accounting

Mental accounting (or psychological accounting) refers to the different values people place on money based on subjective criteria, leading people to make irrational decisions (Thaler, 2015). When framing refers to how a problem is posed for decision-makers, one important feature of mental accounting is narrow framing, which treats individual gambles separately from other portions of wealth (Barberis & Thaler, 2003). Then, people tend to separate decisions that should be combined according to the principle of rationality. Gains and losses are treated separately so that, as predicted by the prospect theory, people are risk-averse when they gain but risk-seeking when they experience loss. For example, individuals have an everyday budget for food and a family budget for entertaining. Therefore, they will not eat expensive food such as lobster or shrimp at home, where the food budget for food is limited because lobster and shrimp are much more expensive than a simple fish dish. However, they will order lobster and shrimp in a restaurant for entertainment even though the cost is much higher than a simple fish dish. If they instead ate lobster and shrimp at home but the simple fish dish in a restaurant, they could save money. However, they would not do so because they budget money into mental accounts for expenses (Zhang & Sussman, 2018) and then think separately about restaurant meals and food at home. As a result, they would choose to limit their food at home (Ritter, 2003).

Lim (2006) shows that investors prefer integrating losses and segregating gains consistent with the mental accounting concepts of Thaler (1985). Milkman & Beshears (2009) estimate the amounts of online grocery purchases with and without coupons redeemed. They observe a rise in grocery spending with coupon redemption and the additional expenditure associated with coupon redemption on groceries that a buyer does not typically purchase. These results support the evidence of mental accounting. Egozcue & Wong (2010) use the ideas of mental accounting, prospect theory and others to develop a model that can explain investors' behavior in segregating or integrating multiple outcomes when evaluating mental accounting. Egozcue *et al.* (2014) further extend the theory by using the ideas of mental accounting, prospect theory and others to develop decision rules for multiple products. Finally, Sui *et al.* (2021) explore how overspending behaviors are related to the mental accounts of wealth, saving goals and expense forecasting. Overspending behavior associated with these three kinds of mental accounts reveals evidence that the expected overspending is susceptible to expenditure forecasts and wealth allocation. In contrast, wealth allocation affects credit overspending, and income overspending is subject to wealth allocation, expenditure forecasts, and savings goals.

Time preference and self-control

The conventional representation of decision making over time is usually modelled by an additively separable utility function with exogenous, declining exponential weights. However, evidence from psychological research proposes that discount rates are dependent upon a range of psychological variables such as consideration of future consequences, conscientiousness, extraversion, experiential avoidance, and self-control (Daly *et al.*, 2009). For example, deferring consumption involves consumer self-control and is linked to mood and emotional states. It is found that discount rates are sometimes bizarrely high, that gains are discounted more heavily than loss, that small magnitudes are discounted more heavily than large magnitudes, that the framing of choice as a delay versus an advance has a large effect on decisions, that time preference differs greatly in different judgment domains (e.g., money versus health). Those visceral influences such as pain or hunger affect inter-temporal choices (Hirshleifer, 2001). Moreover, Barber & Odean (2008) propose an alternative model of decision making in which agents faced with many alternatives consider primarily those options that have attention-attracting qualities. Preferences come into play only after attention has limited the choice set. When options are numerous and search costs high, attention, rather than preferences, may affect choice-making decisions.

Regret aversion and disposition effect

If information about the best course of action under uncertainty arrives after taking a fixed decision, the negative human emotion of regret is often experienced. Loomes & Sugden (1982), Bell (1982), and Fishburn (1982) were the first to develop the regret theory. Regret is the pain that people feel when they consider themselves better off if they had not taken a certain action in the past. The value of regret can be measured as the difference between a made decision and the optimal one. The theory of regret proposes that when facing a decision in an uncertain environment, the regret-averse individuals incorporate the possibility of regret in their decision-making process to avoid its occurrence. Seiler *et al.* (2008) examine the regret aversion in residential real estate markets. They find that in a hypothetical situation, people would experience higher regret if they do not sell their investment property at the all-time high than if they are simply unaware of the potential gain, and that women are more averse to regret than men.

Many scholars have contributed to the advancement of this theory. Egozcue *et al.* (2015) develop a model to obtain the optimal output of a competitive firm, assuming that the firm is regret-averse when it faces price uncertainty. They discover that under certainty, the optimal output will be lower for regret-averse firms than for risk-averse firms. They also show that the optimal output will change when the regret factor changes. Furthermore, Guo *et al.* (2015) investigate hedging behaviors for regret-averse firms in their production. They prove that the separation theorem works well, but the full-hedging theorem does not work well under the regret-averse model. They demonstrate that regret aversion behavior is not related to optimal production levels and that regret-averse firms take different hedged positions compared to risk-averse firms in some circumstances. When firms are more regret-averse in an unbiased futures market, they will take less optimal hedging positions. Furthermore, contrary to the conventional theory, they indicate that regret-averse firms change their production level when forward trading is prohibited. Guo & Wong (2019) extend the theory by first demonstrating that linear-regret firms will produce less than firms under certainty and produce more than risk-averse firms for sure. They provide sufficient conditions for regret-averse firms to produce more than both linear-regret and risk-averse firms and develop properties on the comparative statics of optimal production and the production of regret-aversion firms. Qin (2020) proposes a regret-based capital asset pricing model in which investors maximize the expected portfolio returns while minimizing anticipated regrets. In equilibrium, a risky asset's excess return is proportional to its regret beta that measures the exposure to investors' emotions, and the investors are expected to receive a positive regret premium as compensation for regret aversion. Finally, Ballinari & Müller (2021) test the relationship between regret aversion theory and US stock returns. From their test results, stocks that have a high regret measure offer a low potential for regret. Thus, investors increase the portfolio weight towards these stocks that become overvalued today from the perspective of regret aversion theory and will have low subsequent average returns. The same logic of the argument is applied to the stocks with a low regret measure. These empirical results are consistent with the regret-based capital asset pricing model (Qin, 2020), which predicts that stocks with a high potential for future regret will offer higher average returns in the future.

On the other hand, the regret and the prospect theory have also been extended to explain the disposition effect (Fogel & Berry, 2006). Shefrin & Statman (1985) identify the disposition effect, which considers that investors dislike incurring losses more than they like making profits, and they are eager to gamble on losses. As a result, investors will tend to sell assets that have risen in value but keep assets which prices have declined. In other words, they sell winners rather than losers. The cause of the disposition effect can be explained by the prospect theory mentioned above, which shows that investors are risk-averse when they earn profits but are risk-seeking when incurring losses. Hence, risk-seeking investors tend to keep the losing investments to later bet on the possible rebound in the face of loss. They do so also because they want to avoid the feeling of regret when they realize a loss from making a wrong investment decision previously or when the price rebound occurs after the sale of losing investments.

Choe & Eom (2009) examine whether the disposition effect exists in the Korean stock index futures market. Their findings show strong evidence for the disposition effect. Also, individual investors are much more prone to the disposition effect than institutional and foreign investors. Sophistication and trading experience help reduce the disposition effect. Moreover, the disposition effect is stronger in long positions than in short positions. The conclusion is that the disposition effect may reduce the investment performance. The above results are consistent with Odean (1998). As presented in

Kaustia (2010), empirical results indicate strong evidence for the disposition effect in stock and other asset markets. Household investors are generally more susceptible to the disposition effect than professional investors. The disposition effect is responsible for stock market underreactions and price momentum. Moreover, from Birru's (2015) research study, the disposition effect exists prior to stock splits but is absent following a stock split. It is because oblivious investors cannot properly account for changes in nominal share price due to stock splits and cannot accurately identify the winners and losers. Moreover, momentum is still present even though the disposition effect disappears following a stock split. Therefore, it implies that momentum may be induced by factors aside from the disposition effect. Furthermore, by collecting quantitative data through a questionnaire survey and adopting a structural equation modeling method, Chang (2020) finds that mental accounting has the most significant influence on the disposition effect. The results also show that female investors exhibit a larger disposition effect than male investors.

Disappointment theory

Disappointment, a source of psychological stress, refers to the feeling of dissatisfaction associated with the failure of hope. It is observed that people considering risks when making decisions are disappointed when the outcome of the risk is not evaluated as positively as the expected outcome. Bell (1985) and Loomes & Sugden (1982) were the first to introduce the disappointment theory, which states that individuals will become disappointed discovering that the outcome is worse than they expected, and they will be elated if the outcome is better larger than they expected. People are then averse to disappointment. The theory of disappointment explains why the disappointment-averse people are more likely to choose a certain reward than to risk a greater reward while at the same moment they are eager to choose a greater reward with lower probability when both choices include some risk (Gul, 1991). Readers are suggested to consult Guo *et* *al.* (2021) for more information about the disappointment theory.

The empirical study of Xie *et al.* (2016) supports the view that disappointment aversion leads to the reduction of investors' exposure to the stock markets and indicates that disappointment aversion and risk aversion can significantly explain the global equity premium puzzle. Li *et al.* (2021) study a consumption-based asset pricing model with disappointment aversion and argue that disappointment aversion is playing an important role for leading to a low risk-free rate and a high equity premium.

Cognitive dissonance

Cognitive dissonance is the perception of contradictory information and the relevant information items include people's actions, feelings, ideas, beliefs, and values, and things in the environment (Festinger & Carlsmith, 1959). Hence, cognitive dissonance is a mental conflict that people experience when presented with evidence that their beliefs, values, or assumptions are wrong. Cognitive dissonance is then classified as the pain of regret over erroneous beliefs. The theory of cognitive dissonance asserts that people tend to reduce the cognitive dissonance that is considered irrational. For instance, they may avoid the new information or develop contorted arguments to maintain their beliefs or assumptions. Also, investors avoid negative information about a stock they purchased and focus upon its positive news only (Akerlof & Dickens, 1982; Shiller, 2001). Simo *et al.* (2020) observe that managers' IPO indeterminacy can be explained by cognitive dissonance bias, and financial literacy helps reduce cognitive dissonance.

Money illusion

Money illusion refers to the confusion between real and nominal values. The individuals subject to this bias tend to make economic decisions based on nominal rather than real variables (Fisher, 1928). The existence of money illusion violates the assumption of the rational decision-making process.

Discounted real cash flows at real rates or nominal cash flows at nominal rates can help determine the stock values in a rational model. However, during high inflationary periods, it is possible that investors mistakenly discount real cash flows at nominal rates. If inflation increases, so will the nominal discount rate. If investors discount the same set of cash flows at this higher rate, they will push the stock market's value down. This calculation is incorrect because inflation should have a little net effect on the market value when the same inflation which pushes up the discount rate should also push up future cash flows. Such money illusion may therefore cause variation in Price-Dividend ratios and returns. This illusion seems particularly relevant to understanding the low (high) market valuation during the high (low) inflation periods (Barberis & Thaler, 2003). Furthermore, in experimental asset markets, Noussair *et al.* (2012) find an effect of a nominal shock on real prices. Also, there is an asymmetric response of real prices to inflationary and deflationary nominal shocks, and the deflationary shock has a larger effect on real prices when compared with an inflationary one. These two empirical phenomena can be explained by money illusion.

Availability heuristic

The availability heuristic (or availability bias) is a mental shortcut that relies on immediate information to a given person's mind when assessing a specific topic, concept, method, or decision (Tversky & Kahneman, 1973). Hence, if something or some memory can be recalled, people would think that it must be important, or at least more important than others that are not as readily recalled. The availability heuristic operates when limited attention, memory and processing capacities focus only on subsets of available information. Unconscious associations also create focus. Selective triggering of association causes salience and availability effects. An information signal is salient if it has special characteristics that are good at grabbing hold of our attention or at creating associations that facilitate recall. In the availability heuristic, items or events that are easier to recall are more common. Under the availability heuristic, investors tend to heavily weigh their judgments toward more recent information about a stock's prospects, and investment decisions are made irrationally toward that latest news. The attention of the internet revolution is an empirical example of an availability heuristic that might lead to the market boom of the late 1990s (Hirshleifer, 2001).

Kudryavtsev (2018) investigates the effect of the availability heuristic on subsequent stock returns. The empirical findings document that when there is a major positive (negative) change in stock price, its magnitude would be enlarged by the availability of positive (negative) investment outcomes. The availability heuristic would cause price overreaction to the initial company-specific shock, leading to a subsequent price reversal.

Representative heuristic

The representative heuristic (Tversky & Kahneman, 1974) involves estimating the likelihood of an event in the face of uncertainty, which depends on the degree to which the evidence is perceived to be similar to or typical of the state of the world. People's perceptions of how "representative" a piece of evidence is of a state of the world may be inaccurately related to its conditional probability. People, for example, tend to rely too heavily on small samples and too little on large samples, inadequately discount for the regression phenomenon and selection bias in the generation or reporting of evidence (Hirshleifer, 2001). Under the representative heuristic, people usually make biased judgments because something more representative does not make it more likely. Companies with very low P/E ratios, for example, are thought to be temporarily "undervalued" because investors become overly pessimistic after a string of bad earnings reports or other bad news. The price will adjust if future earnings prove better than the overly pessimistic forecasts. Similarly, equity in companies with high P/E ratios is thought to be temporarily "overvalued" before falling in price (De Bondt & Thaler, 1985).

Lam *et al.* (2010) employ a pseudo-Bayesian approach to accounts for investors' behavioral biases on the weight assignments of the dividends (Thompson & Wong, 1991, 1996; Wong & Chan, 2004). Their model can explain various financial anomalies, such as short-run underreaction, long-run overreaction, magnitude effect, and excess volatility. Lam *et al.* (2012) add more properties to the pseudo-Bayesian model and explain the relationship between investors' behavioral biases and market anomalies. Guo *et al.* (2017b) extend the model further and develop some properties to explain excess volatility, short-term underreaction, long-term overreaction, and their magnitude effects during financial crises and subsequent recovery, by assuming that the earnings shock follows an exponential family distribution and the earnings shock of an asset follows a random walk model with and without drift. In a questionnaire survey, Wong *et al.* (2018) research Hong Kong small investors' conservative and representative heuristics who use momentum or contrarian trading strategies to see whether the theory holds empirically. The study indicates some evidence of representative heuristics.

Overconfidence

Overconfidence is a behavioral bias in which an individual's subjective confidence in his judgments is reliably larger than the factual accuracy of those judgments, especially when confidence is relatively high. Overconfidence implies over-optimism about the individual's ability to succeed in his endeavors. Whether investors who are overconfident and misjudge asset returns have long been wondered can still survive in a competitive asset market. Kyle & Wang (1997) have demonstrated that overconfidence could strictly outperform rationality because an overconfident trader can generate more expected profit and utility than his rational opponents and more than if he was also rational. In a standard Cournot duopoly model, overconfidence functions as a commitment device. As a result, the Nash equilibrium of a two-mutual fund game is a Prisoner's Dilemma in which both mutual funds hire overconfident managers. Overconfidence can thus persist and thrive in the long run. Daniel *et al.* (1998) propose a theory based on investor overconfidence and changes in confidence due to biased self-attribution of investment outcomes. According to the theory, investors will overreact to private information signals while underreacting to public information signals. Gervais & Odean (2001) develop a multi-period market model describing the process by which investors learn about their ability and how a bias in this learning can create overconfident investors. An investor assesses his ability from the number of past successes and failures. When the investor takes too much credit for his successes, it leads him to be overconfident. Overconfidence cannot make the investors wealthier, but the process of accumulating wealth can make investors overconfident. Overconfidence is caused by investors' success so that the overconfident investors can survive in the market.

Also, Odean (1998) discovers that market agents are overconfident, including price-taking traders, strategic-trading insiders and risk-averse market-makers. Overconfidence increases expected trading volume and market depth and it also decreases overconfident traders' expected utility. Benos (1998) investigates an extreme form of posterior overconfidence where some risk-neutral investors overestimate the precision of their private information. The participation of overconfident traders in the market leads to higher transaction volume, larger depth, more volatility, and more information prices. For example, Odean (1999) notes that the annual turnover rate of shares on the New York Stock exchange is greater than 75 percent, and the daily trading volume of foreign-exchange transactions in all currencies (including forwards, swaps, and spot transactions) is equal to about one-quarter of the total annual world trade and investment flow. Odean (1999) presents data on individual trading behavior, which suggests that extremely high volume may be driven, in part, by overconfidence on the part of investors. Excessive trading behavior may reduce the net returns in the market (Barber & Odean, 2000). In the theoretical framework of Gervais and Odean (2001), overconfident investors are predicted to trade excessively, resulting in large trading volume and market volatility. Likewise, Statman *et al.* (2006) empirically confirm the proposition that investors are overconfident about their valuation, and trading skills can explain high observed trading volume. On the other hand, the researches undertaken by Hirshleifer (2001) and Barber & Odean (2001) show that men are more likely to be overconfident than women.

The empirical study of Li & Hung (2013) on a sample of Taiwan-listed companies indicates that overconfident managers are more likely to take part in earnings management behaviors, and there are negative moderating effects of family control on the relationship between managerial overconfidence and earnings management, which arise from family CEOs. Jlassi *et al.* (2014) investigate the effect of overconfidence behavior on volatility in international financial markets. The study documents the evidence of overconfidence which is more significant in the developed markets than in the emerging ones. Overconfidence is found in both up and down markets, except in some Asian and Latin American markets. Overconfidence is also the main factor leading to the global financial crisis, and it still exists even during the recession period. Moreover, the theoretical and empirical investigation of overconfidence in real estate markets is extensively studied by Bao & Li (2016), which document many cases of overconfidence. Ho *et al.'s* (2016) study indicate that banks with overconfident CEOs are more likely to increase banking lending and leverage than other banks before the financial crisis. During crisis years, the business performance of these banks is generally more disastrous, leading to a higher likelihood of CEO turnover or failure than other banks. The empirical test of He *et al.* (2019) shows that internal financing can fund business opportunities and alleviate capital shortages for the listed companies in China but may also cause excessive investment, especially in companies with managerial overconfidence. This overinvestment problem related to managerial overconfidence is more serious in state-owned than non-state enterprises. From the findings of Tang *et al.* (2020), young and male CEOs usually enhance the impact of CEO overconfidence on a firm's value after mergers and acquisitions in China.

Anchoring and adjustment

The anchoring effect is a cognitive bias whereby a particular reference point or anchor influences an individual's decisions. In many situations, once an anchor is set, people will adjust away from it to get to their final solution. However, they adjust insufficiently, and the final guess becomes closer to the anchor than otherwise. In other words, different anchors yield different estimates, which are biased toward the anchors. We call this phenomenon anchoring-and-adjusting (Tversky & Kahneman, 1974), under which investors initially have in their minds some reference points or anchors such as previous stock prices, and then they adjust this past their reference points but insufficiently due to underreaction to new information acquired. Anchoring describes how individuals tend to focus on recent behavior and give less weight to longer-time trends. Einhorn & Hogarth (1986) have developed a model of assessing uncertainty in ambiguous situations. The basic idea is that people use an anchoring–and–adjusting strategy in which an initial probability is used as the anchor (or reference point), and adjustments are made for ambiguity. The anchor probability can come from various sources; it may be a probability that is impressive in memory, the best guess of experts, or a probability that is otherwise available. Psychologists have documented that when people make quantitative estimates, they may be heavily influenced by previous values of the item. For example, a used car salesman always starts negotiating with a high price and then works down. The salesman is trying to get the consumer anchored on the high price so that when he offers a lower price, the consumer will estimate that the lower price represents good value. Furthermore, anchoring can cause investors to underreact to new information (Fuller, 1998). Values in speculative markets, like stock markets, are inherently ambiguous. It is hard to tell the value of, for example, the Hang Seng Index in Hong Kong. There is no agreed-upon economic theory that would provide an answer to this question. In the absence of any better information, the anchor is usually the most recently remembered prices which are likely to be important determinants of prices today. The empirical study of Lieder *et al.* (2018) suggests that the anchoring bias results from people's rational use of their finite time and limited cognitive resources, rather than human irrationality. Furnham & Boo (2011) provide a detailed discussion of the anchoring effect.

Ambiguity aversion

Ambiguity aversion (or uncertainty aversion) refers to a preference for known risks over unknown risks. An ambiguity-averse individual would prefer a choice where the probability distribution is known rather than one with an ambiguous probability distribution. In financial markets, investors are usually uncertain about the probability distribution of an asset's return. The ambiguity-averse investor holds a range of possible probability distributions in mind and maximizes the minimum expected utility under any possible distribution. The investor has a reference probability distribution in mind but wants to ensure that his decisions are good ones even if the reference model is misspecified to some extent. Also, if the investor is concerned that his model of stock returns is misspecified, he will charge a substantially higher equity premium as compensation for the perceived ambiguity in the probability distribution (Barberis & Thaler, 2003). Guidolin & Rinaldi (2013) review theoretical treatments of portfolio choice, equilibrium asset prices, portfolio diversification and volatility of asset returns under ambiguity aversion.

The empirical study of Dimmock *et al.* (2016) discloses the negative correlation between investors' ambiguity aversion and stock market participation, the proportion of portfolio allocation to stocks, and foreign stock ownership. However, the correlation between ambiguity aversion and own-company stock ownership is positive. Ambiguity aversion is also related to portfolio under-diversification, and the ambiguity-averse investors are more likely to sell stocks during the financial crisis. Bianchi & Tallon (2019) indicate that ambiguity-averse investors bear excessive risk due to under-diversification, exhibit a home bias with higher exposure to the domestic relative to the international stock market, and also undertake portfolio rebalancing more actively and a contrarian strategy relative to past market trends in order to keep their risk exposure relatively steady over time. From the study of Dlugosch & Wang (2020), an increase in domestic ambiguity is associated with a fall in foreign bias that is greater for countries with more ambiguity aversion than countries with lower ambiguity aversion.

Ostrich effect

The ostrich effect (or the ostrich problem), a cognitive bias, refers to the investors' behaviors to avoid negative financial information, which brings psychological discomfort (Galai & Sade, 2006). Karlsson *et al.* (2009) present a model linking information collection to investor psychology. The model predicts that investors collect additional information conditional on favorable news and avoid information following bad news. It is found that Scandinavian and American investors monitor their portfolios more frequently in bullish markets than when markets are flat or bearish in support of the evidence of the ostrich effect. Bernard *et al.* (2020) show that managers of retail dispensaries are susceptible to the ostrich effect when they are more likely to acquire store and product performance information. The ostrich effect will diminish if managers can more easily attribute the performance to external factors.

Herd effect

Herd behavior in social psychology refers to the behavior of individuals in a group acting collectively without centralized direction but could also be caused by correlated prevailing information in independently acting individuals.

Hence, people will do what others are doing rather than optimal given their information. As a result, behavior patterns are correlated across individuals. For example, the concept of financial herd migration introduced by Patel *et al.* (1991) indicates that, like migrating birds and trekking wildebeest, which know that traveling in groups offers protection, financial players may migrate in herds such as when institutions increase their debt-equity ratio or their holdings of high-risk securities. However, the transition is slow because financial migration decision-makers must weigh the benefits of moving quickly toward the optimal situation against the cost of moving away from the herd.

On the other hand, herding describes a situation in which investors abandon their beliefs but adopt "moving with the market" or "following the general market trend" to earn excess returns. As a direct consequence, herd behavior leads to the development of trading strategies in financial markets, such as the momentum investment strategy, to outperform the market (Bikhchandani & Sharma, 2001). Alternatively, contrarian investors deliberately invest or speculate counter to the "herd" to earn an excess return.

Yao *et al.* (2014) test the herding behavior in the Chinese stock markets. The results indicate that investors exhibit different levels of herding behavior, and herding in the Chinese B-share markets is strong. Also, herding is more noticeable under bearish market conditions. Lee (2017) studies the herd behavior of the stock markets by proposing a new herding detection measure based on cross-sectional excess co-movement of returns. Except during the US subprime crisis period, the results indicate strong evidence of herding during negative price movements bur with weak or no evidence of herding during periods of positive price movements. Ajaz & Kumar (2018) examine the existence of herd behavior in crypto-currency markets. Herding under up and down market is found, indicating over-enthusiasm and over-reaction. Also, herding depends on market activity rather than market volatility. Kudryavtsev (2019) investigates the effect of herd behavior on S&P 500 index returns. The study assumes that herding would lead to an overreaction of stock prices and subsequent price reversals. As a result, daily stock market returns are expected to be higher (lower) following negative (positive) market returns. The empirical evidence supports the herding effect on the stock market index returns by employing two herding measures. Cakan *et al.* (2019) test herding behavior in the South African housing market. A two-regime Markov switching model provides evidence of herding during the high volatility regime, indicating that herd behavior is driven by increased market uncertainty. The findings also suggest that policy uncertainty is associated with the presence of herding. Batmunkh *et al.* (2020) use a cross-sectional absolute deviation model to examine the presence of herd behavior in the Mongolian stock market. They find herd behavior in the full sample data, bull and bear market periods, and markets' high and low volatility states. They also find herd behavior in four important events: the establishment of the Finance Regulatory Committee of Mongolia, the Global Financial Crises, Mongolia's inclusion in the FTSE Russell Watch list and the economic boom in 2011. Liu *et al.* (2021) provide evidence of a herd effect in Chinese cross-border mergers and acquisitions activities. The political environment also generates a positive herd effect, but exchange rate volatility, degree of openness and cultural distances lead to negative herd effects. Finally, Choijil *et al.* (2022) analyze academic research on herd behavior in financial markets conducted over 30 years and show empirical evidence of herd behavior, especially following the subprime crisis. They conclude that there is no consensus regarding the causes of this phenomenon, but new perspectives have emerged from expanding research on herd behavior.

Conclusion

Unlike the standard finance paradigm, behavioral finance does not uphold the traditional assumption that individuals are fully rational but recognizes that their cognitive bias may limit rationality. Hence, behavioral finance models integrate ideas from cognitive psychology into economic and financial models and investigate how behavioral bias would affect the decisions made by not fully rational market agents in the financial markets (Thaler, 2015). As a result, the behavioral finance models can better explain and predict the phenomena of financial markets compared with the traditional finance in the literature. Daniel Kahneman, a pioneer in behavioral economics and finance; Eugene Fama, a strong proponent of EMH; Robert Shiller and Richard Thaler, important figures in the development of behavioral finance, were awarded the Nobel Prize in Economic Sciences. Their continual arguments for and against the existence of market efficiency and behavioral bias in the financial markets provide academics with a vast array of excellent reading materials for study. Shiller (2003) comments that financial economics had evolved a long way from the days when market efficiency was a pillar of finance to when behavioral finance is increasing its height of dominance in literature. Readers may refer to Alghaith *et al.* (2021) and Tiwari *et al.* (2021) for more theoretical descriptions and applications of behavioral finance.

In this review paper, we swiftly familiarize readers with the introductory concepts of behavioral finance and their salient readings, which lay the solid foundation of behavioral finance theory. These theories are the centerpiece of modern financial economics useful to academics for developing cutting-edge treatments of financial theory that EMH and behavioral finance underpin and for undertaking empirical studies on the behavioral bias in the financial markets. Furthermore, this review paper may be useful to investors for their investment strategies and policymakers for reviewing their policies for the development of financial markets.

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3 The behaviour of small investors in the Hong Kong Stock Market

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Introduntion

In the new millennium, the financial markets have become increasingly volatile. Even in some advanced economies such as Hong Kong, the stock market has experienced wild fluctuations over the past decade. For example, beginning in January 2006, the stock prices of companies traded on the Stock Exchange of Hong Kong surged, followed by an abrupt downturn starting in October 2007. The Hang Seng index rose by 111.7% between January 2006 and October 2007. However, by October 2008, the index had lost more than one-third of its market value as compared to its peak in the previous year.

There are different types of investors who put their money in the stock market. One important type is the large group of small investors. Their investment behaviour is different from other groups such as fund managers and institutional investors. For these small investors, when the stock prices dropped, the cost of entering the stock market decreased, and they tended to increase their investment in stocks. Yet we know little about their investment strategies and how well they are handling their investment in the stock market. The primary objective of this study is to examine the factors, investing characteristics, and decision-making processes that affect local small investors. Informed by behavioural finance, which is a new approach to the study of financial markets, we develop several hypotheses regarding the changes in the opinions and investment behaviour of small investors during and immediately after the buoyant stock market. These hypotheses are then tested with the data collected from 1,199 respondents via a survey questionnaire. The present study attempts to contribute to the study of behavioural finance in the setting of an Asian financial centre (Hong Kong).

This paper is organised as follows: Section 2 provides the background of the study; Section 3 reviews the related literature; Section 4 states the research questions and hypotheses; Section 5 explains the methodology of the present study; Section 6 reports the research findings; and Section 7 provides the conclusion.

Study background

Given the growing connection between the economies of China and Hong Kong, the economic policies of the Chinese government have significant impacts on the Hong Kong economy. This in turn affects local stock prices. On 13 April 2006, the Chinese government announced the Qualified Domestic Institutional Investor (QDII) scheme, which allowed Chinese institutions and residents to invest in financial products overseas through Chinese commercial banks. Market investors were very excited about the scheme. Small investors in mainland China were particularly interested in investing in the Hong Kong stock market. Because of the expectation that more money would flow into the stock market, there was a drastic increase in the Hang Seng index following the announcement by the Chinese government. In effect, the scheme only allowed individual investors in China to invest indirectly in overseas stocks, mainly through listed financial institutions in Hong Kong. These financial institutions set up the QDII funds, and invited the Chinese investors to subscribe to these funds. However, all QDII funds launched to date are reporting losses, and the scheme appears to have lost its attraction for investors. Originally, the Chinese government also explored the possibility of the so-called "through train" program, which allows individual mainland Chinese residents to trade directly in Hong Kong stocks. However, on 3 November 2007, Premier Wen Jiabao stated the need to carefully assess the possible adverse effects of the "through train" program on the stability of Hong Kong's financial system. In addition, the sluggish overseas markets may be another possible reason for Beijing shelving the program indefinitely at that time. Because of this policy change, small investors lost confidence in the "through train" program and sold their stocks in the Hong Kong market, resulting in a significant decrease in the Hang Seng index.

The sub-prime mortgage crisis (2007-2010) was another event that caused a loss of confidence among small investors in the Hong Kong stock market. Once the crisis occurred in the United States in 2007, local investors began to lose confidence in the collateralised securities, and they attempted to leave the stock market as influenced by the liquidity issue. Although many central banks had injected large amounts of money into the financial market, they were unable to stop the spread of the financial crisis throughout the world. In September 2008, the global financial market began to get out of control. Many famous firms, such as investment banks (e.g., Lehman Brothers) and insurance companies (e.g., American International Group), went bankrupt or were taken over by the U.S. government. In Hong Kong, many small investors lost money through their investment in Lehman "mini bonds", which is a type of derivative called credit default swap. Under such conditions, local investors worried a great deal about the global financial crisis and its economic consequences. To avoid the financial risk, many investors sold their stocks in the Stock Exchange of Hong Kong. As a result, the stock prices dropped sharply after the outbreak of the crisis.

Against this backdrop, one may ask the following questions: Did small investors change their opinions and investment behaviour during and immediately after the buoyant stock market of January 2006 to October 2007 in Hong Kong? If so, how did their opinions and investment behaviour change? Is the new behavioural finance approach useful in explaining the change? We conducted the present study to address these questions.

Literature review

According to Sewell (2010), behavioural finance is the study of the influence of psychology on the behaviour of financial practitioners and the subsequent effect on markets. This emerging area is of interest because it helps explain why and how markets might be inefficient. Models of an individual's investment behaviour are developed that integrate insights from psychology with economics. These models also seek to understand and predict systematic financial market implications of the psychological decision-making processes, particularly in times of uncertainty. Below we outline some key concepts in this new area of research that are relevant to this study.

In their pioneering work, Kahneman & Tversky (1979) used cognitive psychology to explain various divergences of economic decision-making based on neo-classical economic theory. They laid out the original version of prospect theory, which can be viewed as an alternative to the theory of expected utility maximisation. Based on Prospect theory, people give less credence to outcomes that are probable versus outcomes that are certain. This tendency, called the "certainty effect", contributes to risk aversion when making choices involving sure gains and to risk seeking when making choices involving sure losses.

Framing, an important concept in behavioural finance, refers to the way a problem is posed for the decision-maker. In many contexts the decision-maker has flexibility in how to think about the problem. According to Shefrin (2003), individuals usually understand and respond to events (e.g., make an investment choice) by relying on the collection of anecdotes and stereotypes that make up their mental and emotional filters. One important feature of mental accounting is narrow framing, which is the tendency to treat individual gambles separately from other portions of wealth. In other words, when offered a gamble, people often evaluate it as if it is the only gamble they face in the world, rather than merging it with pre-existing bets to see if the new bet is a worthwhile addition (Barberis & Thaler, 2003).

Cognitive dissonance, another key concept borrowed from psychology, is the mental conflict that people experience when they are presented with evidence that their beliefs or assumptions are wrong. Thus, cognitive dissonance might be classified as a sort of pain of regret, or regret over mistaken beliefs (Shiller, 2001). It will affect an individual's subsequent decision-making.

Overconfidence implies over-optimism about the individual's ability to succeed in his or her endeavours. Benos (1998) studied an extreme form of posterior overconfidence, where some risk-neutral investors over-estimated the accuracy of their private information. The participation of overconfident traders in the market often led to higher transaction volumes and more volatility. As shown in the study by Barber & Odean (2000), overconfidence can explain high trading levels and the resulting poor performance of individual investors.

Anchoring refers to the decision-making process in which quantitative assessments are required and where these assessments may be influenced by suggestions. People have in their minds some reference points—known as anchors—such as previous stock prices. When they receive new information, they may adjust their reference points inadequately (i.e., under-react to the newly acquired information). Anchoring describes how individuals tend to focus on recent behaviour and give less weight to longer time trends (Tversky & Kahneman, 1974).

Herd behaviour means that small investors follow what the majority do in the market. Herding is closely linked to impact expectations, fickle changes without new information, bubbles, fads, or frenzies. However, herding requires a coordination mechanism. This mechanism could be a widespread rule to coordinate based on some signals in the market (e.g., price movement), or on an individual's ability to observe other decision-makers and the market trends (Salmon, 2001).

Research questions and hypotheses

The theories and concepts written on behavioural finance are relatively new. Whether or not they can be applied to a real-world setting is still an area of controversy. More theoretical development and empirical studies are needed. To explain the change in the behaviour of small investors during and immediately after the buoyant stock market in Hong Kong, we attempt to set several research questions based on prospect theory and the concepts discussed in the previous section.

The following five questions are to be addressed in the present study. After discussing these questions with some theoretical explanations, we propose the corresponding hypotheses to be tested with empirical data.

i. *Is there a relationship between the belief of small investors in their ability to predict the market trend and their opinion of whether the market was overvalued during the buoyant stock market?*

If small investors think that they can predict the market trend, they tend to be overconfident, which in turn affects their judgment about the market price. The first question can be turned into the following hypothesis:

H1: A significant relationship exists between the belief of small investors in their ability to predict the future market development and their belief about whether the market was overvalued during the buoyant stock market.

ii. *Is there a relationship between the reasons given by small investors for making changes in their security holdings and the reason they believed was most important for the sharp* *correction in the market that* began at the end of October 2007?

When small investors have herd behaviour, they are likely to sell their stocks as a result of the sharp correction in the market. Herding affects the reason given by an investor to justify their decision to sell their stocks. Hence, we put forward the following hypothesis:

H2: A significant relationship exists between the reasons given by small investors for making changes in their security holdings today and the reason they believed was most important for the sharp correction in the market.

iii. Is there a relationship between the most important factor small investors gave for making changes in their security holdings during the buoyant stock market and the most important factor they gave for the overvaluation of the market during the buoyant stock market?

Small investors may have mental accounting during the buoyant stock market. They often believe that the probabilities of recent price increases in connection with the buoyant stock market are given too much weight. In addition, they think in terms of having a "safe" part of their portfolio that is protected from downside risk, and a "risky" part that is designed to increase their wealth. Based on the above reasoning, we propose the following hypothesis:

H3: A significant relationship exists between the most important factor small investors gave for making changes in their security holdings and the most important factor they gave for the overvaluation of the market during the buoyant stock market.

iv. Is there a relationship between the opinion of small investors on whether the market will recover if there is a similar economic downturn to the one that occurred after October 2007 and their opinion on the market value today?

Small investors often have some reference points or anchors. A small investor who considers the market to be undervalued today may think that it will recover in the next few years to levels that prevailed during the buoyant stock market. In other words, they are confident and optimistic about the future. We thus propose the following hypothesis:

H4: A significant relationship exists between the opinion of small investors on whether the market will recover if there is a similar economic downturn to the one that occurred after October 2007 and their opinion on the market value today.

v. Is there a relationship between how small investors value the information given in a situation when a decision has to be made and their belief in the probability that stock prices will continue to rise after three days of continuous increase?

According to prospect theory, small investors will hold on to losing positions in the hope that prices will eventually recover. The theory also predicts they will be risk-averse in gains. In other words, when small investors believe that the Hang Seng Index will increase in value the next day, they will sell their stocks in the buoyant stock market. Therefore, we develop the following hypothesis:

H5: A significant relationship exists between how small investors value the information given in a situation when a decision has to be made and their belief in the probability that the Hang Seng Index will continue to rise after three days of continuous increase.

Data and method

The data for the present study were collected from small investors in Hong Kong through a survey questionnaire. The main purpose of the survey is to collect their opinions, investment behaviour, and financial decision-making behaviour in the speculative stock market. The survey was conducted between October and November 2008. Since the majority of Hong Kong's population is Chinese, the questionnaire was written in Chinese. After a pilot test on ten respondents, some amendments (such as rewording of some questions to eliminate ambiguities) were made before we finalised the questionnaire.

We selected the respondents using non-probability sampling. A group of undergraduate students helped to distribute the questionnaires to the respondents. In the end, there were 1,199 selected respondents who completed and returned the survey.

The questionnaire was designed to elicit information about demographics, investment experience and behaviour, and factors affecting the financial decision-making of the respondents. We took an existing questionnaire developed by Johnsson, Lindblom & Platan (2002) in Lund University, Sweden, and modified it for this study. The first part of the questionnaire focused on the respondents' investment experience and perceptions about the investment conditions, and the factors that affect their financial decision-making. The second part collected respondents' personal information, including gender, age, employment status, and average monthly income.

The profile of the respondents is reported in Table 1[1]. Just under half (44.5%) of respondents were female and 55.4% were male. The majority of respondents were under the age of 50 (85.6%), and only 14.4% were aged 51 or above. Regarding their employment status, 64.9% of respondents were employees, 10.3% were self-employed, 6.7% were retired, and 18.2% were classified as "other", which includes housewives and students. Finally, the respondents' mean income was $14,564, while the median income was $12,034. In view of the above demographic profile of the respondents, we believe that they are representative of small investors in Hong Kong.

To test hypotheses 1-5, we compare an individual's responses to different items in the questionnaire. The relationship of these responses is indicated by Cramer's V and Chi-square (χ^2) test.

[1] Refer to Hon (2012) for Table 1.

Results

Table 2[2] shows the distribution of respondents' answers to various question items in the questionnaire. The items were designed to reflect some important concepts in behavioural finance. The response to one item is intended to be related to the response to another item, as stated in the hypotheses.

To test Hypothesis 1, we compare the responses to items 1 and 2, which indicate the relationship between overconfidence and cognitive dissonance. We expect a significant relationship between the belief of smaller investors in their ability to predict the market (i.e., overconfidence), and their opinion of whether the market was overvalued between January 2006 and the end of October 2007 (i.e., cognitive dissonance). As shown in Table 3[3], the Cramer's V value is 0.139, and the relationship is significant at the 0.01 level. Given this finding, Hypothesis 1 is supported.

Hypothesis 2 is tested by comparing the responses to items 3 and 4. It is a more wide-ranging query concerning the composition and characteristics of investments and is based on a theory of herd behaviour as a cause of both overvaluation and the decline of the market. A significant relationship is expected to exist between the reason given by small investors for making changes to their security holdings and the reason they believed was most important for the sharp correction in the market that began in October 2007. For example, if a small investor believed that the forecasts by analysts were important to the downturn, that investor would plausibly focus on analysts' forecasts today in order to be well-informed about important news stories that may affect his or her security holdings. The Cramer's V value for the two is 0.099, which is significant at the 0.05 level. Thus, Hypothesis 2 is also supported.

Hypothesis 3 is tested by comparing respondents' answers to items 5 and 6. Item 5 pertains to the most important factor small investors gave for making changes to their security holdings during the buoyant stock market. Mental accounting

[2] Refer to Hon (2012) for Table 2.
[3] Refer to Hon (2012) for Table 3.

theory is the concept behind this item. The comparison between the two items is an exploration of the linkage between the concepts of mental accounting and cognitive dissonance. Small investors tend to focus on recent behaviour and give less weight to longer time trends. The probabilities of recent price increases in connection with a buoyant stock market may be given too much weight, which can reinforce herd behaviour. We thus expect a significant relationship between the sources of information people actually used and the sources they believed to be the most important in the buoyant stock market. For example, the Internet was widely available and popular, and there were a number of Internet brokers and numerous websites providing financial information on companies. In addition, newspapers gave "hot stock tips" on a daily basis. Therefore, we predict that some of this widely available information would have affected people and their perceived reasons for the buoyant stock market. The Cramer's V value is 0.088, and the relationship is not significant at the 0.05 level. In contrast to the hypothesis, no relationship is found between responses to items 5 and 6. Thus, Hypothesis 3 is not supported.

Hypothesis 4 is tested by comparing the responses to items 7 and 8. The comparison was used to determine whether there was a relationship between confidence and optimism on one hand, and anchoring on the other hand. A small investor who considers the market to be undervalued today is likely to believe that the market will recover in a few years to levels that prevailed during the buoyant stock market. This belief is expected to be related to his or her opinion regarding the market value today. The Cramer's V value for the two is 0.102, which is significant at the 0.01 level. Thus, Hypothesis 4 is supported.

Hypothesis 5 is tested by comparing the responses to items 9 and 10. It specifies the relationship between how much small investors value the information they have in a situation when a decision has to be made and their belief that the stock price index will continue to rise after three days of continuous increases. The existence of such a relationship implies that Kahneman and Tversky's classic value function (i.e., prospect theory) is correct. The result reveals that the Cramer's V value is 0.214, and the relationship is significant at the 0.01 level. Given this finding, Hypothesis 5 is supported. It is worthy to note that no matter how many days the stock market has increased in value, the probability that it will go up or down in the next day is 50-50. For small investors, some patterns of stock prices are thought to exist even for data that are random in nature. Yet continuous price increases are almost impossible. This is consistent with the overconfidence hypothesis. Conservation can also help to explain why small investors give too much weight to the previous probabilities of events in a given situation, as they are reluctant to change their opinions.

Conclusion

The primary objective of this study was to identify some factors and decision-making processes that affect the investment behaviour of small investors in Hong Kong. Obviously, there was a change in their opinion and behaviour during and immediately after the buoyant stock market of January 2006 to October 2007. During the buoyant market, small investors were overconfident and bought more stocks. They also exhibited herd behaviour. However, once the sharp correction to the market occurred after October 2007, most of the small investors sold their stocks. According to the new approach of behavioural finance, small investors always have some reference points (or anchors) in mind, such as the stock purchase price. If a stock appreciates (e.g., during the buoyant stock market) and the small investors continue to use purchase price as a reference point, the stock price will be in the concave, risk-averse part of an investor's value function. The stock's expected return will then be used by small investors to justify its risk. However, if the small investors lower their expectation of the stock's return, they are likely to sell the stock. On the other hand, if the stock price falls (e.g., immediately after the buoyant stock market), it will be in the convex, risk-seeking part of an investor's value function. In such a situation, the small investors will continue to hold the stock, even if its expected return falls below the level that would have been necessary to justify its original purchase.

Based on prospect theory and some key concepts in behavioural finance, we developed five hypotheses and tested with a data set collected from 1,199 small investors in Hong Kong. The study produced several findings that are largely consistent with the predictions of behavioural finance. First, there is a significant relationship between the number of small investors who thought they could predict the market during the buoyant stock market period and whether the market was overvalued during that period. This finding implies that small investors tended to be overconfident and often bought the stock during the buoyant stock market.

Second, a significant relationship is found between the reason given by small investors for changing their current security holdings and the reason given for the sharp correction in the market. This finding suggests that herd behaviour occurred frequently among the small investors, and they tended to sell their stock during the sharp correction period.

Third, no significant relationship is found between the factor that small investors considered to be the most important in making changes to their security holdings during the buoyant stock market and the factor they felt was most important in causing the overvaluation of the market during that same time period. In other words, small investors had no mental accounting during the buoyant stock market. They often thought in terms of having a "safe" part of their portfolio that was protected from downside risk, and a "risky" part of their portfolio that was designed to increase wealth.

Fourth, we find a significant relationship between the opinion of small investors on whether the market would recover in the event of an economic downturn similar to the one that occurred after October 2007 and their opinion of the market value today. This finding suggests that small investors have some reference points (i.e., anchors) in mind when they make their investments in the stock market. For example, a small investor who believes the market is undervalued today may plausibly think that the market will recover in a few years to levels that prevailed during the buoyant stock market.

Finally, there is also a significant relationship between how small investors value information in a situation when they have to make a decision and their belief in the probability that the stock price index would continue to rise after three days of continuous increase. This finding provides empirical support for Kahneman and Tversky's classic value function (i.e., prospect theory). Small investors tend to hold on to a position of loss in the hope that the stock prices will eventually recover. Prospect theory also predicts that small investors will be risk-averse to gains, which means that they believe the stock price index will continue to increase in value, and hence they will sell their stock in a buoyant stock market.

Although the present study is exploratory in nature, some new results are obtained that are in line with the predictions of behavioural finance. The present study thus enhances our understanding of the investment behaviour of smaller investors in Hong Kong. Nevertheless, this study also has several limitations, particularly in its research design. First, we used a questionnaire survey to collect the data rather than using experimental design, which can better test a causal relationship. Second, the survey data were collected via non-random sampling rather than random sampling. Third, we focused on the relationships between responses to different question items, and provided a simple test of these relationships. It would be better to develop a sophisticated model and test the relationships in the model with advanced statistics. In conclusion, more empirical research is needed on the investment behaviour of small investors. As well, more studies should be conducted in other Asian countries in the future.

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4 The dilemma of investment decision for small investors in the Hong Kong Stock Market

By
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Introduction

The financial markets have become increasingly volatile after 2000 Dot.com bubble. Even in some advanced economies such as Hong Kong, the stock market has experienced wild fluctuation over the past decade. There are different types of investors who put their money in the stock market. One important type is the large group of small investors. Their investment decision is different from other groups such as fund managers and institutional investors. Financial advisers have traditionally underserved small investors in the money management arena. With the ever increasing ranks of small investors in the participation of stock market, they ignore this tremendous client base at their own peril (Malhotra, 2010). Small investors want equal access to information and equal consideration. The objective of this study is to examine the key factors (determinants) and the dilemma of investment decision that affect local small investors. For some small investors, they are easy to make investment decision, but for other small investors, they are easy to make no investment decision. The dilemma of investment decision is a problem offering two possibilities neither easy make investment decision nor easy make no investment decision. It means that a problem offers two possibilities neither of which is practically acceptable. The literature in behavioral finance suggests that this is a new approach to study stock market, we create ranking orders of four determinants that are common for all investment decisions and for all small investors. Some determinants should play some role in the investment decision of the small investors. But how big or small this role should be, and how to measure the level of the investment decision? This paper addresses the determinants of possible ways to measure the level of investment decision.

The snowball method was adopted to select target small investors aged 18 or above in Hong Kong. Our students had different channels to contact with their friends; the first respondent referred a friend. The friend also referred a friend, etc. Students were also through their families' networks to contact with their family members' friends and colleagues. This sampling technique is often used in hidden populations which are difficult for us to access; snowball sampling uses a small pool of initial informants to nominate, through our students' networks, other participants who meet the eligibility criteria and could potentially contribute to this study. The term "snowball sampling" reflects an analogy to a snowball increasing in size as it rolls downhill (Morgan, 2008).

The survey's observation period covers the Chinese government "through train" program and sub-prime mortgage crisis of 2006-2008. The personal survey was conducted between October and November 2008.We conducted the survey from three classes of finance courses in Hong Kong Shue Yan University. There were about 40 students in each class. We distributed 1,200 questionnaires to our students. There were 1,199 selected respondents who completed and returned the questionnaires and this represents a response rate of 99.92 per cent. We took an existing questionnaire developed by Johnsson *et al.* (2002) in Lund University, Sweden, and modified it for this study. Details of the survey and of the results are reported in two papers (Hon, 2012 & 2011).

This paper is organized as follows. Section 2 reviews the related literatures. Section 3 explains the method and data. Section 4 reports the results, and the last section contains the conclusion.

Literature review

Cohen & Kudryavtsev (2012) found that respect to decisions about stocks, irrationality cannot be established. Investment in stocks was influenced by expectations, past experience in the capital market, and knowledge about the past performance of selected market indices. Wang *et al.* (2011) conducted a survey on risk perceptions of investment products in the German-speaking area of Switzerland. They found that knowledge-related scales were highly correlated with risk-related scales, whereas the correlation between perceived risk and historical risk measures was much lower. Williams' (2007) paper develops a general model of investor choice to analyze socially responsible investment (SRI). They show that SRI may be driven more by investor attitudes toward the social aims of firms rather than by financial return. Noting that overconfidence can be partitioned into certainty and knowledge, Bhandari & Deaves (2006) find that highly-educated males who are nearing retirement, who have received investment advice, and who have experience investing for themselves, tend to have a higher certainty level. For some groups knowledge matched certainty. Because highly educated males do not have higher levels of knowledge they conclude that they are more subjective to overconfidence.

Caginalp *et al.* (2000) paper attempts to model the behavior of asset prices in experimental settings by proposing a "momentum model" of asset price changes. The momentum model predicts that higher levels of liquidity lead to larger price bubbles, a results that is confirmed in the experiments.

Method and data

Factor analysis is employed to identify the key factors (determinants) that affect the investment decisions of small investors on stock market in Hong Kong. Most scholars will agree that the pure investment decision and no investment decision are absolutely opposite to each other in terms of key factors. Let create ranking order of determinants that are common for all investment decisions: reaction to announcements, personal background, monitor investment and reference group. But why they are so different? Rotated principal component loadings, scree test, Kaiser-Meyer-Olkinand Bartlett's test, reliability test are used to examine possible differences in the perceived importance of the key factors. This ranking is different for every small investor. As a result, each small investor has used some key factors from the literature as potential determinants of the investment decision. We can say even more; in the case of pure investment decision and no investment decision these rankings are exactly opposite as we will show here. The dilemma for investment decision is popular for small investors. So, for some small investors, they are easy to make investment decision, but for other small investors, they are easy to make no investment decision. Can these differences be measured? Let try to do that using the idea of ranking correlation developed by the British mathematician Kendall (1955) to measure these differences as differences between determinants ranking orders. In order to compare two ordered sets (on the same set of objects); the approach of Kendall is to count the number of different pairs between the two ordered sets. The number that gives a distance between these sets is called the "symmetric difference distance" (the symmetric difference is a set operation which associates with two sets of elements that belong to only one set).

$$\tau = 1 - \frac{2 \text{ x } [d_{\Delta}(\mathscr{P}1, \mathscr{P}2)]}{N\,(N-1)}$$

The symmetric difference distance between two sets of ordered pairs $\mathscr{P}_1$ and $\mathscr{P}_2$ is denoted $d_\Delta(\mathscr{P}_1, \mathscr{P}_2)$.

N is number of ranked elements (i.e. determinants), in our case N = 4. With N = 4 elements we assume arbitrarily that first order is equal to 1234. Therefore, with two rank orders provided on N determinants, there are N! (i.e. N! = 4! = 4 x 3 x 2 x 1 = 24) different possible outcomes (each corresponding to a given possible order) to consider for computing the sampling distribution of Kendall coefficient can have values between -1 and +1: $-1 \leq \tau \leq +1$ where -1 is the largest possible distance (equal to -1, obtained when one order is the exact reverse of the other order) and +1 is the smallest one (equal to +1, obtained when both orders are identical).The Kendall coefficient τ can be interpreted as the difference between the probability to have determinants in the same order and the probability that they are in the different order:

$$\tau = P\ (\text{same}) - P\ (\text{different}).$$

Let use the Kendal coefficient between two ordered sets for selected three small investors: B, F and X.

Results

Demographics are often used to profile conventional investors for marketing financial products. A number of characteristics appear to be common, for example, share ownership tends to be higher among men than women, and tends to increase with age, income, and educational attainment (ASX, 2005; ICI, 2005). The profile of the respondents is reported in table 1[1]. The majority of the respondents were under the age of 50 (85.6%), and only 14.4% were aged 51 or above. The median income was $11,660.

Table 2[2] shows the combined cross tabulation results of item 3 and item 5 which states that 34.1% of the respondents under the age of 50 think that they monitor their investments with a short-term horizon more often today compared with

[1] Refer to Hon (2014) for Table 1.
[2] Refer to Hon (2014) for Table 2.

the period before the market decline at the end of October 2007; whereas 36.4% of the respondents aged 51 or above think that they monitor their investments with a short-term horizon more often today compared with the period before the market decline at the end of October 2007. Compare with those respondents under the age of 50, it is observed that a slightly higher percentage (+2.3%) of the respondents aged 51 or above think that they monitor their investments with short-term investment horizon more often today.

Table 3[3] shows the combined cross tabulation results of item 4 and item 5 which states that 31.3% of the respondents under the age of 50 think that they monitor their investments with a long-term horizon more often today compared with the period before the market decline at the end of October 2007; whereas 36.0% of the respondents aged 51 or above think that they monitor their investments with a long-term horizon more often today compared with the period before the market decline at the end of October 2007. Compare with those respondents under the age of 50, it is observed that a slightly higher percentage (+ 4.7%) of the respondents aged 51 or above think that they monitor their investments with a long–term investment horizon more often today.

The importance of the influence of various items on the behaviour of small investors when they invested in stock market is presented in table 4[4]. All the items are statistically significant with high mean values.

The correlation analysis is employed to obtain a correlation matrix based on ten items for each dimension, which is then used as an input of the factor analysis (see table 5[5]).

The unidimensionality is the extent to which the items are strongly associated with each other, and represent a single factor, which is a necessary condition for Bartlett test of Sphericity ($\rho < 0.000$) and the Kaiser-Meyer-Olkin (KMO). KMO measure of sampling adequacy index (with a value of

[3] Refer to Hon (2014) for Table 3.
[4] Refer to Hon (2014) for Table 4.
[5] Refer to Hon (2014) for Table 5.

0.546) confirmed the appropriateness of the data for exploratory factor analysis.

The communality measures the percent of variance in a given variable explained by all the factors jointly and may be interpreted as the reliability of the indicator. Hence, the higher the communality, the more the common factors can explain the variance of the standardized variable. As shown in table 6[6], Factor 1, 2, 3, 4 and 5 had communality above 0.7 (0.813, 0.811, 0.716, 0.704 and 0.720 respectively). The eigenvalue for a given factor measures the variance in all the variables which is accounted for by that factor. The ratio of eigenvalues is the ratio of explanatory importance of the factors with respect to the variables. If a factor has a low eigenvalue, then it is contributing little to the explanation of variances in the variables and may be ignored as redundant with more important factors. Eigenvalues measure the amount of variation in the total sample accounted for by each factor. Factors 1, 2, 3, 4 and 5 had eigenvalues above 1.000 (1.877, 1.545, 1.268, 1.052 and 1.013 respectively). The five factors, collectively, accounted for a satisfactory 67.547% of the variance. The following scree plot graphically displays the eigenvalues for each factor and suggests that there are five factors. Figure 1[7] demonstrates that a five-factor solution was obtained.

Complex variables may have loadings on more than one factor, and they make interpretation of the output difficult. Rotation may therefore be necessary. Varimax rotation is most frequently chosen. Ordinarily, rotation reduces the number of complex variables and improves interpretation (see table 7[8]).

The cumulative factors revealed that the first factor accounts for 18.768% of the variance. The second factor accounts for 34.219% of the variance. The third factor accounts for 46.897% of the variance. The fourth factor accounts for 57.417% of the variance. Finally, the fifth factor accounts for 67.547% of the variance. There were no negative

[6] Refer to Hon (2014) for Table 6.
[7] Refer to Hon (2014) for Figure 1.
[8] Refer to Hon (2014) for Table 7.

loadings of any consequence on factor I, factor II, factor III, factor IV or factor V after the rotation. We found five factors affecting the behaviour of small investors in the Hong Kong stock market, as follows: factor A might be interpreted as reference group which comprises commentators' recommendations from newspapers/TV/magazines, relatives/ friends, the Internet, investment consultants, and companies' annual reports; factor B as monitor investments which comprises themonitor short-term and long-term investments; factor C as personal background which comprises age, personal income; factor D as reaction to announcements which comprises announcements and other information from companies, forecasting the future market development and factor E as cognitive style which comprises factor for bear market and reason for investment failure.

A final step would be to determine Cronbach's alpha coefficient of internal consistency to ensure that the items comprising the factors produce a reliable scale. The reliability test is reported in table 8[9]. This was undertaken to further reduce the number of factors. The internal reliability of the first structure was tested and the decision results provide evidence as to the weakness of the structure since two factors (factor A and B) exceeded the adopted criteria. The cut-off value adopted was 0.5 and the acceptable level of item-to-total correlation was set above 0.3 (Nunnally, 1978). It was found that factor A contains two items and relates to "reference group". Factor B is made up of two items and refers to "monitor investments". An examination of the factors comprising the attitudes to help-seeking scale indicates that factors C, D and E have the lowest corrected item-total correlations. If these three factors were removed from the scale, the alpha if item deleted column shows that overall reliability would increase slightly (see table 9[10]).

Based on these results, we deleted the weakest factor (factor E: cognitive style) in our analysis. So, we can derive the following ascending order of importance:

[9] Refer to Hon (2014) for Table 8.
[10] Refer to Hon (2014) for Table 9.

1. Reaction to announcements (Announcements)
2. Personal background (Background)
3. Monitor investments (Investments)
4. Reference group (Group)

Let create ranking orders of the four determinants that are common for all investment decision and respectively for all small investors. To get the determinants ranking orders for each small investor, we should follow ascending order of importance.

The determinants order the pure investment decision: [Announcements, Background, Investments, Group] with the following ranking: $\mathcal{R}_1$ = [1, 2, 3, 4,].

This ranking is different for every small investor. As an illustration, table 10[11] shows the entire N! = 4 x 3 x 2 x1= 24 possible rank orders for a set of N = 4 determinants along with its value of τ with the "canonical order" (i.e., 1234). As a result, each small investor has different level of investment decision. Let find the Kendall rank correlation coefficients for small investor using initially the pure investment decision ranking order as the standard, and later we will do the same using the no investment decision ranking order as the standard.

Choice of small investors: B, F, X

Small investor B: [Announcements, Background, Group, Investments]

with the ranking: $\mathcal{R}_2$ = [1, 2, 4, 3].

We are comparing two ordered sets. We should look at the number of different pairs between two sets which allow us to get to something which is called the "symmetric difference distance" between these two sets.

$$\tau = 1 - \frac{2 \times [d_{\Delta}(\mathcal{P}_1, \mathcal{P}_2)]}{N(N-1)}$$

The symmetric difference distance between two sets of ordered pairs $\mathcal{P}_1$ and

[11] Refer to Hon (2014) for Table 10.

$\mathscr{P}_2$ is denoted $d_\Delta(\mathscr{P}_1, \mathscr{P}_2)$. N is number of ranked determinants, in our case N = 4. Kendall coefficient of correlation is obtained by normalizing the symmetric difference such that it will take values between -1 and +1 with -1 corresponding to the largest possible distance (equal to -1, obtained when one order is the exact reverse of the other order) and +1 corresponding to the smallest possible distance (equal to +1, obtained when both orders are identical).

The Kendall coefficient of correlation of determinants ranking for the small investor B and the pure investment decision is 0.67:

$\mathscr{P}_1$ = {[1, 2], [1, 3], [1, 4], [2, 3], [2, 4], [3, 4]}.

$\mathscr{P}_2$ = {[1, 2], [1, 4], [1, 3], [2, 4], [2, 3], [4, 3]}.

The set of pairs which are in only one set of ordered pairs is {[3, 4], [4, 3]}. So, the value of $d_\Delta(\mathscr{P}_1, \mathscr{P}_2) = 2$. That means that the value of the Kendall rank correlation coefficient between two orders of investment decision is:

$$\tau = 1 - \frac{2 \times 2}{4 \times 3} = 0.67$$

Small investor F: [Announcements, Group, Investments, Background]

with the ranking: $\mathscr{P}_3$ = [1, 4, 3, 2].

$\mathscr{P}_1$ = {[1, 2], [1, 3], [1, 4], [2, 3], [2, 4], [3, 4]}.

$\mathscr{P}_3$ = {[1, 4], [1, 3], [1, 2], [4, 3], [4, 2], [3, 2]}.

The set of pairs which are in only one set of ordered pairs is {[2, 3], [3, 2], [2, 4], [4, 2], [3, 4], [4, 3]}. So, the value of $d_\Delta(\mathscr{P}_1, \mathscr{P}_3) = 6$. That means that the value of the Kendall rank correlation coefficient between two orders of determinants is:

$$\tau = 1 - \frac{2 \times 6}{4 \times 3} = 0$$

Small investor X: [Group, Investments, Background, Announcements]

with the ranking: $\mathscr{P}_4$ = [4, 3, 2, 1].

$\mathscr{P}_1$={[1, 2], [1, 3], [1, 4], [2, 3], [2, 4], [3, 4]}.

$\mathscr{P}_4$ ={[4, 3], [4, 2], [4, 1], [3, 2], [3, 1], [2, 1]}.

The set of pairs which are in only one set of ordered pairs is {[1, 2], [2, 1], [1, 3], [3, 1], [1, 4], [4, 1], [2, 3], [3, 2], [2, 4], [4, 2], [3, 4], [4, 3]}. So, the value of $d_\Delta(\mathscr{P}_1, \mathscr{P}_4) = 12$. That means that the value of the Kendall rank correlation coefficient between two orders of determinants is:

$$\tau = 1 - \frac{2 \times 12}{4 \times 3} = -1$$

Because the determinants ranking order of the no investment decision is extremely opposite to the determinants ranking order of the pure investment decision. The Kendall rank correlation coefficient between them is **τ = - 1.** Respectively for the above discussed small investors, the Kendall rank correlation coefficients with the no investment decision order would be: -0.67 for small investor B; +1 for small investor X, and 0 for small investor F.

We can conclude that small investor B is the closest to the pure investment decision setting priority and small investor X is the farthest from the pure investment decision among them. Small investor F is a classic case of dilemma for investment decisions.

Conclusion

Using factor analysis, we create four key factors (determinants) that capture the investment decision of small investors in the stock market in Hong Kong. Their investment decision has uniform views as to the ascending order of importance of reaction to announcements, personal background, monitor investments and reference group. To get the determinants ranking orders for small investor in the pure investment decision, we should follow ascending order of importance. This ranking is different for every small investor. As a result, each small investor has different levels of investment decision. We have reported evidence from three small investors (B, F, X) that the determinants ranking order of the no investment decision is extremely opposite to the determinants ranking order of the pure investment decision. The Kendall rank correlation coefficient between them is **τ= - 1.** Respectively for the above discussed small investors, the Kendall rank correlation coefficients with the no investment decision order would be: -0.67 for small investor B; +1 for small investor X and 0 for small investor F. We can conclude that small investor B is the closest to the pure investment decision setting priority and small investor X is the farthest from the pure investment decision among them. Small investor F is a classic case of dilemma for investment decision.

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5 Volatility between commodity and stock sectors: evidence in Hong Kong and the implication of hedging effectiveness

By
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Introduction

Investing in commodity in the past was difficult for some people as those markets were barely reachable, especially for retail investors. With technological and financial innovations, investors nowadays have more channels to access the commodity markets. They can indirectly invest in commodity through, for example, commodity mutual funds and commodity exchange-traded funds (ETFs). Some commodities such as gold and oil can also be traded through commodity futures contracts.

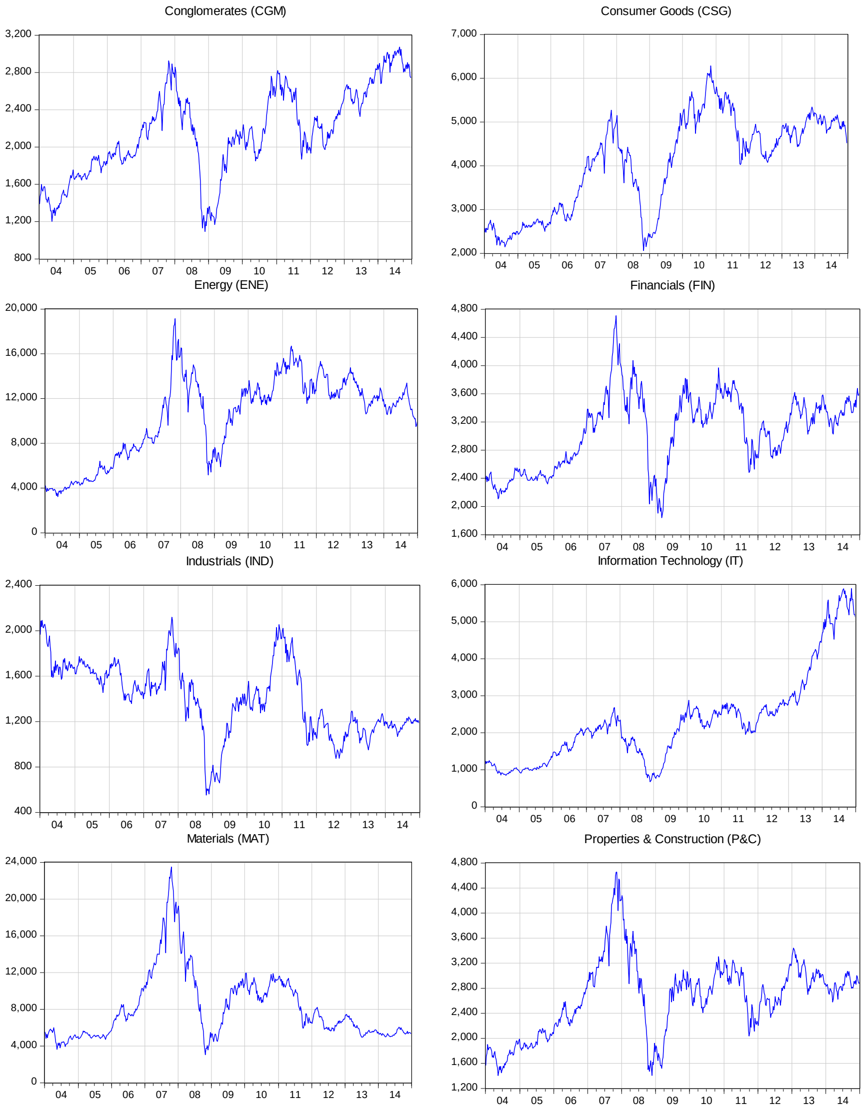
From the perspective of portfolio management, there is evidence that taking a position in commodity generates a substantial portfolio diversification effect regardless of the investors' investment style (Conover *et al.* 2010). There is a lack of research that attempts to assess the use of commodity in portfolio optimization in Hong Kong equity positions at the sectoral level, so this paper makes this attempt.

The Hang Seng Composite Industry Indexes were launched under the Hang Seng Composite Index (HSCI) in Hong Kong in 2001. There are a total of 11 Industry Indexes, computed by a free-float-adjusted market capitalization-weighted methodology with a 10% cap on individual stocks; this restricts huge, listed companies from dominating the indexes' movements. Figure 1 displays those indexes' movements in the last 10 years. Before 2007, most of the industry indexes were rising, except industrials. During the global financial crisis from 2007 till 2008, all indexes consistently experienced a negative shock, but to different degrees. After the crisis, they recovered, and fell again in 2011 due to the uncertainty produced by the European sovereign debt crisis. By the end of 2014, some of them had reclaimed the loss caused by the crises.

In this paper, we use the Thomson Reuters Core Commodity CRB Index Total Return (CRB) and the Thomson Reuters Equal Weight Continuous Commodity Index (CCI) as proxies for commodity prices, which mirror the price movements of commodity futures contracts. The CRB and CCI are tradable on the ICE Futures Exchange. Investors can readily take positions in the index as they are also replicated by some ETFs, for example, the Lyxor UCITS ETF Commodities Thomson Reuters/Core Commodity CRB TR, and the GreenHaven Continuous Commodity Index Fund. Figures 2 and 3 show the trends of the two indexes. They all underwent similar market shocks. Unlike the Hang Seng Composite Industry Indexes, after 2011, they declined most of the time. With different compositions of each commodity index, they demonstrate distinctive responses to market shocks.

We adopt the multivariate threshold GARCH modeling approach to extract the time-varying correlations between the global commodity market and the Hong Kong equity sectors. We are able to estimate the optimal hedge ratios and evaluate the hedging effectiveness ratios in various Hong Kong equity sectors. The results provide alternatives to diversify and manage stock portfolios.

The paper is organized as follows. Section 2 discusses the literature review and Section 3 describes the methodology. Sections 4 and 5 present the data and empirical results, respectively. The concluding remarks will be shown in the final section.



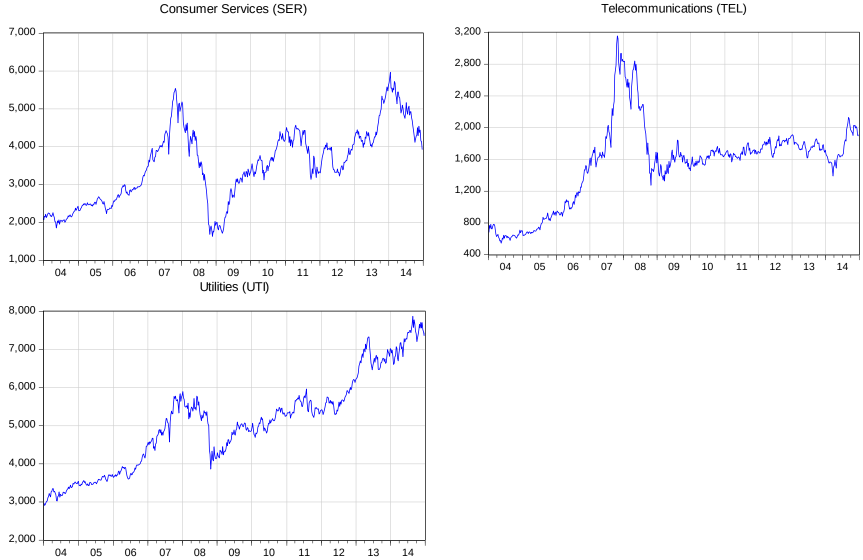


Figure 1. *Hang Seng Composite Industry Indexes*
Source: Hang Seng Bank

Figure 2. *Thomson Reuters Core Commodity CRB Index*
Source: Thomson Reuters/Core Commodity CRB

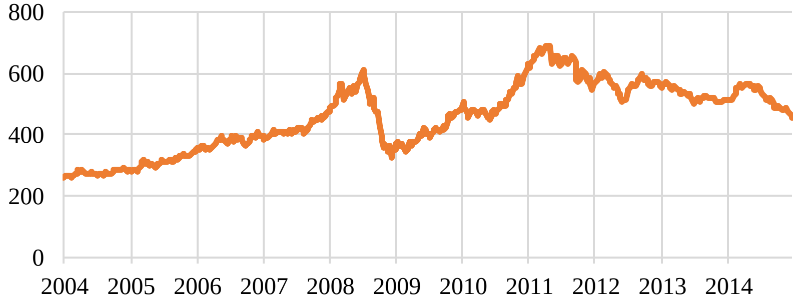


Figure 3. *Thomson Reuters Equal Weight Continuous Commodity Index*
Source: Thomson Reuters

Literature review

Since 2004, the correlation between the commodity market and the stock market has increased; evidence shows that the co-movements between these two markets became even higher after the financial crisis in 2008 (Steen & Gjolberg 2012). Steen & Gjolberg (2012) concluded that there was no strong evidence yet that the co-movement would be sustained.

Chevallier & Ielpo (2013) studied the cointegration between GSCI sub-indexes and the S&P 500 in the US. Their analysis suggested that different commodities markets exhibited unstable cointegrating relationships with the equity market in the US during the period from 1993 to 2011. This reinforces the idea of applying GARCH models in hedging strategy since the commodities' future prices are hard to predict, which, in turn, leads to time-varying conditional correlation and an optimal hedge ratio (Baillie & Myers 1991).

Many previous studies put a lot of effort into modeling the conditional variances and covariances so as to measure the hedging effectiveness. Kroner & Ng (1998) applied multivariate GARCH models to equities and estimated the risk-minimizing portfolio weights and hedge ratio. Arouri, Jouini, & Nguyen (2011) further used this technique on commodity-stock portfolios; they compared multivariate volatility models, namely VAR-GARCH, BEKK-GARCH, DCC-GARCH, and CCC-GARCH, in terms of optimal weights, hedge ratios, and hedging effectiveness. Their results indicate that VAR-GARCH models often perform better than the other three models in the case of the US. Similar methodologies are also applied to study the returns and volatility spillovers between oil price and the Gulf Cooperation Council (GCC) countries (Arouri *et al.* 2011) and between gold and the Indian stock market (Kumar, 2014).

Commodities, such as gold and oil, as hedging instruments has been an interesting topic in the field of investment. For instance, Baur and& Lucey (2010) found that gold is a hedge for stock in the US and the UK. Zheng (2014) also pointed out that there is a persistent negative relationship between investor sentiment and commodity futures return, implying the perceived hedge value involved in the commodity market.

Methodology

To capture the features of the financial data, a generalized autoregressive conditional heteroskedasticity (GARCH) approach is adopted in this paper as it allows modeling of the returns and the volatilities of commodity and equities simultaneously. The hedge ratios will then be computed. Finally, the hedging effectiveness will be assessed.

Threshold-GARCH Model

In order to enable the spillover effect between the commodity market and the equity market, multivariate GARCH is applied. Firstly, the mean equation is defined in the form of a vector autoregressive (VAR) model:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} + \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{1}$$

where y_{it} denotes the variables at time t; ε_{it} denotes the error term of the model; and c_i and c_{ij} represent the intercepts and coefficients, respectively. This VAR(1) model estimates the relations between the current return, the past return itself, and the cross-market past return.

A simple bivariate VECH model is specified as follows:

$$h_{ii,t} = w_1 + \alpha_{11}\varepsilon_{i,t-1}^2 + \alpha_{12}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \alpha_{13}\varepsilon_{j,t-1}^2 + \beta_{11}h_{ii,t-1} + \beta_{12}h_{ij,t-1} + \beta_{13}h_{jj,t-1} \tag{2}$$

$$h_{ij,t} = w_2 + \alpha_{21}\varepsilon_{i,t-1}^2 + \alpha_{22}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \alpha_{23}\varepsilon_{j,t-1}^2 + \beta_{21}h_{ii,t-1} + \beta_{22}h_{ij,t-1} + \beta_{23}h_{jj,t-1} \tag{3}$$

$$h_{jj,t} = w_3 + \alpha_{31}\varepsilon_{i,t-1}^2 + \alpha_{32}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \alpha_{33}\varepsilon_{i,t-1}^2 + \beta_{31}h_{ii,t-1} + \beta_{32}h_{ij,t-1} + \beta_{33}h_{jj,t-1} \tag{4}$$

where $h_{ij,t}$ denotes the conditional covariance of i and j at time t; w_k, α_{mn} and β_{mn} are parameters.

Restrictions on parameters are required to transform the VECH model into a diagonal form (Bollerslev, Engle & Wooldridge, 1988):

$$h_{ii,t} = w_1 + \alpha_{11}\varepsilon_{i,t-1}^2 + \beta_{11}h_{ii,t-1} \tag{5}$$

$$h_{ij,t} = w_2 + \alpha_{22}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta_{22}h_{ij,t-1} \tag{6}$$

$$h_{jj,t} = w_3 + \alpha_{33}\varepsilon_{j,t-1}^2 + \beta_{33}h_{jj,t-1} \tag{7}$$

In addition, an asymmetry in volatility is not uncommon in the financial market. Therefore, following Glosten, Jagannathan & Runkle (1993), a dummy variable is added into each equation as follows:

$$h_{ii,t} = w_1 + \alpha_{11}\varepsilon_{i,t-1}^2 + \beta_{11}h_{ii,t-1} + d_{11}I_i\varepsilon_{i,t-1}^2 \tag{8}$$

$$h_{ij,t} = w_2 + \alpha_{22}\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta_{22}h_{ij,t-1} + d_{22}\left(I_i\varepsilon_{i,t-1}\right)\left(I_j\varepsilon_{j,t-1}\right) \tag{9}$$

$$h_{jj,t} = w_3 + \alpha_{33}\varepsilon_{j,t-1}^2 + \beta_{33}h_{jj,t-1} + d_{33}I_j\varepsilon_{j,t-1}^2 \tag{10}$$

Putting each part in place, the diagonal representation of the threshold-GARCH (1,1) model is

$$\begin{bmatrix} h_{ii,t} \\ h_{ij,t} \\ h_{jj,t} \end{bmatrix} = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} + \begin{bmatrix} \alpha_{11} & 0 & 0 \\ 0 & \alpha_{22} & 0 \\ 0 & 0 & \alpha_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{i,t-1}^2 \\ \varepsilon_{i,t-1}\varepsilon_{j,t-1} \\ \varepsilon_{j,t-1}^2 \end{bmatrix} + \begin{bmatrix} \beta_{11} & 0 & 0 \\ 0 & \beta_{22} & 0 \\ 0 & 0 & \beta_{33} \end{bmatrix} \begin{bmatrix} h_{ii,t-1} \\ h_{ij,t-1} \\ h_{jj,t-1} \end{bmatrix} + \begin{bmatrix} d_{11} & 0 & 0 \\ 0 & d_{22} & 0 \\ 0 & 0 & d_{33} \end{bmatrix} \begin{bmatrix} I_i \varepsilon_{i,t-1}^2 \\ (I_i \varepsilon_{i,t-1})(I_j \varepsilon_{j,t-1}) \\ I_j \varepsilon_{j,t-1}^2 \end{bmatrix} \quad (11)$$

where matrix w is a 3×1 full rank matrix; α, β and d are diagonal 3×3 rank one matrices, and I_i and I_j are dummy variables, where

$$I_i = \begin{cases} 1, & \text{if } \varepsilon_i < 0 \\ 0, & \text{otherwise} \end{cases} \quad (12)$$

$$I_j = \begin{cases} 1, & \text{if } \varepsilon_j < 0 \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

Optimal hedge ratio and hedging effectiveness

It is suggested that investors can hedge the investment risk incurred in the equity market by investing in a commodity market with an optimal hedge ratio. Following Ballie & Myers (1991) and Kroner & Sultan (1993), the hedge ratio can be computed by

$$\delta_{i,t} = -\frac{h_{ij,t}}{h_{ii,t}} \quad (14)$$

For each dollar invested in asset j, an investor should invest $\delta_{i,t}$ dollars in asset i. When $\delta_{i,t}$ is negative, it implies the investor has to short sell in order to do the hedging.

In order to assess the hedging performance, Kroner & Sultan (1993), and Ku, Chen, & Chen (2007) define the hedging effectiveness index (HE) as

$$HE = \frac{h_{p,t}^{unhedged} - h_{p,t}^{hedged}}{h_{p,t}^{unhedged}} \tag{15}$$

where $h_{p,t}^{unhedged}$ denotes the variance of an unhedged portfolio, which consists only of asset j; i.e. the position in the equity sector in our study. Also, $h_{p,t}^{hedged}$ denotes the variance of a hedged portfolio, which is the stock-commodity portfolio based on the hedge ratio. A larger HE indicates a more effective hedging performance.

Data

The data used in this paper include the Thomson Reuters Core Commodity CRB Index Total Return (CRB), the Thomson Reuters Equal Weight Continuous Commodity Index (CCI), and the 11 Hong Kong Hang Seng Composite sector indexes. Those 11 Hang Seng Composite sub-indexes include energy (ENE), materials (MAT), industrial goods (IND), consumer goods (CSG), services (SER), tele-communications (TEL), utilities (UTI), financials (FIN), property and construction (PC), information technology (IT), and conglomerates (CGM).

The weekly data samples, from 2 January 2004 to 26 December 2014, are collected from *Datastream*, and total 574 observations. All the data are taken as the natural logarithm.

Emprical results

Before introducing the GARCH model, the Augmented Dickey-Fuller (ADF) unit root test is performed. The results reported in Table 1 show that all variables in the level under study are non-stationary and stationary in the first difference. Hence, the natural log-difference data, which are the continuous compounded return series, are used for empirical study.

Table 1. *Unit Root Test*

Variable in Level	ADF	Variable in the First Difference	ADF
CCI	-1.153	ΔCCI	-22.552***
CRB	-2.100	ΔCRB	-23.523***
CGM	-2.358	ΔCGM	-23.629***
CSG	-1.862	ΔCSG	-24.548***
ENE	-1.933	ΔENE	-23.564***
FIN	-2.612	ΔFIN	-23.904***
IND	-2.728	ΔIND	-23.974***
IT	-1.443	ΔIT	-25.731***
MAT	-1.860	ΔMAT	-20.926***
P&C	-2.468	ΔP&C	-24.573***
SER	-2.009	ΔSER	-23.885***
TEL	-1.802	ΔTEL	-23.287***
UTI	-2.824	ΔUTI	-25.237***

Notes: An intercept and a linear trend are included in the test equation. The number of lag length chosen in the test equation is based on Schwarz information criteria; *, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

After that, we estimate the mean equation and variance equation using the VAR (1) – TGARCH (1,1) model given in equations (1) and (11). The results in the mean equations are presented in Table 2, which includes the results of the GARCH model estimation for CRB and Hang Seng Composite Industry Indexes in Panel A, and for CCI and Hang Seng Composite Industry Indexes in Panel B.

Table 2. *Mean Equation Estimation for VAR (1)-TGARCH (1,1) Model*

	c_1	c_{11}	c_{12}	c_2	c_{21}	c_{22}
Panel A: Thomson Reuters Core Commodity CRB Index (CRB)						
CGM	0.0945	-0.0163	0.0484	0.2139**	0.1272**	-0.0132
CSG	0.1286	0.0029	0.0333	0.2461**	0.0841*	-0.0486
ENE	0.1230	0.0196	-0.0112	0.2562	0.1383*	-0.0904**
FIN	0.1101	0.0071	-0.0126	0.0935	0.0316	0.0028
IND	0.1086	0.0185	-0.0083	-0.0655	0.0649	-0.0329
IT	0.1131	0.0161	0.0009	0.4509***	0.1109	-0.0786*
MAT	0.1030	0.0141	0.0010	0.0965	0.1396*	0.0415
P&C	0.0896	0.0011	0.0296	0.1493	0.1028	-0.0169
SER	0.1021	-0.0070	0.0469	0.3347***	0.1331**	-0.0408
TEL	0.1346	0.0213	0.0069	0.1826	0.1186**	-0.0747*
UTI	0.1063	0.0080	0.0489	0.2312***	0.0310	-0.0273

Panel B: Thomson Reuters Equal Weight Continuous Commodity Index (CCI)						
CGM	0.1204	0.0051	0.0339	0.1904*	0.1265**	-0.0150
CSG	0.1319*	0.0188	0.0250	0.2436**	0.0996*	-0.0501
ENE	0.1211	0.0334	-0.0060	0.1996	0.1539*	-0.0871*
FIN	0.1204	0.0396	-0.0217	0.0857	0.0470	-0.0061
IND	0.1232*	0.0367	-0.0153	-0.0630	0.0686	-0.0384
IT	0.1235	0.0347	0.0007	0.4225***	0.1276	-0.0747*
MAT	0.1100	0.0262	0.0005	0.0658	0.1950**	0.0290
P&C	0.1018	0.0212	0.0198	0.1339	0.1170	-0.0235
SER	0.1240*	0.0072	0.0345	0.3098**	0.1578**	-0.0496
TEL	0.1433*	0.0482	-0.0063	0.1496	0.1175*	-0.0763*
UTI	0.1279*	0.0289	0.0159	0.2095***	0.0353	-0.0269

Notes:

c_1, c_{11} and c_{12} are the intercept, coefficient of lagged return of the CRB or CCI and slope coefficient of lagged return of the sub-index respectively, for the CRB or CCI equation.

c_2, c_{21} and c_{22} is the intercept, slope coefficient of lagged return of CRB or CCI and slope coefficient of the lagged return of the sub-index respectively, for the Hang Seng Industry sub-index equation.

*, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

From the results in Table 2, first, neither the lagged returns on commodity nor the lagged returns on equity sectors have a statistically significant effect on the current commodity returns. Second, uni-directional return spillover is found from the commodity market to some industry indexes, namely CGM, CSG, ENE, MAT, SER, and TEL, as shown by the significance of c_{21}. The positive coefficient, c_{21}, shows that if the return on commodity increased last week, those industry indexes would rise this week. Third, the autoregressive process exists for the ENE, IT, and TEL indexes, meaning that the current returns on those industry indexes are also determined by their past values. However, the negative coefficient, c_{22}, implies that positive returns on equity sectors last week were not good news for the equity performance this week. This could be the result of the investors' short-term speculation as the stock price is driven down when investors reap their profit.

Tables 3 and 4 present the results from the variance equations for CRB and CCI, respectively. In Table 3, the volatilities of CRB and CCI, indicated by $h_{ii,t}$, are determined by their own ARCH terms and GARCH terms (except for TEL, as α_{11} is insignificant). However, the asymmetric effect is absent in $h_{ii,t}$.

Furthermore, the volatility of the Hang Seng Composite Industry Indexes ($h_{jj,t}$) is positively related to its lagged volatility at a 99% significance level. For the ENE, MAT, TEL, and UTI indexes, the past innovations, represented by the ARCH term ($\varepsilon^2_{j,t-1}$), have a positive influence over the volatility of the corresponding industry indexes. Asymmetric effects are confirmed in the CGM, CSG, FIN, IND, IT, MAT, P&C, and SER indexes when the positive coefficients indicated by d_{33} suggest that negative lagged returns would increase the volatility of the corresponding industry indexes.

As for the covariance equation ($h_{ij,t}$), the ARCH effect and GARCH effect are significant in all industry sectors' equations. In addition, the overall asymmetric effect does not exist.

Table 3. *Variance Equation Estimation for VAR (1) – TGARCH (1,1) Model - Thomson Reuters Core Commodity CRB Index (CRB)*

	$h_{ii,t}$				$h_{ij,t}$				$h_{jj,t}$			
	w_1	α_{11}	β_{11}	d_{11}	w_2	α_{22}	β_{22}	d_{22}	w_3	α_{33}	β_{33}	d_{33}
CGM	0.1596*	0.0613**	0.8993***	0.0186	0.0239	0.0368*	0.9077***	0.0368	0.1768**	0.0221	0.9161***	0.0726**
CSG	0.1641*	0.0634**	0.9019***	0.0081	0.1597*	0.0685**	0.7738***	0.0375	1.4232***	0.0739	0.6639***	0.1736**
ENE	0.1486*	0.0530***	0.9182***	0.0009	0.2283***	0.0624***	0.8862***	-0.0056	0.9243***	0.0735***	0.8553***	0.0340
FIN	0.1284*	0.0490**	0.9151***	0.0202	-0.0005	0.0438**	0.9115***	0.0408*	0.1228*	0.0392*	0.9078***	0.0827**
IND	0.1528*	0.0621**	0.9058***	0.0135	-0.0142	0.0410**	0.9141***	0.0333	0.1516	0.0271	0.9226***	0.0819***
IT	0.1331*	0.0638***	0.9108***	0.0021	0.05888	0.0343*	0.9183***	0.0102	0.4472**	0.0185	0.9259***	0.0495**
MAT	0.1689*	0.0683***	0.8985***	0.0033	0.1239**	0.0538***	0.8858***	0.0178	0.6522***	0.0424*	0.8733***	0.0970***
P&C	0.1528*	0.0636***	0.8995***	0.0166	0.0301	0.0364*	0.9014***	0.0417	0.3167**	0.0208	0.9034***	0.1048***
SER	0.1548*	0.0617**	0.9016***	0.0178	0.0274	0.0422*	0.8996***	0.0384	0.3089***	0.0288	0.8976***	0.0829***
TEL	0.2007**	0.0402	0.9060***	0.0334	0.0589	0.0549***	0.9057***	-0.0079	0.2245*	0.0750***	0.9054***	0.0019
UTI	0.1261	0.0657***	0.9128***	0.0019	0.0337	0.0641***	0.8951***	-0.0080	0.1566**	0.0626*	0.8777***	0.0332

Notes:
$h_{ii,t}$ and $h_{ij,t}$ denote the variances of log-differenced CRB and the sub-index respectively at time t;
$h_{ij,t}$ denotes the covariance of log-differenced CRB and the sub-index at time t.
w_1, α_{11}, β_{11} and d_{11} are the intercept, slope coefficient of $\varepsilon^2_{i,t-1}$, slope coefficient of $h_{ii,t-1}$ and slope coefficient of $I_i\varepsilon^2_{i,t-1}$ respectively in the equation $h_{ii,t}$.
w_2, α_{22}, β_{22} and d_{22} are the intercept, slope coefficient of $\varepsilon_{i,t-1}\varepsilon_{j,t-1}$, slope coefficient of $h_{ij,t-1}$ and slope coefficient of $(I_i\varepsilon_{i,t-1})(I_j\varepsilon_{j,t-1})$ respectively in the equation $h_{ij,t}$.
w_3, α_{33}, β_{33} and d_{33} are the intercept, slope coefficient of $\varepsilon^2_{j,t-1}$, slope coefficient of $h_{jj,t-1}$ and slope coefficient of $I_j\varepsilon^2_{j,t-1}$ respectively in the equation $h_{jj,t}$.
*, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

Table 4. *Variance Equation Estimation for VAR(1)-TGARCH(1,1) Model - Thomson Reuters Equal Weight Continuous Commodity Index (CCI)*

	$h_{ii,t}$				$h_{ij,t}$				$h_{jj,t}$			
	w_1	α_{11}	β_{11}	d_{11}	w_2	α_{22}	β_{22}	d_{22}	w_3	α_{33}	β_{33}	d_{33}
CGM	0.1003**	0.0455**	0.9179***	0.0181	0.0070	0.0322*	0.9174***	0.0352	0.1856**	0.0228	0.9169***	0.0685**
CSG	0.1073*	0.0514**	0.9133***	0.0117	0.1741**	0.0582**	0.7564***	0.0474	1.6960***	0.0659	0.6264***	0.1915***
ENE	0.0944*	0.0466***	0.9267***	0.0007	0.1486**	0.0597***	0.8871***	0.0053	0.9349***	0.0766***	0.8493***	0.0392
FIN	0.0766*	0.0425**	0.9289***	0.0126	0.0021	0.0406**	0.9206***	0.0307	0.1182*	0.0387	0.9124***	0.0744**
IND	0.1079**	0.0529**	0.9146***	0.0123	-0.0035	0.0349*	0.9205***	0.0309	0.1698*	0.0230	0.9265***	0.0776***
IT	0.0767*	0.0544***	0.9229***	0.0039	0.0421	0.0219	0.9298***	0.0141	0.4019**	0.0088	0.9367***	0.0515***
MAT	0.1018*	0.0580***	0.9112***	0.0052	0.1051**	0.0482***	0.8886***	0.0229	0.7569***	0.0401*	0.8666***	0.1013***
P&C	0.0940*	0.0523***	0.9152***	0.0135	0.0221	0.0320*	0.9101***	0.0370	0.3281**	0.0196	0.9049***	0.1019***
SER	0.1005*	0.0511**	0.9150***	0.0148	0.0323	0.0407**	0.9000***	0.0356	0.3854***	0.0325	0.8853***	0.0859***
TEL	0.0999**	0.0326	0.9329***	0.0164	0.0226	0.0494***	0.9202***	0.0011	0.2224*	0.0748***	0.9076***	0.0000
UTI	0.0838*	0.0592***	0.9206***	0.0003	0.0300	0.0597***	0.8944***	-0.0035	0.1740**	0.0603*	0.8689***	0.0460

Notes:
$h_{ii,t}$ and $h_{jj,t}$ denote the variances of log-differenced CRB and the sub-index respectively at time t;
$h_{ij,t}$ denotes the covariance of log-differenced CRB and the sub-index at time t.
w_1, α_{11}, β_{11} and d_{11} are the intercept, slope coefficient of $\varepsilon_{i,t-1}^2$, slope coefficient of $h_{ii,t-1}$ and slope coefficient of $I_i\varepsilon_{i,t-1}^2$ respectively in the equation $h_{ii,t}$.
w_2, α_{22}, β_{22} and d_{22} are the intercept, slope coefficient of $\varepsilon_{i,t-1}\varepsilon_{j,t-1}$, slope coefficient of $h_{ij,t-1}$ and slope coefficient of $(I_i\varepsilon_{i,t-1})(I_j\varepsilon_{j,t-1})$ respectively in the equation $h_{ij,t}$.
w_3, α_{33}, β_{33} and d_{33} are the intercept, slope coefficient of $\varepsilon_{j,t-1}^2$, slope coefficient of $h_{jj,t-1}$ and slope coefficient of $I_j\varepsilon_{j,t-1}^2$ respectively in the equation $h_{jj,t}$.
*, ** and *** denote statistical significance at the 10%, 5% and 1% level respectively.

Table 5 shows the descriptive statistics for the estimates of the conditional correlation in the VAR-TGARCH model. During the sample period, MAT and ENE have a larger correlation with the CRB and CCI due to their nature of business. The figures for UTI and TEL are defensive investment choices in the equity market and less volatile in terms of conditional correlation with the commodity markets. The time-varying conditional correlations are exhibited in Appendix 3.

Table 5. *Descriptive Statistics for Conditional Correlation*

	Mean	Median	Maximum	Minimum	Std. Dev.
Panel A: Thomson Reuters Core Commodity CRB Index (CRB)					
CGM	0.2671	0.2427	0.7002	-0.1200	0.1714
CSG	0.2261	0.2193	0.6210	-0.1773	0.1306
ENE	0.4452	0.4683	0.6823	-0.3356	0.1350
FIN	0.2390	0.2255	0.7331	-0.2146	0.2048
IND	0.1774	0.1443	0.8241	-0.1670	0.1981
IT	0.2299	0.2254	0.6596	-0.0776	0.1120
MAT	0.3182	0.3080	0.6472	-0.0306	0.1277
P&C	0.2473	0.2136	0.6760	-0.0707	0.1587
SER	0.2568	0.2244	0.7455	-0.0853	0.1782
TEL	0.2004	0.2005	0.8102	-0.2000	0.1459
UTI	0.1618	0.1735	0.5125	-0.446	0.1588
Panel B: Thomson Reuters Equal Weight Continuous Commodity Index (CCI)					
CGM	0.2575	0.2147	0.6883	-0.1098	0.1712
CSG	0.2509	0.2402	0.6633	-0.1033	0.1158
ENE	0.4135	0.4152	0.7275	-0.2654	0.1411
FIN	0.2463	0.2185	0.6766	-0.1121	0.1779
IND	0.2012	0.1568	0.8173	-0.0894	0.1753
IT	0.2298	0.2138	0.6754	0.01260	0.0866
MAT	0.3461	0.3314	0.6618	-0.0108	0.1233
P&C	0.2539	0.2299	0.7336	-0.0685	0.1498
SER	0.2820	0.2519	0.7668	-0.0967	0.1618
TEL	0.2023	0.1818	0.8332	-0.1063	0.1483
UTI	0.1888	0.1904	0.5149	-0.2973	0.1373

The hedge ratio is the amount of short position an investor needs to take in a commodity for each dollar invested in a specific industry sector. Table 6 shows the estimation results of the optimal hedge ratio. The estimates of the hedge ratio range from -0.7935 to -0.1315 for the CRB case, while they range from -0.8794 to -0.1841 for the CCI case. Appendix 3 plots the time-varying optimal hedge ratios.

Table 6. Descriptive Statistics for Optimal Hedge Ratio

	Mean	Median	Maximum	Minimum	Std. Dev.
Panel A: Thomson Reuters Core Commodity CRB Index (CRB)					
CGM	-0.3403	-0.3025	0.0903	-0.9941	0.2335
CSG	-0.2875	-0.2580	0.1735	-1.3074	0.1999
ENE	-0.7935	-0.8018	0.8494	-1.8008	0.2953
FIN	-0.3261	-0.2757	0.2316	-1.3435	0.3030
IND	-0.3310	-0.2620	0.1649	-1.5423	0.3647
IT	-0.3952	-0.4044	0.1181	-0.9957	0.1899
MAT	-0.6163	-0.5476	0.0924	-1.7278	0.3148
P&C	-0.3984	-0.3483	0.1558	-1.3485	0.2841
SER	-0.3634	-0.3204	0.1778	-1.2203	0.2707
TEL	-0.3036	-0.2684	0.2550	-2.1759	0.3099
UTI	-0.1315	-0.1307	0.3887	-0.6086	0.1412
Panel B: Thomson Reuters Equal Weight Continuous Commodity Index (CCI)					
CGM	-0.3937	-0.3012	0.1056	-1.4487	0.2924
CSG	-0.3760	-0.3430	0.1772	-1.5019	0.2188
ENE	-0.8794	-0.8379	0.9454	-2.2339	0.3800
FIN	-0.3856	-0.3127	0.1961	-1.4039	0.3234
IND	-0.4297	-0.3323	0.1158	-1.6677	0.3932
IT	-0.4701	-0.4476	-0.0396	-1.4171	0.1866
MAT	-0.7961	-0.7268	0.0341	-2.1844	0.3671
P&C	-0.4864	-0.3975	0.1735	-2.0363	0.3409
SER	-0.4708	-0.4089	0.2040	-1.3561	0.2996
TEL	-0.3785	-0.2802	0.1945	-3.0671	0.4221
UTI	-0.1841	0.1789	0.2997	-0.9930	0.1513

Notes: The negative value of hedge ratio implies short selling is required in order to hedge the risk exposure to a particular sector in the equity market.

ENE and MAT have the largest absolute values of the means of the hedge ratio among the 11 sectors. For instance, an investor can choose to short \$0.7935 CRB or \$0.8794 CCI for each dollar invested in ENE. If the transaction cost is taken into account, the larger amount of the short position might imply a higher cost of hedging.

The mean hedge ratios of UTI in the CRB and CCI cases are the smallest in the absolute values. For \$1 invested in UTI, an investor can short either \$0.1315 or \$0.1841 to hedge the UTI portfolio. Its low standard deviation implies that investors might not need to adjust the hedge ratio frequently so as to achieve dynamic hedging. We can also observe the stable movement of hedge ratios after 2009, especially between 2010 and 2012, as exhibited in Appendix 3.

Table 7 shows the estimation results of hedging effectiveness. The hedging effectiveness ratios vary from about 4% to 29%. Among all of the Hang Seng Composite Industry Indexes, it is found that the commodity indexes work best at hedging ENE portfolios, as more than 26% risk can be eliminated in a hedged portfolio with CRB or CCI. CRB and CCI are ineffective in hedging TEL portfolios, with only about 5% of variance immunized. Comparing the HE using CRB with using CCI, it is unanimous that CCI is a more effective hedging instrument than CRB, regardless of industry sectors. Therefore, our results conclude that CCI is a better hedging instrument than CRB.

Table 7. *Hedging Effectiveness Ratio (%)*

	CRB	CCI
CGM	18.172	19.852
CSG	11.481	15.067
ENE	26.544	28.764
FIN	15.373	16.019
IND	11.168	13.088
IT	7.681	8.219
MAT	15.021	20.619
P&C	13.193	15.467
SER	14.529	17.517
TEL	4.828	5.572
UTI	6.673	7.838

Conclusion

This paper applies VAR (1)–TGARCH (1,1) to model the volatility spillovers between global commodity returns and stock sector returns on the Hong Kong Hang Seng Composite Industry Indexes. The purposes are to estimate the conditional covariances and the optimal hedge ratios, and to measure the effectiveness of using global commodity indexes to hedge against the volatility of the Hong Kong equity sector markets. As two different proxies for the performance of commodity markets, CRB and CCI have similar fluctuations in terms of the conditional correlations with the Hang Seng Composite Industry Indexes.

In general, the results show that the current volatilities of commodity indexes rely, positively, on their lagged values and innovations, while the current volatilities of the industry indexes are positively related to their previous variances. The covariances between the commodity market and the stock industry sectors can be explained by their past shocks and covariances. The asymmetric effect is only observed in the industry sector markets. The optimal hedge ratios, on the other hand, advocate that hedging ENE and MAT, which have higher conditional correlations with the commodity market, needs a larger amount of money sold short for the commodity contract. The hedging effectiveness ratios demonstrate that hedging by use of global commodity contracts is very effective in the ENE and MAT portfolios. Moreover, CCI performs better than CRB for hedging the equity sector portfolios in Hong Kong.

The study provides empirical support for the practical usage of commodity in a risk-hedging strategy in the Hong Kong equity market. It draws implications regarding the dynamic relationships between the global commodity market and the Hong Kong stock sector over the last ten years, which could be helpful for portfolio managers and investors in their portfolio diversification strategy.

Appendices

Appendix 1. *Compositions of Commodity Indexes (as of the beginning of 2015)*

Table A1. *Weights of Thomson Reuters Core Commodity CRB Index*

19 Commodities	Exchange	Weights (100%)	
Crude Oil	NYMEX	23.00%	Energy (39.00%)
Natural Gas	NYMEX	6.00%	
Heating Oil	NYMEX	5.00%	
RBOB Gasoline	NYMEX	5.00%	
Copper	COMEX	6.00%	Metals (20.00%)
Gold	COMEX	6.00%	
Aluminum	LME	6.00%	
Silver	COMEX	1.00%	
Nickel	LME	1.00%	
Cocoa	NYBOT	5.00%	Softs (21.00%)
Coffee	NYBOT	5.00%	
Cotton	NYBOT	5.00%	
Sugar	NYBOT	5.00%	
Orange Juice	NYBOT	1.00%	
Corn	CBOT	6.00%	Agriculture (20.00%)
Soybeans	CBOT	6.00%	
Live Cattle	CME	6.00%	
Wheat	CBOT	1.00%	
Lean Hogs	CME	1.00%	

Source: Thomson Reuters

Table A2. *Weights of Thomson Reuters Equal Weight Continuous Commodity Index*

17 Commodities	Exchange	Weights (100%)	
Crude Oil	NYMEX	5.88%	Energy (17.65%)
Natural Gas	NYMEX	5.88%	
Heating Oil	NYMEX	5.88%	
Copper	COMEX	5.88%	Metals (23.53%)
Gold	COMEX	5.88%	
Platinum	COMEX	5.88%	
Silver	COMEX	5.88%	
Cocoa	ICE	5.88%	Softs (23.53%)
Coffee	ICE	5.88%	
Cotton	ICE	5.88%	
Sugar	ICE	5.88%	
Corn	CBOT	5.88%	Agriculture (35.29%)
Soybeans	CBOT	5.88%	
Soy Oil	CBOT	5.88%	
Wheat	CBOT	5.88%	
Lean Hogs	CME	5.88%	
Live Cattle	CME	5.88%	

Source: Thomson Reuters

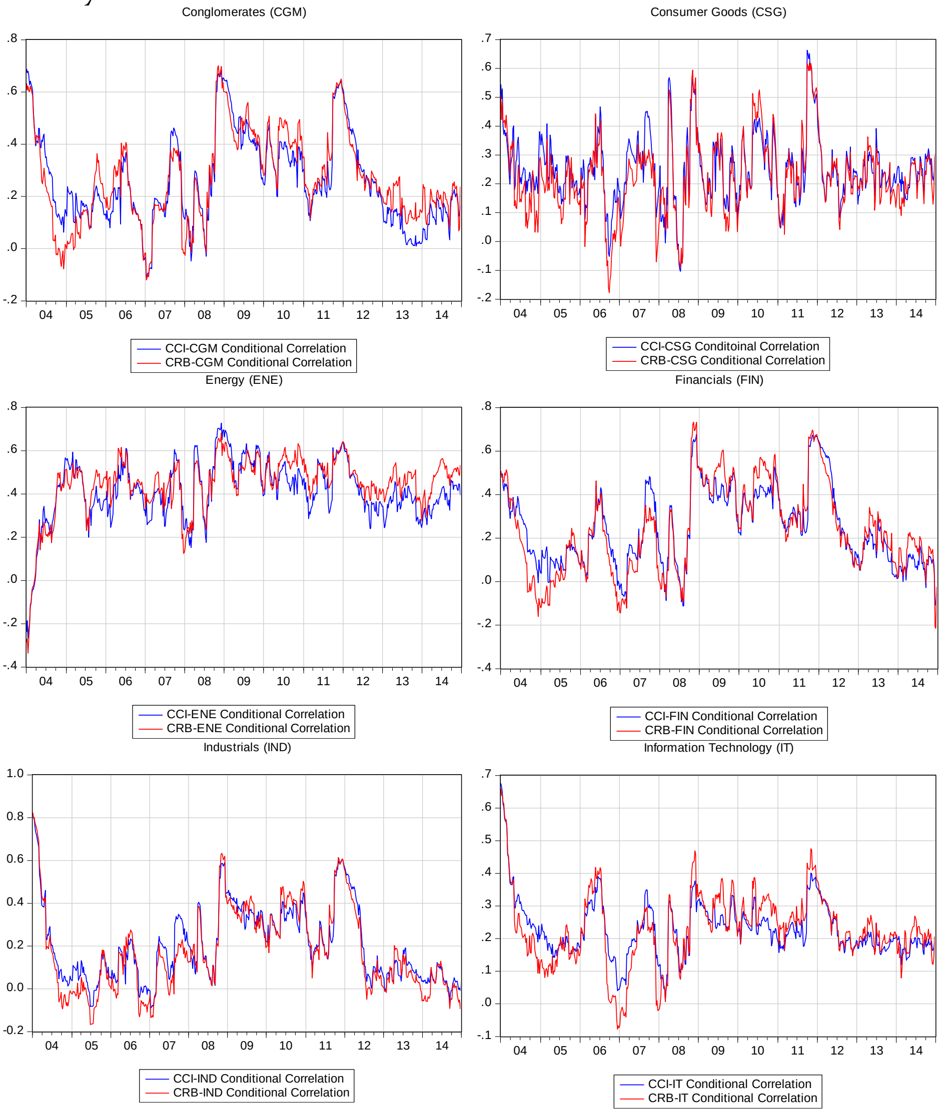
Appendix 2. *Descriptive Statistics for Conditional Covariance*

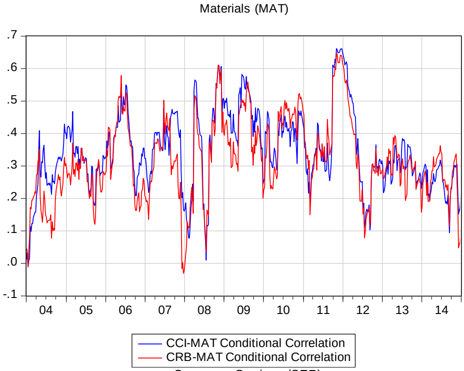
Table A3. *Descriptive Statistics for Conditional Covariance*

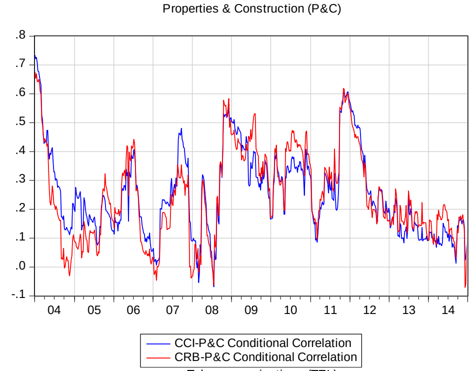
	Mean	Median	Maximum	Minimum	Std. Dev.
Panel A: Thomson Reuters Core Commodity CRB Index (CRB)					
CGM	2.7287	1.3600	30.4095	-0.5881	4.5646
CSG	1.8398	1.1739	24.6539	-1.2034	2.5342
ENE	5.1885	3.6780	40.5756	-6.7598	5.7725
FIN	2.7632	1.0564	35.7399	-1.1932	5.0034
IND	3.0838	1.2276	47.0428	-1.0547	6.0926
IT	2.6680	1.7554	21.2353	-0.6367	3.0089
MAT	4.3433	2.5121	43.3050	-0.3923	5.6465
P&C	3.0801	1.5745	32.4102	-0.9643	4.6713
SER	2.9145	1.3265	34.8635	-1.0966	4.8810
TEL	2.0806	1.2885	17.2990	-1.8137	2.8185
UTI	1.0181	0.6386	15.8191	-2.4858	2.0626
Panel B: Thomson Reuters Equal Weight Continuous Commodity Index (CCI)					
CGM	2.2353	1.0670	22.9270	-0.4394	3.5638
CSG	1.6499	1.0962	19.1916	-1.0087	2.0162
ENE	4.2654	2.7758	35.7704	-3.8572	5.1358
FIN	2.2375	1.0244	24.4134	-1.2135	3.5876
IND	2.6699	1.1605	34.6034	-0.5012	4.6284
IT	2.1493	1.5520	13.1598	0.1285	2.0175
MAT	3.9673	2.2383	35.1687	-0.1389	4.8539
P&C	2.5971	1.3558	23.9703	-1.0336	3.6397
SER	2.5339	1.2949	26.7563	-1.2001	3.7665
TEL	1.8798	1.0835	15.1850	-0.8024	2.4689
UTI	0.9391	0.5796	12.1691	-1.6069	1.5572

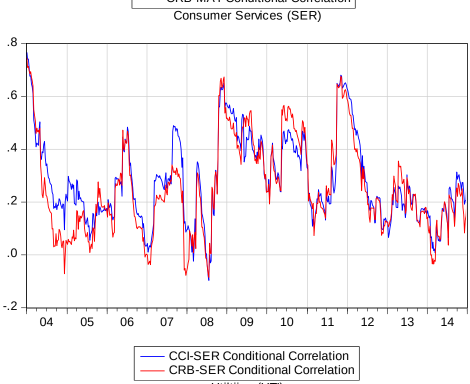
Appendix 3. *Time-varying Conditional Correlation and Hedge Ratios*

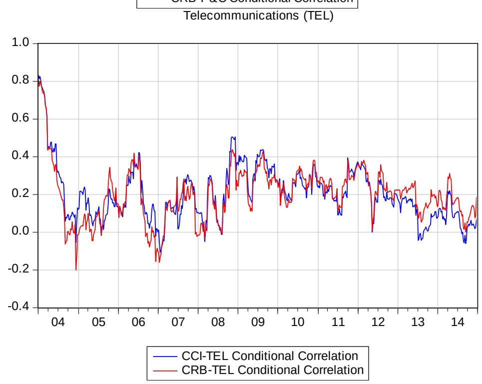
Figure A1. *Time-varying Conditional Correlation between Commodity Indexes and Industry Indexes*




Materials (MAT)
CCI-MAT Conditional Correlation
CRB-MAT Conditional Correlation


Properties & Construction (P&C)
CCI-P&C Conditional Correlation
CRB-P&C Conditional Correlation


Consumer Services (SER)
CCI-SER Conditional Correlation
CRB-SER Conditional Correlation


Telecommunications (TEL)
CCI-TEL Conditional Correlation
CRB-TEL Conditional Correlation

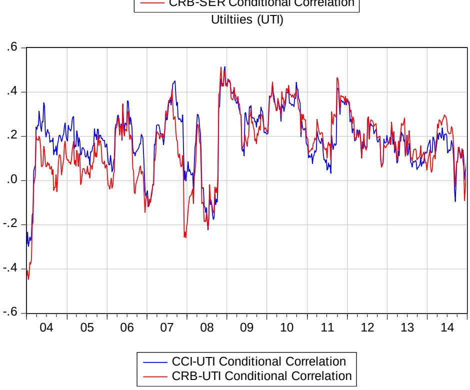
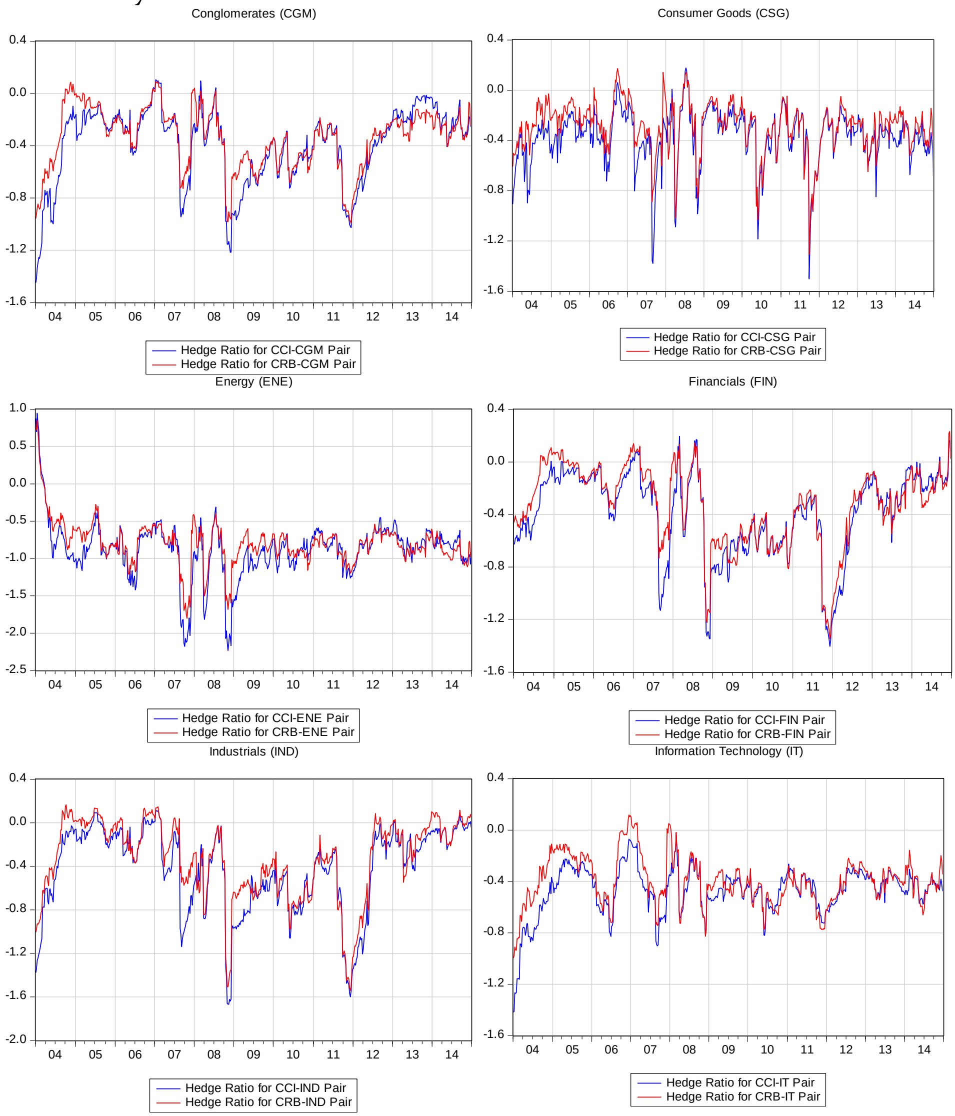
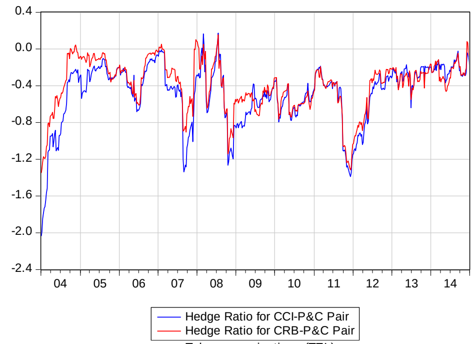

Utiltiies (UTI)
CCI-UTI Conditional Correlation
CRB-UTI Conditional Correlation

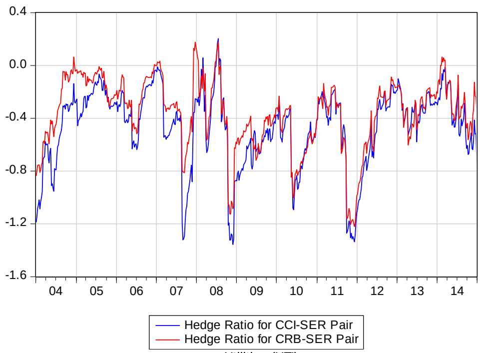
Figure A2. *Time-varying Optimal Hedge Ratios for Pairs of Commodity Indexes and Industry Indexes*



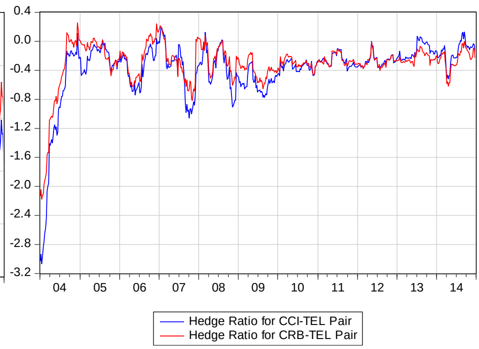
Properties & Construction (P&C)



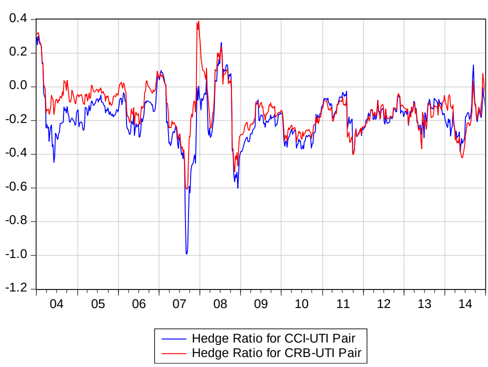
Consumer Services (SER)



Telecommunications (TEL)



Utilities (UTI)



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6 Study on the performance of initial public offerings in Hong Kong

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Introduction

The paper analyzes the long-run return of initial public offerings (IPOs) on the Stock Exchange of Hong Kong (SEHK). Since the 2000s, China has started to partially privatize some state-owned enterprises (McGuinness, 2006); Hong Kong has become the largest listing market for these enterprises (Chong, *et al.*, 2010; McGuinness, 2012). The funds raised by IPOs have dropped significantly since 2011, as the funds raised by H shares decreased to less than HKD100 billion, which was the lowest level since 2005. Many small-scale Chinese private firms were listed during 2010 and 2011 after the boom in the IPO market in Hong Kong in 2009, but it was repeatedly revealed by external auditors and research institutions that their financial statements were problematic or even fraudulent. In addition to a weak performance in H shares, the IPO market in Hong Kong has cooled down since 2011 because of a decrease in sources and weak confidence in IPOs; the gross proceeds and the number of issues fell to the lowest level since the subprime tsunami in 2008.

As studies on IPOs in Hong Kong after the financial tsunami in 2008 are still few, especially regarding the long-run performance of IPOs of the Growth Enterprise Market (GEM) and state-owned enterprises, this study is perhaps the first attempt to understand it. The study uses the research methods of Ritter (1991) and Allen *et al.* (1999) to analyze the long-run performance of IPOs. It uses a sample of 253 IPOs listed on the SEHK which are categorized by different themes, such as year, annual volume of listing, subscription ratio, industry, prestige of underwriters, state-owned enterprises, and the GEM. Cross-sectional and regression methods are used to examine the performance of IPOs and the results are consistent with theories such as the asymmetric information model (Rock, 1986), the fads hypothesis (Aggarwal & Rivoli, 1990), the existence of "hot issue markets" (1984), and ex-ante uncertainty (Beatty & Ritter, 1986). Moreover, underwriters are categorized by Megginson-Weiss (1991) ranking and the relationship of underwriter prestige with underpricing will be analyzed.

The paper is organized as follows. Section 2 reviews previous studies of the long-run performance of IPOs. The data are described in Section 3. The methodology is shown in Section 4. Section 5 reports and analyzes the results. The conclusion follows in the final section.

Literature review

Early studies of the long-run performance of the US IPOs documented the existence of short-run positive returns and long-run underperformance. Ibbotson (1975) found that the US IPOs listed during the 1960s had a positive performance in the first year, a negative performance in the next three years, and a generally positive performance in the fifth year. The phenomenon of IPO performance was explored by Aggarwal & Rivoli (1990), using 1598 IPOs during 1977-1987 and the NASDAQ index as the sample and benchmark, respectively. They found that investors who applied for an IPO during this period would receive an average first-day excess return of 10.67% and an average market-adjusted return of -13.73% at the 250-day post listing. Ritter (1991) used the 1526 IPOs that went public in the US during 1975-1984. Those IPOs had an average initial raw return of 14.32% but underperformed a group of matching firms by 29.13% after three years.

Similarly, Dawson (1987) found that in Hong Kong, the average market-adjusted initial return of 21 IPOs during 1978-1984 was 13.8%, but that those IPOs underperformed the market by 9.3% at the 12th month. Cheng *et al*. (2006) reported 19.06% initial returns and -58.19% three-year market returns using a buy-and-hold strategy for 386 IPOs during 1986-1998. For the GEM, Deng *et al*. (2010) studied 178 IPOs during 1999-2003 and found an average initial underpricing rate of 20.94%. This result is like that of Vong (2006), who discovered a mean underpricing level of 18.32% in 213 IPOs during 1999-2005. For Chinese state-owned enterprises, McGuinness (2012) studied 42 H-Share IPOs during 2005-2009 and found the average initial return to be 22.22%.

The underpricing of IPOs can be explained by the phenomenon of asymmetric information on the IPO market (Rock, 1986). Assume that the new shares are priced at their expected value. Then the informed investors would crowd out the others when good issues are offered, and they withdraw from the market when bad issues are offered. The offering firm must price the shares at a discount to attract the uninformed investors to purchase these new issues.

Aggarwal & Rivoli (1990) suggest that fads are likely to explain IPO initial underpricing and aftermarket underperformance because (i) fads are likely to occur when estimation of the true intrinsic value of the firm is difficult; (ii) risky securities are likely to be subject to high levels of noise trading; (iii) IPO investors appear to be more speculative; and (iv) the marginal investors in initial trading may be over-optimistic.

Ritter (1984) provides evidence of the existence of “hot issue markets”. In some periods, the average initial returns were extremely high because many firms with high risk listed during this time. After that, the volume of IPOs would increase to take “windows of opportunity”, and usually the high-volume periods were associated with a poor long-run performance (Ritter, 1991). Hence it is expected that there is a negative relationship between annual volume of IPOs and aftermarket returns.

Beatty & Ritter (1986) found that the degree of underpricing is positively related to the ex-ante uncertainty about the ex-post value of IPOs. Vong (2006) concluded that some proxies, such as the age of firms and the gross proceeds from the offerings, are used to determine the ex-ante uncertainty. However, it is expected that issues of the GEM or state-owned enterprises should have a higher initial return followed by a worse aftermarket underpricing.

Beatty & Ritter (1986) developed another proposition that focuses on the role of underwriters in enforcing an underpricing equilibrium. Underwriters who violate this underpricing equilibrium will lose either potential investors (if they don't underprice enough) or issuers (if they underprice too much), and thus their market share will be weakened. In the 1970s to 1980s, studies by Hayes (1971), Neuberger & Hammond (1974), Neuberger & LaChapelle (1983), Johnson & Miller (1988), and Carter & Manaster (1990) found that short-run excess returns are smaller when new offerings are taken by prestigious underwriters. While the above studies concentrate on the categorical definition of underwriters' reputation, the study by Megginson & Weiss (1991) considers another measure of reputation. According to them, an underwriter's prestige is captured by the number of underwritten offerings and their market shares. Although a modified measure of reputation is tested in their study, the same inverse relation between underwriter prestige and underpricing emerges. Carter *et al.* (1998) examined categorical as well as the continuous definitions of reputation and concluded that both measurements are inversely related to underpricing, with the former proxy performing better in explaining initial returns. Dimovski *et al.* (2011) suggest that more prestigious underwriters are associated with a higher level of underpricing in the Australian IPO market. For the Hong Kong IPO market, McGuinness (1992) however found that the impact of underwriter prestige on underpricing was minimal, supported by the results of Vong & Zhao (2008) as well as Lin & Hsu (2008).

Data

Our sample data are from 253 IPOs during 2008-2012 which are required to meet the following criteria: (1) the company is listed on the Main Board and Growth Enterprise Market (GEM) of the Hong Kong Stock Exchange (HKEx); (2) the offering is listed in the HKEx for the first time,[1] and funds are raised through Introduction and Offer for Subscription, Sale and Placing; and (3) equity securities such as common and preference stocks and REITs are included, but debt securities such as iBonds and RMB sovereign bonds, and derivatives securities such as warrants and callable bull/bear contracts are excludable.

Table 1. *Distribution of IPOs by year during 2008 to 2012*

Year	Total Number of IPOs	Number of IPOs in the Sample	Percentages included
2008	31	27	87.10
2009	69	65	94.20
2010	103	100	97.09
2011	90	61	67.78
2012	62	0	0.00
Total	355	253	71.27

Source: HKEx Fact Book

Table 1 presents the distribution of the IPOs by year, and it indicates that 71.27% of the IPOs are included in the analysis of the long-run (two-year) performance. Most of the data used in this research are obtained from the database of Yahoo! Finance. The offering dates and prices are obtained from the HKEx Fact Book during 2008-2012.

[1] Transformation from the GEM to the Main Board is not considered in the research. Only the IPOs which are listed in the HKEx for the first time are counted.

Methodology

The methodology we employed follows Allen *et al.* (1999) and Ritter (1991). This paper first calculates both initial returns and market-adjusted returns. Several cross-sectional and time-series analyses are then adopted to explore factors affecting IPO performance, and consequently regression analyses are attempted.

Returns analyses

Following Ritter (1991) and Allen *et al.* (1999), returns are measured from two intervals: (1) the initial return period (usually the first transaction day of IPOs), defined as the offering date to the close of the first trade date; and (2) the aftermarket period, defined as the two years after the IPO, exclusive of the initial return period. In order to settle the inconsistence problem of the aftermarket period, for IPOs not listed on the first transaction date each month, the time interval between the second transaction date and the last trading day of the listing month is defined as month 0 (Allen *et al.*, 1999). For example, the month 0 of an IPO which starts trading on 15 March 2010 will be the period from 16 March to the last transaction day of March, and the aftermarket period will begin from 16 March 2010 and be finished on 30 March 2012, which is the last transaction day of the 24th month of the IPO.

The initial return is defined as the percentage change of the IPO price from the subscription price and the closing price on the first transaction day. It could be written as:

$$IR_i = \frac{P_i - S_i}{S_i} \tag{1}$$

where P_i = closing price on the first transaction day of IPO_i and S_i = subscription price of IPOi.

Following Agarwal *et al.* (2008), the 1-month, 6-month, 12-month, and 24-month aftermarket returns with their average market-adjusted returns (ARs) are presented, but mainly the 24-month aftermarket return (also known as the two-year aftermarket return) will be used in the following analysis.

These returns are equally weighted returns and adopted from the price change from the bonus issue and stock split;[2] however, dividend reinvestment, right issues, and placement are not considered to impact IPO returns.

The market-adjusted returns (ar_t) could be derived from the following equation. For raw return, the formula is:

$$R_{it} = \frac{P_{i,L}}{P_i} - 1 \tag{2}$$

where R_{it} = return for IPOi during the aftermarket period, such as the first 24 transaction months; $P_{i,L}$ = closing price of IPOi on the last transaction day of the aftermarket period; and P_i = closing price of IPOi on the first trading day.

The corresponding market return can also be estimated from the equation (2), and the benchmark used is the Hang Seng Index (HSI). The market-adjusted return for IPOi during the aftermarket period is defined as:

$$ar_{it} = r_{it} - r_{mt} \tag{3}$$

where ar_{it} = market-adjusted return for IPOi in the aftermarket period; r_{it} = return for IPOi during the aftermarket period; and r_{mt} = market (HSI) return in the aftermarket period.

The average market-adjusted return (AR_t) on a portfolio of n IPOs during the aftermarket period is the arithmetic average of the market-adjusted returns (ar_{it}):

$$AR_t = \frac{1}{n}\sum_{i=1}^{n} ar_{it} \tag{4}$$

The t-statistics for the AR_t series are measured as:

[2] Current stock price will be adjusted by the following equation if a bonus issue and stock split are offered to shareholders. The adjusted price (before issue) will be compared with the subscription price for calculation of the returns. Price per share before issue = (price per share after issue x number of shares after issue) / number of shares before issue.

$$t(AR_t) = AR_t \cdot \frac{(n_t)^{1/2}}{sd_t} \quad (5)$$

where n_t = number of IPOs trading in the aftermarket period and sd_t = cross-sectional standard deviation in the aftermarket period.

Hypotheses

Eight hypotheses are obtained from the existing evidence about long-run IPO performance. The first hypothesis is concerned with the long-run performance of IPOs.

Hypothesis 1: H_o: IPOs do not significantly underperform the market in the long run.

The evidence for the possible explanations of the long-run performance of IPOs will be presented in hypotheses 2 to 8. The fads explanation suggests the following relationships. It suggests that the long-run performance of IPOs is negatively related to the initial underpricing, and that the long-run return of IPOs across annual volume of IPOs, industries, subscription ratio, underwriters, state-owned enterprises, and the GEM is negative. The null hypotheses to test the fads explanation are defined as follows:

Hypothesis 2: *H_o: The long-run return of IPOs is not a negative function of initial underpricing.*

Hypothesis 3: *H_o: The long-run return of IPOs is not a negative function of annual volume of listing.*

Hypothesis 4: *H_o: The long-run return of IPOs is not a function of industry category.*

Hypothesis 5: *H_o: The long-run return of IPOs is not a function of subscription ratio.*

Hypothesis 6: *H_o: The long-run return of IPOs is not a function of market shares of underwriters.*

Hypothesis 7: *H_o: The long-run return of IPOs is not a function of Chinese state-owned enterprises.*

Hypothesis 8: *H_o: The long-run return of IPOs is not a function of the GEM.*

Time-series and cross-sectional analyses

The paper uses several time-series and cross-sectional analyses. These enable the investigation of the hypotheses 2 to 8.

The initial return, two-year return, and two-year adjusted return of the IPOs in the sample are classified into different groups based on each factor. Then the average return for each factor is investigated to see whether there are systematic patterns across the returns and the factors employed as a classification basis.

Regression analyses

As each variable is not independent, multiple regressions will be undertaken to clarify the effect of each factor. The multiple regressions can be shown as:

$$2YRR_i = \beta_1 IR_i + \beta_2 RM_i + \beta_3 Volume_i + \beta_4 Ratio_i + \beta_5 SOE_i + \beta_6 GEM_i + \sum \beta_j CAT_j + \varepsilon_i \qquad (6)$$

$$2YRAR_i = \beta_1 IR_i + \beta_2 RM_i + \beta_3 Volume_i + \beta_4 Ratio_i + \beta_5 SOE_i + \beta_6 GEM_i + \sum \beta_j CAT_j + \varepsilon_i \qquad (7)$$

where 2YRRi is two-year raw return for IPOi; 2YRARi is two-year adjusted return for IPOi; IRi is initial return; RMi is market return; $Volume_i$ is volume of annual listing; $Ratio_i$ is subscription ratio; SOE_i is a dummy variable on state-owned enterprises; GEM_i is a dummy variable on IPOi listed in the GEM; and CAT_j is a dummy variables on industry j in which the IPOi is operated.

Results

Initial and aftermarket performance

Table 2 shows the results of statistical analysis of IPOs in Hong Kong during 2008-2012. The average initial return for 355 IPOs in total listed on the HKEx during 2008-2012 is 8.38%. The highest initial return is 156.52%, which belongs to Oriental City (Stock Code: 8325), a 28 August 2009 IPO listed on the GEM at $0.23 per share. From 2008 to 2009, the IPO underpricing rate increased from 7.92% of the average return and 3.23% of the median return in 2008 to 14.74% of the average return and 6.94% of the median return in 2009 as the economy recovered from the US subprime financial tsunami; however, the difference between initial returns was broader. During 2010-2012, the IPO initial returns dropped to below 1.5% of the median return because most listed companies are small-to-medium scale. Figure 1 shows the tendency that initial returns during 2008-2012 are normally distributed with right-tailed skewness. It reveals that 66.2% of IPOs had positive initial returns and 69.57% had initial returns between -10% and 20%. Only 4.79% of IPOs had first-day returns greater than 50%, while less than 2% of IPOs had initial returns below -20%.

Table 2. *Statistical Analysis of IPOs Underpricing Rate*

Year	IPO Underpricing rate					
	Number of Samples	Mean (%)	Median (%)	Standard Deviation (%)	Max. Value (%)	Min. Value (%)
2008	31	7.92	3.23	24.67	117.65	-19.23
2009	69	14.74	6.94	30.64	156.52	-61.09
2010	103	8.29	1.23	21.20	108.33	-29.82
2011	90	4.42	1.12	17.44	70.00	-39.19
2012	62	7.40	1.57	22.36	140.00	-27.00
Total	355	8.38	2.03	23.15	156.52	-61.09

Source: HKEx Fact Book

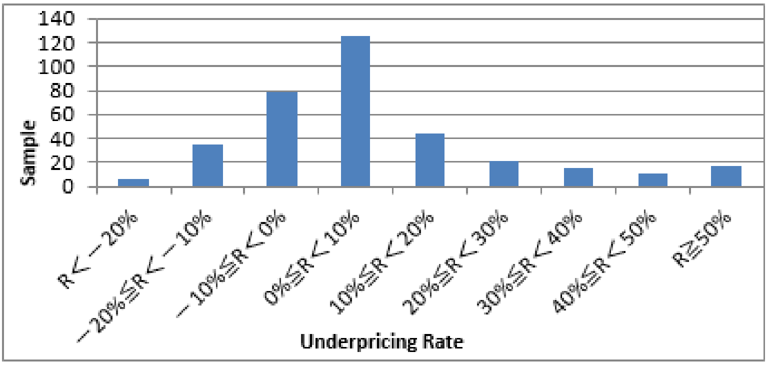

Figure 1. *Distribution of IPO underpricing rate*
Source: HKEx Fact Book

Table 3 presents the average market-adjusted return (AR) for initial return and 1-month, 6-month, 12-month, and 24-month post-listing returns for IPOs listed during 2008-2012. The average market-adjusted return rises to 8.47% after being adjusted by the market return using the Hang Seng Index (HSI) as the benchmark. Because some IPOs have not been listed for two years, the number of firms trading in our sample decreased from the first month and was eventually 253 in the 24th month (the second year).[3] Apart from the average market-adjusted returns (ARs) of the first trading day, all ARs are insignificant. The AR at the end of the first listing month is -1.73%. This result suggests that the initial underpricing of the IPOs is adjusted in the early aftermarket periods. Furthermore, the 24-month AR is -3.78%, and the arithmetic average raw return and median return for that period are -4.83% and -33.06%, respectively.

Table 3. *Abnormal return for IPOs listed during 2008 to 2012*

Month	Sample	AR (%)	t-stat
Initial Return	355	8.47	6.90
1	346	-1.73	-1.49
6	346	-0.45	-0.18
12	335	-1.18	-0.37
24	253	-3.78	-0.67

Source: HKEx Fact Book

From the above tables and figures, the initial and aftermarket returns for those IPOs listed during 2009-2011 are negatively related. It is not surprising in view of the disappointing returns that the financial statements of many private enterprises operated in Mainland China were subject to criticisms by external audit firms and research institutions, and this situation was called the "Storm of Private Enterprises".

Cross-sectional and time-series results

Aftermarket performance categorized by initial returns

[3] Some IPOs are excluded because of suspension or delisting.

In Table 4, the 253 IPOs with data available are categorized by initial returns. This permits an examination of the relationship between the initial return and the two-year aftermarket performance, which includes normal return and adjusted return. The IPOs are divided into five groups ordered from the lowest to the highest return. However, Table 4 does not show a clear relationship between the initial returns and aftermarket performances. To clarify the relationship, Table 5 shows a negative relationship between the initial returns and aftermarket performances after excluding outliers with extremely high long-run returns and combining ranges with negative initial returns.[4] The IPOs in the higher ranges of initial return have the worst two-year normal returns. The pattern is also evident in the two-year market-adjusted return if the last two-year market-adjusted return is not considered. Therefore, it may signify that the two-year aftermarket performances are negatively related to the initial returns. The reverse relationship is consistent with the overreaction hypothesis which is reported by Allen *et al.* (1999) and Ritter (1991). In conclusion, the hypothesis 2 that the long-run return of IPOs is not a negative function of initial underpricing is rejected.

Table 4. *Aftermarket Performance categorized by Initial Return*

Range of Initial Return (IR) (%)	2-Year Return (%)	2-Year Market Adjusted Return (%)
- 61.09 < IR < - 5.29	-11.78	-9.43
- 5.29 < IR < 0.00	-2.12	-2.51
0.00 < IR < 6.94	18.52	18.99
6.94 < IR < 21.45	-7.40	-8.34
21.45 < IR < 156.52	-21.36	-0.18
All (Mean)	-4.83	-3.78
All (Median)	-33.06	-23.81

Source: HKEx Fact Book

[4] Three outliers are Chanceton Financial (Code: 8020) and Forton (Code: 1152) from the second range and China Singyes Solar Technologies (Code: 750) from the third range.

Table 5. *Aftermarket performance categorized-4, by Initial Return (excluding Outliers and combining the ranges with negative returns)*

Range of Initial Return (IR) (%)	2-Year Return (%)	2-Year Market Adjusted Return (%)
- 61.09 < IR < 0.00	-7.00	-6.01
0.00 < IR < 6.94	-7.94	-6.60
6.94 < IR < 21.45	-14.90	-14.40
21.45 < IR < 156.52	-21.36	-0.18
All (Mean)	-4.83	-3.78
All (Median)	-33.06	-23.81
Mean (Excluding Outliers)	-11.66	-11.21
Median (Excluding Outliers)	-33.05	-23.80

Source: HKEx Fact Book

Aftermarket performance categorized by year

In Table 6, IPOs are classified by the year of listing. The results show that the returns of IPOs vary from year to year. The mean and median of the initial returns are positive, suggesting that the initial underpricing commonly occurs in each year. The two-year normal and market-adjusted returns in 2008 were 18.99% and 23.30%, respectively, which are the highest levels during 2008-2011. However, the listing volume of IPOs in 2008 was at the lowest level in those five years, and this may be due to the slumping stock market performance in Hong Kong caused by the US subprime financial tsunami. In 2010, 100 IPOs were listed in the HKEx because market recovery occurred by Quantitative Easing policies and a boom in the IPO market in Hong Kong. However, the two-year normal and market-adjusted returns were -27.47% and -23.67%, respectively, which are the lowest return levels, as the "Storm of Private Enterprises" occurred. The issuance volumes of IPOs in 2009 and 2011 are between those in 2008 and 2010; however, a similar phenomenon is shown in the two-year performances in those years. To summarize, the negative relationship between the number of IPOs and the long-run returns exists and it matches with the findings of Allen *et al.* (1999). Hence the hypothesis 3 that the long-run return of IPOs is not a negative function of annual volume of listing is rejected.

Table 6. *Initial and aftermarket Performance categorized by Year*

Year	Number of IPOs	Initial Return (%)	Two-year Return (%)	Two-year Adjusted Return (%)
2008	27	7.66	18.99	23.30
2009	65	15.66	6.41	4.34
2010	100	8.95	-27.47	-23.67
2011	61	4.91	9.76	8.17
All (Mean)		9.56	-4.83	-3.78
All (Median)		3.00	-33.06	-23.81

Source: HKEx Fact Book

Aftermarket performance categorized by Industry

Table 7 gathers IPOs by industry, based on the categorization system by HKEx. As some industries are similar, they will be included in a single group for the following regression analysis; for example, banks, insurance, and other financials, can be grouped into "Financials". The categorization of IPOs by industry is presented in Appendix 1.

According to Table 7, firms going public in 2008-2012 were not evenly distributed over all industries. As part of the strategy for consumption development in China, many companies related to consumer goods such as Textiles, Clothing and Accessories, Health and Personal Care, Household Goods and Electronics, as well as Food and Beverages, are listed in Hong Kong for raising capital. Some famous examples include Prada, L'Occitane, and Coach, as well as RUSAL, Vale S.A., and Glencore. Many property firms located in China were also listed in Hong Kong because of difficulty in financing property development in China due to the strict control of real-estate prices by the Chinese government. Suspension of listing in the IPO market in Mainland China and depression in China's stock market since 2010 are further reasons for listing in Hong Kong by firms operated in China.

Table 7. *Initial and aftermarket Performance categorized by Industry*

Industry	Number of IPOs	Initial Return (%)	Two-Year Return (%)	Two-Year Adjusted Return (%)
Agricultural Products	1	-61.09	-75.23	-56.22
Automobiles	5	5.45	5.71	9.31
Banks	3	-0.17	-12.92	-5.83
Basic Materials	14	9.01	-29.16	-36.51
Coal	4	-0.23	-36.82	-39.35
Construction	14	12.12	49.14	47.62
Diversified Metals & Minerals	3	-1.06	-60.07	-67.38
Food & Beverages	16	15.13	16.08	12.03
Health & Personal Care	17	11.09	-12.57	-11.50
Hotels, Casinos & Leisure Facilities	8	5.90	46.44	49.23
Household Goods & Electronics	17	9.18	-1.53	1.51
Industrial Goods	18	10.45	-25.07	-18.00
Insurance	4	10.29	4.40	10.62
IT Hardware	9	4.58	-51.81	-47.12
Media & Publishing	7	21.75	-17.57	-10.93
Metals	16	0.04	-32.84	-32.46
Mining	2	-1.94	25.98	-11.32
Oil & Gas	5	-2.37	25.73	14.92
Other Financials	12	27.01	45.96	45.70
Properties	21	-1.69	-18.87	-14.94
Retailers	7	25.41	-48.57	-38.37
Software & Services	1	47.66	-70.89	-139.02
Support Services	4	15.78	12.12	12.26
Telecommunications	3	9.18	37.27	31.19
Textiles, Clothing & Accessories	27	15.98	17.18	19.63
Transportation	7	2.19	-38.54	-30.05
Utilities	8	8.63	-26.06	-22.80

Source: HKEx Fact Book

Excluding industries having only one IPO, the industry of Other Financials has the highest initial return (27.01%), while the industry of Oil and Gas has the lowest (only -2.37%). As most firms operating in the industry of Other Financials are small-scale (capitalization less than HKD200 million) and listed in the GEM, the initial return of the industry is 2.67% if those outliers are eliminated. From the long-run returns, the Construction industry has the best two-year returns (49.14% and 47.62% for normal and market-adjusted returns, respectively), and the firms operating in IT Hardware have the worst two-year returns (-51.81% and -47.12% for normal and market-adjusted returns, respectively). However, the long-run results of these best performers fall significantly when outliers are eliminated. The two-year normal and market-adjusted returns fall to -4.74% and -1.05%, respectively when China Singyes Solar Technologies (Code: 750) and Tsun Yip (Code: 8356) are excluded. Allen *et al.* (1999) suggest that the long-run performance of industries is very sensitive to the exceptional performance of individual issues. After adjusting for such issues, the long-run returns decline dramatically, causing the long-run returns in most industries to be negative. The wide variations in the long-run performance and the underperformance in many industries are also consistent with the findings of Allen *et al.* (1999) and Ritter (1991). Ritter (1991) interprets these results as being consistent with the fads hypothesis. Therefore, the hypothesis 4 that the long-run return of IPOs is not a function of industry category is rejected.

Aftermarket performance categorized by subscription ratio

The subscription ratio is the proportion of the number of shares applied for subscriptions to the number of shares offered. In general, a higher subscription ratio reflects a more popular degree of demand for shares in offer for subscription by retail investors because they can only subscribe IPOs from this channel, and it is expected that the higher the subscription ratio, the higher the initial returns but the lower the aftermarket returns (Agarwal *et al.,* 2008).

The subscription ratios and returns of the sample IPOs (N=253) categorized by year are shown in Table 8. For those IPOs listed by 'introduction', the study treats their subscription ratio as zero because the amount of listing shares is only provided to certain investors, such as institution investors or clients of underwriters. The secondary stock market had a weak performance in 2008, and subsequently the mean subscription ratio was only 23.68. The lowest mean subscription level in 2008 indicates that many retail investors were not confident about the performance of IPOs; the same phenomenon in subscription rates occurred in 2011 because of "Storm of Private Enterprises". However, in 2009 and 2010

IPOs became popular, and the average of their subscription ratios exceeded 100 times after the recovery from the global financial crisis. Table 8 also shows that there is a reverse relationship between subscription ratio and the two-year normal return, and a negative relationship also exists between subscription ratio and the two-year market-adjusted return. Therefore, the hypothesis 5 that the long-run return of IPOs is not a function of subscription ratio is rejected.

Table 8. *Aftermarket returns categorized by Subscription Ratio*

Year	Number of IPOs	Mean of Subscription Ratio (Times)	Initial Return (%)	Two-year Return (%)	Two-year Adjusted Return (%)
2008	27	23.68	7.66	18.99	23.30
2009	65	137.24	15.66	6.41	4.34
2010	100	144.39	8.95	-27.47	-23.67
2011	61	67.90	4.91	9.76	8.17
Overall	253	111.23	9.56	-4.83	-3.78

Source: HKEx Fact Book

Aftermarket performance categorized by underwriter prestige

Table 9 presents the performance in IPOs by underwriters based on the market shares of the top 15 underwriters in Hong Kong during 2008-2012. The greater the market share of each underwriter, the greater prestige each underwriter has, and underwriter prestige depends on the proportion of the number of IPOs they sponsor to the total number of IPOs in the sample. The underwriter market in Hong Kong is dominated by the US and European Investment banks; however, no one became the absolute leader as the largest market share was only 14.23% for Morgan Stanley in 2012. Apart from Merrill Lynch, the average initial returns of all underwriters shown in Table 9 are positive. In this study, we treat the above investment banks as prestigious underwriters. They usually create initial underpricing. For example, they set the offer price lower than investor anticipation and strengthened promotion in road shows to increase investor interest in the IPOs they sponsored. Therefore, the phenomenon is consistent with the underpricing equilibrium found by Beatty & Ritter (1986). However, there is no clear relationship between underwriter prestige and initial or two-year returns (McGuinness, 1992; Lin & Hsu, 2008). Therefore, the hypothesis 6 that the long-run return of IPOs is not a function of market share of underwriters cannot be rejected.

Table 9. *Initial and aftermarket Performance categorized by Underwriters (Top 15 Underwriters)*

Underwriter	Market Share (%)	Number of IPOs	Initial Return (%)	Two-Year Return (%)	Two-Year Adjusted Return (%)
Morgan Stanley	14.23	36	3.50	-23.79	-19.17
UBS	11.07	28	7.33	1.46	1.54
Citigroup	7.91	20	5.54	-24.10	-23.26
Credit Suisse	7.91	20	3.73	-24.85	-22.81
J.P. Morgan	7.91	20	5.29	-11.70	-5.87
Goldman Sachs	6.72	17	1.16	14.03	19.78
CCB	6.32	16	0.26	-14.54	-11.96
Macquarie	6.32	16	0.85	-11.96	-7.45
China International Capital Corporation	5.14	13	3.93	-5.07	-3.25
Deutsche Bank	5.14	13	0.98	-18.00	-15.11
Merrill Lynch	5.14	13	-2.00	-19.54	-11.35
HSBC	4.35	11	8.76	6.75	4.21
BNP Paribas	3.56	9	8.23	10.75	7.90
Guotai Junan Capital limited	3.56	9	4.01	-25.66	-21.68
ICBC	3.56	9	8.18	-18.45	-17.82

Source: HKEx Fact Book

Aftermarket performance categorized by state-owned enterprises

Table 10 shows the IPO performance of 27 state-owned enterprises from Mainland China during 2008-2012 by year. The number and scale of state-owned enterprises have dropped significantly since 2008. The average and median initial returns of the state-owned enterprises were only 3.25% and 1.15%, respectively. Moreover, the long-run IPO performances of the state-owned enterprises are negative. The average two-year normal and market-adjusted returns are -10.44% and -4.8%, respectively, and they become -1.21% and 5.11%, respectively if the firms were first listed in Hong Kong. This phenomenon may be caused by the weak performance of China's market during the slowdown of economic growth in China and the policy risk (Lam *et al.,* 2010). It is consistent with the findings of Cheng (2010), which showed that the Chinese state-owned enterprises have positive short-run returns but a negative long-run performance. Hence the hypothesis 7 that the long-run return of IPOs is not a function of Chinese state-owned enterprises is rejected.

Table 10. *Initial and aftermarket Performance categorized by State-owned Enterprises*

Year	Number of IPOs	Initial Return (%)	Two-year Return (%)	Two-year Adjusted Return (%)
2008	6	-1.79	34.15	42.24
2009	8	10.14	-12.29	-0.13
2010	9	1.21	-29.88	-37.85
2011	4	1.61	-5.44	-10.32
All (Mean)		3.25	-10.44	-4.80
All (Median)		1.15	-20.38	-13.03

Source: HKEx Fact Book

Aftermarket performance categorized by GEM

Table 11 shows 22 IPOs listed in the GEM with returns during 2008-2012 by year. There is a tendency that a positive initial return is found in each year, and the average and median initial returns of those IPOs are 43.57% and 34.13%, respectively. This result is consistent with the findings of Vong & Zhao (2008) and Deng *et al.* (2010), which suggest that the substantial initial returns are caused by asymmetric information and huge uncertainty.

Table 11. *Initial and aftermarket Performance categorized by GEM*

Year	Numbers of IPOs	Initial Return (%)	Two-year Return (%)	Two-year Adjusted Return (%)
2008	2	20.27	-33.67	-13.92
2009	5	84.59	14.92	23.37
2010	7	44.66	4.69	10.07
2011	8	22.80	63.14	62.66
All (Mean)		43.57	24.78	30.03
All (Median)		34.13	-44.92	-33.26

Source: HKEx Fact Book

Table 12 shows the initial and aftermarket performance categorized by the GEM, excluding outliers after the three

IPOs which have more than 100% of the substantial return listed in the GEM are excluded.[5] The results of initial returns are consistent with those of Table 11; however, the average two-year normal and market-adjusted returns are -43.26% and -36.50%, respectively. This shows that there is a negative relationship between initial return and aftermarket return, and this is generally consistent with the results of aftermarket performance categorized by initial return, as shown in Tables 4 and 5. Hence, the hypothesis 8 that the long-run return of IPOs is not a function of the GEM is rejected.

Table 12. *Initial and aftermarket Performance categorized by GEM excluding outliners*

Year	Number of IPOs	Initial Return (%)	Two-year Return (%)	Two-year Adjusted Return (%)
2008	2	20.27	-33.67	-13.92
2009	4	78.24	-17.06	-8.40
2010	6	47.54	-58.64	-53.38
2011	7	25.35	-47.79	-44.55
All (Mean)		42.96	-43.26	-36.50
All (Median)		36.00	-47.06	-44.58

Source: HKEx Fact Book

Regression results

The multiple regression results for Equation (6) are shown in Table 13. The adjusted R^2 of the multiple regression is 0.2087, indicating that 20.87% of the variation in the long-run return is explained by the whole set of explanatory variables. This explanatory power is lower than the evidence reported by Allen *et al.* (1999), which is 32.45%, but higher than that of Ritter (1991), which is only 7%.

The annual volume of IPOs and subscription ratio still have a significantly negative effect on the two-year normal return. Conversely, the estimated coefficient on state-owned enterprises becomes positive but still insignificant. The signs of the estimated coefficients of the initial return, market return, and GEM are still the same, namely positive for market

[5] The three IPOs are Jiangchen International (Code: 8305), Tsun Yip (Code: 8356), and Chanceton Financial (Code: 8020).

return and negative for initial return and GEM; however, initial return becomes statistically insignificant. Some of the results are consistent with those reported by Allen *et al.* (1999), which showed that the signs of initial return and annual volume of IPOs were negative, while there was a positive relationship between market return and the two-year normal return.

Table 13. *Multiple Regression results with the 2-year normal return as the dependent variable*

Independent Variables	Estimated Coefficient	Standard Error	P-value
Initial Return	-0.0056	0.2513	0.9823
Market Return	0.0111***	0.0029	0.0001
Volume	-0.0058***	0.0019	0.0029
Ratio	-0.0461**	0.0228	0.0437
SOE	0.0744	0.1264	0.5567
GEM	-0.3256	0.2927	0.2671
CAT1	0.3731**	0.1805	0.0398
CAT2	0.4700*	0.2633	0.0755
CAT3	-0.0020	0.2499	0.9936
CAT4	-0.2678	0.2564	0.2973
CAT5	-0.0543	0.1736	0.7548
CAT6	0.3518**	0.1564	0.0255
CAT7	0.1344	0.2047	0.5120
CAT8	0.2926	0.2064	0.1575
Adjusted R^2	0.2087		

Notes: The dependent variable is two-year return calculated as log $(1+2YRR_i)$ = log $(P_{i,L}/P_i)$ where $P_{i,L}$ is the close price of IPO_i in the 24th month and P_i is the close price of IPO_i on the first trade day.
Initial Return is calculated as $IR_i = (P_i - S_i)/S_i$ where P_i is the close price of IPO_i on the first trade day and S_i is Subscription Price of IPOi
Market Return is calculated as $2YRRM_i = M_{i,L}/M_i$ where $M_{i,L}$ is the close price of the benchmark. Index (HSI) in the 24th month and M_i is the close price of Benchmark Index on the first trade day
Volume is annual volume of IPOs
Ratio is subscription ratio and expressed as log (1 + Subscription ratio)
SOE is dummy variable of State-owned Enterprises
GEM is a dummy variable of Growth Enterprises Market; and CAT_i refers to a dummy variable of an industry category
CAT1 denotes Consumer Goods; CAT2 Financials; CAT3 Industrial Goods; CAT4 Information Technology; CAT5 Materials; CAT6 Properties and Construction; CAT7 Services; and CAT8 others. The details are shown in Appendix 1.
***, ** and * denote statistical significance at 1%, 5% and 10%, respectively.

For all dummy variables of industry, the signs of categories 3 to 5 are negative, and the rest are positive. However, those estimated coefficients, except for categories 1, 2, and 6, are statistically insignificant. If the level of significance and confidence of estimated coefficients are neglected, Financials (Category 2) seem to have the best long-run performance because of substantial aftermarket positive returns on some firms categorized in Other Financials. In contrast, the long-run return of Information Technology (Category 4) is negative because substantial loss occurs in some firms operating in Hardware which are not of interest to investors.

Another multiple regression for Equation (7) with two-year market-adjusted returns as the dependent variable was undertaken. The results in Table 14 show that there are no marked changes in significance of the estimated coefficients when compared with the multiple regression results of the two-year normal return shown in Table 13.[6] However, the adjusted R^2 is 0.1608, which indicates that the explanatory power of the equation drops.

Table 14. *Multiple Regression results with 2-year market adjusted return as the dependent variable*

Independent Variables	Estimated Coefficient	Standard Error	P-value
Initial Return	0.0223	0.2315	0.9233
Market Return	0.0049	0.0032	0.1266
Volume	-0.0062***	0.0018	0.0005
Ratio	-0.0486**	0.0219	0.0279
SOE	0.0821	0.1127	0.4680
GEM	-0.2815	0.2748	0.3067
CAT1	0.4624***	0.1623	0.0048
CAT2	0.5311**	0.2463	0.0321
CAT3	0.1566	0.2223	0.4818
CAT4	-0.0067	0.2012	0.9736
CAT5	0.0166	0.1656	0.9216
CAT6	0.4357***	0.1469	0.0033
CAT7	0.2279	0.1859	0.2214
CAT8	0.3479*	0.2028	0.0875
Adjusted R^2	0.1608		

See Notes to Table 13

[6] The coefficient of market return in Equation (7) is statistically insignificant. It may be due to the fact that the dependent variable is a market adjusted return.

Conclusion

The study examined the long-run performance of IPOs in Hong Kong listed during 2008-2012 and possible explanations for their aftermarket performance. The average initial return for the sample of 253 IPOs is 8.38%. The result is rather lower than the data reported by Cheng *et al*. (2006) and Vong (2006). This perhaps is the consequence of the weak performance on stocks listed in Hong Kong and China as well as the "Storm of Private Enterprises". The -1.73% market-adjusted return at the end of the first month after listing suggests that the high initial underpricing is quickly reversed in the early aftermarket period. This is consistent with the results of Allen *et al*. (1999).

The cross-sectional analysis of the long-term performance of IPOs supports the overreaction hypothesis. The two-year market-adjusted return is -3.78%, which suggests that IPOs in Hong Kong underperform in the long run on average. After removal of the outliers which have extremely high returns, the adjusted return is -11.21%, which provides further evidence of underperformance in the IPO market in Hong Kong and strong disparity among long-run performances in the IPOs. The results are consistent with the findings of Dawson (1987) and Cheng *et al*. (2006). Furthermore, after removal of outliers, IPOs having higher initial returns tend to perform worst in the long run. This negative relationship is also consistent with the overreaction hypothesis reported by Aggarwal & Rivoli (1990) as well as Ritter (1991).

Regarding evidence related to the market fads hypothesis, the evidence from IPOs in Hong Kong is mixed. The highest volume of IPOs in 2010, together with the highest long-run underperformance, appears to be consistent with the fad hypothesis. Therefore, the annual volume of IPOs is negatively related to the two-year normal and market-adjusted returns. However, these results do not fully match the results of Allen *et al*. (1999).

Analysis by industrial sector appears to be ambiguous, with the performance of IPOs in different industries varying widely, which is consistent with the findings of Allen *et al*. (1999). The long-run performance of several industries is very sensitive to the exceptional performance of individual issues. After adjusting for such issues, the long-run performance in most industries becomes negative. The wide variation in the long-run performance and the underperformance in many industries can be consistent with the fads hypothesis.

Consistent with the findings of Agarwal *et al.* (2008) that the higher the subscription ratio, the higher the initial returns but the lower the aftermarket returns, the study finds that the initial return is higher, and the long-run return is lower if an IPO has significant demand for shares offered for subscription. This is consistent with the fads hypothesis.

This study also finds that there is no clear relationship between underwriter prestige and long-run performance if we use market share to determine underwriter prestige. The result is different from those of Megginson & Weiss (1991), McGuiness (1992), and Lin & Hsu (2008). However, the positive initial returns for all underwriters under study appear to match the underpricing equilibrium found by Beatty & Ritter (1986).

When considering the situation of Chinese state-owned enterprises in IPOs, the average initial return is positive, although it is only 3.25%, which is much lower than the return of 22.22% reported by McGuiness (2012). Also, the two-year normal and market-adjusted returns are -10.44% and -4.8%, respectively. The negative relationship between state-owned enterprises and aftermarket returns is consistent with the findings of Cheng (2010). On the other hand, there is also a negative relationship between the GEM and aftermarket return. These two relationships further confirm the overreaction hypothesis reported by Aggarwal & Rivoli (1990).

Regression analyses provide some evidence supporting the previous results. Initial return, annual volume of issue, subscription ratio, and GEM are negatively related to the aftermarket-adjusted return, but only the coefficients of the annual volume and subscription ratio are statistically significant. Market returns have a positive and statistically significant effect on the long-run performance. As for the issues of state-owned enterprises, the results contrast with those in the cross-sectional analysis and the coefficient is not significant. The long-run performance of IPOs is, to a certain degree, affected by some of the industries under consideration.

After consideration of both cross-sectional and regression analysis, the conclusion is that some indicators, such as annual volume of IPOs, subscription ratio, and some dummy indicators of industry categorization have a stronger explanatory power for long-run performance.

Appendices

Appendix 1. *Categorization of IPOs by Industry*

Category	Industry	Number of IPOs
CAT1: Consumer Goods	Agricultural Products	1
	Automobiles	5
	Food & Beverages	16
	Health & Personal Care	18
	Household Goods & Electronics	17
	Textiles, Clothing & Accessories	27
CAT2: Financials	Bank	3
	Insurance	4
	Other Financials	12
CAT3: Industrial Goods	Industrial Goods	18
CAT4: Information Technology	IT Hardware	9
	Software & Services	1
CAT5: Materials	Basic Materials	14
	Diversified Metals & Minerals	3
	Metals	16
	Mining	2
CAT6: Properties & Construction	Construction	14
	Properties	21
CAT7: Services	Hotel, Casino & Leisure Facilities	7
	Media & Publishing	7
	Retailers	7
	Support Services	4
	Transportation	7
CAT8: Others	Coal	4
	Oil & Gas	5
	Telecommunication	3
	Utilities	8

Source: HKEx Fact Book

Appendix 2. *Names of IPOs and their returns during Years 2008 - 2011*

Year 2008

Code	Company	State-owned Enterprise	GEM	Offer Price ($)	Listing Date	First-day Close Price ($)	Initial Return (%)	2-Year Close Price ($)	2-Year Return (%)	2-Year Market Adjusted Return (%)
869	Playmates Toys			0.62	1/2/2008	0.64	3.23	0.74	15.63	30.20
708	New Media			0.68	12/2/2008	1.48	117.65	0.51	-65.54	-55.45
196	Honghua			3.83	7/3/2008	3.51	-8.36	1.26	-64.10	-58.49
1186	China Railway Construction	Y		10.70	13/3/2008	12.02	12.34	9.57	-20.38	-15.62
151	Want Want China			3.00	26/3/2008	2.91	-3.00	5.51	89.35	95.44
757	Solargiga Energy			2.92	31/3/2008	2.92	0.00	1.70	-41.78	-34.74
98	Xingfa Aluminium			2.28	31/3/2008	2.12	-7.02	1.80	-15.09	-8.05
8348	Tianjin Binhai Teda Logistics	Y	Y	1.98	30/4/2008	2.07	4.55	1.65	-20.29	-2.25
848	Maoye International			3.10	5/5/2008	3.04	-1.94	2.54	-16.45	8.07
789	Artini China			2.22	16/5/2008	2.00	-9.91	0.76	-62.00	-39.15
743	Asia Cement (China)			4.95	20/5/2008	6.80	37.37	3.56	-47.65	-26.18
8340	Vinco Financial		Y	0.25	20/5/2008	0.34	36.00	0.18	-47.06	-25.59
1368	Xtep International			4.05	3/6/2008	3.80	-6.17	6.46	70.00	87.42
832	Central China Real Estate			2.75	6/6/2008	2.67	-2.91	1.77	-33.71	-16.20
3813	Pou Sheng International			3.05	6/6/2008	2.61	-14.43	0.90	-65.52	-48.01
800	A8 Digital Music			1.90	12/6/2008	2.58	35.79	4.50	74.42	86.99
2722	Chongqing Machinery & Electric	Y		1.30	13/6/2008	1.05	-19.23	1.88	79.05	89.95
1812	Shandong Chenming Paper	Y		9.00	18/6/2008	7.50	-16.67	5.86	-21.87	-8.16
691	China Shanshui Cement	Y		2.80	4/7/2008	3.00	7.14	4.18	39.33	41.17
623	SinoMedia			2.63	8/7/2008	2.62	-0.38	2.10	-19.85	-18.95
756	Tianyi Fruit			0.63	10/7/2008	0.70	11.11	2.70	285.71	289.34
880	SJM			3.08	16/7/2008	3.04	-1.30	6.85	125.33	126.24
887	Emperor Watch & Jewellery			0.43	21/7/2008	0.47	9.30	0.58	23.40	30.07
1766	China South Locomotive & Rolling Stock	Y		2.60	21/8/2008	2.63	1.15	6.55	149.05	148.34
963	Bloomage BioTechnology			1.00	3/10/2008	1.04	4.00	2.42	132.69	102.07
1387	Renhe Commercial			1.13	22/10/2008	1.18	4.42	1.48	25.42	-36.47
834	China Kangda Food			1.49	22/12/2008	1.70	14.09	0.76	-55.29	-112.83
						Average	7.66		18.99	23.30

Year 2009

Code	Company	State-owned Enterprise	GEM	Offer Price ($)	Listing Date	First-day Close Price ($)	Initial Return (%)	2-Year Close Price ($)	2-Year Return (%)	2-Year Market Adjusted Return (%)
852	Strong Petrochemical			2.50	12/1/2009	2.46	-1.60	6.40	160.16	92.33
750	China Singyes Solar Technologies			1.05	13/1/2009	1.18	12.38	5.43	360.17	288.62
802	RCG			6.63	10/2/2009	9.79	47.66	2.85	-70.89	-139.02
246	Real Gold Mining			6.25	23/2/2009	6.25	0.00	11.76	88.16	11.02
794	Come Sure			1.12	26/2/2009	1.20	7.14	0.97	-19.17	-100.15
841	Asia Cassava Resources			1.02	23/3/2009	1.20	17.65	2.24	86.67	11.71
886	Silver Base			3.45	8/4/2009	3.11	-9.86	6.39	105.33	41.45
1333	China Zhongwang			7.00	8/5/2009	6.63	-5.29	3.31	-50.08	-86.27
215	Hutchison Telecommunications Hong Kong			1.06	8/5/2009	0.93	-12.26	2.54	173.12	136.92
67	Lumena Resources			2.00	15/6/2009	2.38	19.00	3.13	31.51	10.43
773	China Metal Recycling			5.18	22/6/2009	6.32	22.01	9.47	49.84	25.82
396	Hing Lee (HK)			1.02	22/6/2009	1.40	37.25	1.59	13.57	-10.45
1361	361 Degrees International			3.61	29/6/2009	3.90	8.03	4.77	22.31	1.42
1338	BaWang International			2.38	3/7/2009	3.03	27.31	1.28	-57.76	-81.03
866	China Qinfa			2.52	3/7/2009	2.68	6.35	3.40	26.87	3.59
90	Amber Energy			1.66	10/7/2009	2.71	63.25	1.26	-53.51	-80.23
449	Chigo Holdings			2.27	13/7/2009	2.51	10.57	5.70	127.09	97.04
2009	BBMG	Y		6.38	29/7/2009	9.97	56.27	11.32	13.54	2.09
2288	Sundart International			4.18	21/8/2009	3.90	-6.70	1.52	-61.03	-62.69
8325	Oriental City		Y	0.23	28/8/2009	0.59	156.52	0.69	16.95	14.78
72	Modern Media			1.29	9/9/2009	1.37	6.20	2.50	82.48	98.11
8296	Sino-Life		Y	0.72	9/9/2009	1.04	44.44	0.26	-75.00	-59.37
633	China All Access			1.60	16/9/2009	1.81	13.13	1.51	-16.57	1.23
1099	Sinopharm	Y		16.00	23/9/2009	18.52	15.75	20.75	12.04	30.58
1618	Metallurgical Corporation of China	Y		6.35	24/9/2009	5.61	-11.65	1.51	-73.08	-56.66
1234	China Lilang			3.90	25/9/2009	3.87	-0.77	7.60	96.38	112.71

Year 2009

Code	Company	State-owned Enterprise	GEM	Offer Price ($)	Listing Date	First-day Close Price ($)	Initial Return (%)	2-Year Close Price ($)	2-Year Return (%)	2-Year Market Adjusted Return (%)
1968	Peak Sport Products			4.10	29/9/2009	3.40	-17.07	2.16	-36.47	-20.19
1668	China South City			2.10	30/9/2009	1.62	-22.86	0.98	-39.51	-23.46
845	Glorious Property			4.40	2/10/2009	3.79	-13.86	1.23	-67.55	-65.04
1313	China Resources Cement	Y		3.90	6/10/2009	3.90	0.00	6.30	61.54	66.09
8351	Eternite International		Y	0.25	7/10/2009	0.41	62.00	0.66	62.96	69.44
1717	Ausnutria Dairy	Y		4.00	8/10/2009	5.10	27.50	1.54	-69.80	-62.23
893	China Vanadium Titano-Magnetite Mining			3.50	8/10/2009	3.68	5.14	1.64	-55.43	-47.86
2168	Yingde Gases Group			10.08	8/10/2009	10.78	6.94	8.38	-22.26	-14.69
8305	Jiangchen International		Y	0.30	8/10/2009	0.63	110.00	1.53	142.86	150.43
1128	Wynn Macau			10.08	9/10/2009	10.78	6.94	22.25	106.40	114.00
829	Shenguan			3.10	13/10/2009	4.33	39.68	8.46	95.38	102.85
1238	Powerlong Real Estate			2.75	14/10/2009	2.80	1.82	1.20	-57.14	-47.91
712	Comtec Solar Systems			2.10	30/10/2009	1.98	-5.71	1.46	-26.26	-17.58
1628	Yuzhou Properties			2.70	2/11/2009	2.68	-0.74	1.90	-29.07	-12.28
891	Trinity			1.65	3/11/2009	2.46	49.09	5.44	121.14	136.44
3333	Evergrande Real Estate			3.50	5/11/2009	4.70	34.29	3.01	-35.96	-19.71
1318	Greens			1.62	6/11/2009	1.82	12.35	0.46	-74.73	-57.13
591	China High Precision Automation			4.00	13/11/2009	5.16	29.00	2.74	-46.90	-26.66
846	Mingfa			2.39	13/11/2009	2.15	-10.04	1.71	-20.47	-0.23
906	CPMC	Y		5.39	16/11/2009	6.11	13.36	3.51	-42.55	-20.96
960	Longfor Properties			7.07	19/11/2009	8.01	13.30	8.86	10.61	31.16
389	China Tontine Wines			1.25	19/11/2009	1.48	18.40	0.98	-33.78	-13.23
1777	Fantasia			2.18	25/11/2009	2.23	2.29	0.71	-68.16	-47.72
631	Sany Heavy Equipment International			4.80	25/11/2009	7.03	46.46	10.67	51.71	72.15
73	Asian Citrus			51.25	26/11/2009	19.94	-61.09	4.94	-75.23	-56.22
1988	China Minsheng Banking	Y		9.08	26/11/2009	8.80	-3.08	7.40	-15.86	3.14
1928	Sands China			10.38	30/11/2009	9.32	-10.21	21.75	133.37	150.93
465	Futong Technology Development			1.63	4/12/2009	1.91	17.18	1.23	-35.60	-17.54
1866	China XLX Fertiliser			5.02	8/12/2009	5.20	3.59	1.99	-61.73	-45.29
1638	Kaisa			3.45	9/12/2009	3.44	-0.29	1.34	-61.05	-45.83
916	China Longyuan Power	Y		8.16	10/12/2009	8.93	9.44	6.07	-32.03	-16.98
331	PCD Stores			1.95	15/12/2009	2.55	30.77	1.07	-58.04	-42.55
8248	Perception Digital		Y	0.72	16/12/2009	1.08	50.00	0.29	-73.15	-58.45
947	Mobi Development			3.38	17/12/2009	3.05	-9.76	0.94	-69.34	-55.70
1080	Shengli Oil & Gas Pipe			2.20	18/12/2009	1.86	-15.45	0.79	-57.53	-44.58
1006	China Corn Oil			3.59	18/12/2009	4.36	21.45	3.02	-30.73	-17.79
1823	Huayu Expressway			1.28	23/12/2009	1.29	0.78	0.85	-34.11	-20.54
2601	China Pacific Insurance	Y		28.00	23/12/2009	28.30	1.07	22.10	-21.91	-8.34
837	Carpenter Tan			2.58	29/12/2009	3.93	52.33	3.70	-5.85	8.40
						Average	15.66		6.41	4.34

Year 2010

Code	Company	State-owned Enterprise	GEM	Offer Price ($)	Listing Date	First-day Close Price ($)	Initial Return (%)	2-Year Close Price ($)	2-Year Return (%)	2-Year Market Adjusted Return (%)
486	RUSAL			10.80	27/1/2010	9.65	-10.65	5.90	-38.86	-40.64
1878	Southgobi Energy Resources			126.04	29/1/2010	112.00	-11.14	45.80	-59.11	-60.44
953	Meike International			1.43	1/2/2010	1.44	0.70	0.67	-53.47	-60.02
1966	China Sce Property			2.60	5/2/2010	2.72	4.62	1.75	-35.59	-45.27
1938	Chu Kong Petroleum and Natural Gas			4.50	10/2/2010	4.51	0.22	3.02	-33.04	-41.30
2010	Ruinian International			3.00	19/2/2010	2.77	-7.67	2.84	2.53	-5.89
948	Z-Obee			1.80	1/3/2010	1.87	3.89	1.02	-45.45	-43.07
1280	Huiyin Household Appliances			1.69	25/3/2010	2.44	44.38	0.51	-79.10	-78.03
881	Zhongsheng			10.00	26/3/2010	10.72	7.20	15.40	43.66	46.02
1998	Flyke			1.90	29/3/2010	2.16	13.68	1.20	-44.44	-41.23
830	Far East Global			1.18	30/3/2010	1.29	9.32	1.40	8.53	12.36
923	Fook Woo			2.30	31/3/2010	2.70	17.39	1.37	-49.26	-46.04
1999	Man Wah			6.80	9/4/2010	6.70	-1.47	4.04	-39.70	-34.68
778	Fortune REIT			3.94	20/4/2010	3.84	-2.54	4.17	8.59	11.04
1863	Sijia			3.28	29/4/2010	3.68	12.20	2.11	-42.66	-44.18

Year 2010

Code	Company	State-owned Enterprise	GEM	Offer Price ($)	Listing Date	First-day Close Price ($)	Initial Return (%)	2-Year Close Price ($)	2-Year Return (%)	2-Year Market Adjusted Return (%)
877	O-Net Communications			2.90	29/4/2010	3.99	37.59	1.97	-50.63	-52.14
973	L'occitane International			15.08	7/5/2010	14.40	-4.51	18.94	31.53	38.01
503	Lansen Pharmaceutical			3.91	7/5/2010	4.56	16.62	1.86	-59.21	-52.73
2222	NVC Lighting			2.10	20/5/2010	2.04	-2.86	1.78	-12.75	-8.06
2378	Prudential			60.39	25/5/2010	57.86	-4.19	81.70	41.20	43.08
2268	Youyuan International			2.58	27/5/2010	2.52	-2.33	1.66	-34.09	-29.96
2188	China Titans Energy Technology			1.18	28/5/2010	1.46	23.73	0.54	-63.01	-57.26
8337	Directel		Y	0.30	2/6/2010	0.38	26.67	0.21	-44.74	-44.58
873	International Taifeng			2.06	11/6/2010	1.67	-18.93	1.88	12.57	14.74
8295	Asian Capital		Y	0.20	18/6/2010	0.26	27.50	0.14	-45.10	-40.93
2228	Costin New Materials			2.38	21/6/2010	2.36	-0.84	3.30	39.83	46.86
2128	China Liansu			2.60	23/6/2010	2.60	0.00	3.33	28.08	34.86
325	Trauson			3.52	29/6/2010	3.83	8.81	3.07	-19.84	-15.86
1020	Sinoref			0.76	7/7/2010	0.71	-6.58	0.40	-43.66	-43.36
951	Chaowei Power			2.18	7/7/2010	1.98	-9.17	4.55	129.80	130.10
1788	Guotai Junan International	Y		4.30	8/7/2010	4.14	-3.72	2.26	-45.41	-44.15
976	Chiho-Tiande			2.43	12/7/2010	2.39	-1.65	4.00	67.36	70.64
1019	Convoy Financial Services			1.20	13/7/2010	1.52	26.67	0.99	-34.87	-31.76
2118	Tian Shan Development			1.40	15/7/2010	1.46	4.29	1.74	19.18	21.44
1900	China ITS			3.49	15/7/2010	3.49	0.00	1.01	-71.06	-68.80
1288	Agricultural Bank of China	Y		3.20	16/7/2010	3.27	2.19	3.16	-3.36	-1.13
936	Manta			1.00	19/7/2010	1.12	12.00	1.52	35.71	37.18
640	Infinity Chemical			0.60	12/8/2010	0.93	55.00	0.50	-46.24	-38.55
2233	West China Cement			1.69	23/8/2010	1.94	14.79	1.21	-37.63	-30.90
1428	Bright Smart Securities & Commodities			1.60	25/8/2010	1.74	8.75	0.55	-68.39	-62.81
2238	Guangzhou Automobile	Y		9.00	30/8/2010	9.19	2.11	5.41	-41.13	-35.08
8356	Tsun Yip		Y	1.28	30/8/2010	1.63	27.34	7.90	384.66	390.71
2198	China Sanjiang Fine Chemicals			3.38	16/9/2010	3.33	-1.48	2.18	-34.53	-30.61
853	MicroPort Scientific			6.10	24/9/2010	8.29	35.90	3.85	-53.56	-47.78
1633	Magic			3.30	24/9/2010	4.51	36.67	3.24	-28.16	-22.38
1039	Changfeng Axle (China)			4.00	24/9/2010	4.50	12.50	0.63	-86.00	-80.22
867	China Medical System			5.06	28/9/2010	5.64	11.46	7.59	34.64	40.38
926	Besunyen			3.12	29/9/2010	3.58	14.74	0.55	-84.64	-77.76
1698	Boshiwa International			4.98	29/9/2010	7.02	40.96	1.68	-76.07	-69.19
8321	China Automobile Interior Decoration		Y	0.93	29/9/2010	1.23	32.26	0.14	-88.62	-81.74
967	Sound Global			5.45	30/9/2010	5.23	-4.04	3.30	-36.90	-30.11
1682	Ford Glory			0.60	5/10/2010	1.25	108.33	0.90	-28.00	-23.59
1021	Midas			5.43	6/10/2010	5.83	7.37	2.87	-50.77	-45.36
1308	SITC International			4.78	6/10/2010	4.53	-5.23	2.06	-54.53	-49.11
1918	Sunac China			3.48	7/10/2010	3.37	-3.16	4.10	21.66	27.09
2468	Trony Solar			4.50	7/10/2010	5.07	12.67	0.63	-87.57	-82.14
2208	Xinjiang Goldwind Science & Technology	Y		17.98	8/10/2010	19.06	6.01	2.95	-84.52	-78.85
3683	Great Harvest Maeta			1.13	11/10/2010	1.17	3.54	1.21	3.42	10.16
2266	Kosmopolito Hotels			2.20	11/10/2010	1.88	-14.55	1.71	-9.04	-2.30
1733	Winsway Coking Coal			3.70	11/10/2010	3.38	-8.65	1.25	-63.02	-56.27
975	Mongolian Mining			7.02	13/10/2010	7.90	12.54	3.79	-52.03	-44.28
580	Sun King Power Electronics			1.93	13/10/2010	2.50	29.53	0.41	-83.60	-75.86
956	China Suntien Green Energy			2.66	13/10/2010	2.64	-0.75	1.58	-40.15	-32.41
8269	Wealth Glory		Y	0.25	14/10/2010	0.51	104.00	0.16	-68.63	-59.36
1685	Boer Power			6.38	20/10/2010	7.25	13.64	2.80	-61.38	-53.25
1029	IRC			1.80	21/10/2010	1.65	-8.33	0.95	-42.42	-33.94
1700	Springland International			5.93	21/10/2010	6.68	12.65	3.81	-42.96	-34.47
1278	China New Town Development			1.71	22/10/2010	1.20	-29.82	0.29	-75.83	-67.86
460	Sihuan Pharmaceutical			4.60	28/10/2010	5.77	25.43	3.04	-47.31	-40.55
1299	AIA			19.60	29/10/2010	23.05	17.60	30.70	33.19	39.49
1230	Yashili International			4.20	1/11/2010	3.68	-12.38	2.29	-37.77	-30.91
238	Evergreen International			4.60	4/11/2010	5.80	26.09	1.52	-73.79	-63.58
1600	China Tian Lun Gas			2.05	10/11/2010	2.14	4.39	3.80	77.57	87.65
1087	HL Technology			2.80	16/11/2010	2.42	-13.57	0.92	-61.98	-54.97
842	Leoch International			5.35	16/11/2010	4.67	-12.71	1.07	-77.09	-70.07
1091	CITIC Dameng	Y		2.75	18/11/2010	2.92	6.18	0.77	-73.63	-66.83
1101	China Rongsheng Heavy Industries			8.00	19/11/2010	7.96	-0.50	1.27	-84.05	-77.37

Year 2010

Code	Company	State-owned Enterprise	GEM	Offer Price ($)	Listing Date	First-day Close Price ($)	Initial Return (%)	2-Year Close Price ($)	2-Year Return (%)	2-Year Market Adjusted Return (%)
8207	Credit China		Y	0.75	19/11/2010	1.07	42.67	0.74	-30.47	-23.79
1086	Goodbaby International			4.90	24/11/2010	5.80	18.37	2.70	-53.45	-49.13
1110	Kingworld Medicines			1.60	25/11/2010	2.05	28.13	1.30	-36.59	-32.14
8312	Brilliance Worldwide		Y	0.23	25/11/2010	0.35	52.17	0.09	-74.29	-69.84
1117	China Modern Dairy			2.89	26/11/2010	2.51	-13.15	1.94	-22.71	-19.01
1090	Da Ming International			2.10	1/12/2010	2.12	0.95	1.59	-25.00	-22.45
2099	China Gold International	Y		44.68	1/12/2010	42.95	-3.87	27.40	-36.20	-33.65
1831	Shifang			3.03	3/12/2010	2.65	-12.54	0.38	-85.66	-82.81
1048	Novo			4.20	6/12/2010	4.18	-0.48	2.10	-49.76	-47.26
1768	Sateri			6.60	8/12/2010	6.50	-1.52	1.75	-73.08	-71.19
6210	Vale S.A. Common-Common DR			270.00	8/12/2010	265.20	-1.78	153.50	-42.12	-40.23
6230	Vale S.A. Common-Preferred DR			236.60	8/12/2010	233.00	-1.52	151.60	-34.94	-33.05
468	Greatview Asptic Packaging			4.30	9/12/2010	4.92	14.42	4.19	-14.84	-12.62
1728	China Zheng Tong Auto Services			7.30	10/12/2010	7.39	1.23	5.39	-27.06	-24.88
1555	MIE			1.70	14/12/2010	1.70	0.00	2.43	42.94	46.25
1282	World Wide Touch Technology			0.95	15/12/2010	0.96	1.05	0.17	-82.29	-80.91
3618	Chongqing Rural Commercial Bank	Y		5.25	16/12/2010	5.27	0.38	4.24	-19.54	-19.49
1798	China Datang Corporation Renewable Power	Y		2.33	17/12/2010	2.18	-6.44	0.99	-54.59	-54.33
1112	Biostime International			11.00	17/12/2010	10.70	-2.73	24.20	126.17	126.42
327	PAX Global Technology			2.88	20/12/2010	2.89	0.35	1.60	-44.64	-44.72
940	China Animal Healthcare			2.50	21/12/2010	2.36	-5.60	1.62	-31.36	-29.89
1157	Zoomlion	Y		14.98	23/12/2010	16.18	8.01	14.85	-8.24	-7.17
1085	Hengxin Technology			2.25	23/12/2010	2.22	-1.33	0.84	-62.16	-61.09
						Average	8.95		-27.47	-23.67

Year 2011

Code	Company	State-owned Enterprise	GEM	Offer Price ($)	Listing Date	First-day Close Price ($)	Initial Return (%)	2-Year Close Price ($)	2-Year Return (%)	2-Year Market Adjusted Return (%)
1089	Sumpo Food			0.68	11/1/2011	0.77	13.24	0.32	-58.44	-58.31
2011	KEE			1.33	12/1/2011	1.35	1.50	0.57	-57.78	-56.14
1323	Newtree			1.95	13/1/2011	1.76	-9.74	2.03	15.34	17.44
8265	Powerwell Pacific		Y	0.80	26/1/2011	0.87	8.75	0.84	-3.45	-2.97
1143	Telefield International			1.20	27/1/2011	1.23	2.50	0.40	-67.48	-67.27
1121	Baofeng Modern International			2.00	28/1/2011	1.80	-10.00	1.38	-23.33	-23.81
8087	China 33 Media		Y	1.80	28/2/2011	1.80	0.00	0.22	-87.78	-86.42
8098	CL		Y	0.49	8/3/2011	0.62	27.84	0.25	-59.68	-53.72
3688	Top Spring International			6.23	23/3/2011	5.30	-14.93	5.74	8.30	10.61
1378	China Hongqiao			7.20	24/3/2011	7.90	9.72	3.83	-51.52	-48.83
3360	Far East Horizon	Y		6.29	30/3/2011	6.87	9.22	5.13	-25.33	-20.42
6488	SBI Holdings			80.23	14/4/2011	79.50	-0.91	135.20	70.06	75.38
1181	Tang Palace (China)			1.65	19/4/2011	2.31	40.00	1.49	-35.50	-32.17
1011	China NT Pharma			4.54	20/4/2011	3.82	-15.86	0.94	-75.39	-70.54
1623	Hilong			2.60	21/4/2011	2.73	5.00	3.17	16.12	21.92
87001	Hui Xian Real Estate Investment			5.24	28/4/2011	4.75	-9.35	4.06	-14.53	-10.04
2789	Yuanda China			1.50	17/5/2011	1.66	10.67	0.81	-51.20	-48.98
2299	Billion Industrial			5.18	18/5/2011	5.28	1.93	5.04	-4.55	-1.86
8132	Fairson		Y	0.30	18/5/2011	0.51	70.00	0.17	-66.67	-63.98
2607	Shanghai Pharmaceuticals	Y		23.00	20/5/2011	23.00	0.00	15.14	-34.17	-30.69
1150	Milan Station			1.67	23/5/2011	2.77	65.87	0.43	-84.48	-83.07
805	Glencore International			66.53	25/5/2011	64.90	-2.45	39.00	-39.91	-38.35
2083	China Flooring			2.95	26/5/2011	2.94	-0.34	1.51	-48.64	-46.42
8193	GreaterChina Professional Services		Y	0.72	31/5/2011	0.83	15.28	0.20	-75.90	-70.45
3363	Zhengye International			1.43	3/6/2011	1.44	0.70	0.64	-55.56	-46.20
2282	MGM China			15.34	3/6/2011	15.60	1.69	20.70	32.69	42.04

Year 2011

Code	Company	State-owned Enterprise	GEM	Offer Price ($)	Listing Date	First-day Close Price ($)	Initial Return (%)	2-Year Close Price ($)	2-Year Return (%)	2-Year Market Adjusted Return (%)
935	Dragon Crown			1.10	10/6/2011	1.14	3.64	0.93	-18.42	-11.21
958	Huaneng Renewables	Y		2.50	10/6/2011	2.43	-2.80	2.81	15.64	22.85
1910	Samsonite International			14.50	16/6/2011	13.40	-7.59	18.68	39.40	44.64
871	Xiangyu Dredging			3.19	20/6/2011	2.45	-23.20	1.82	-25.71	-22.03
1145	Courage Marine			0.99	24/6/2011	1.07	8.08	0.27	-74.77	-68.59
1913	Prada			39.50	24/6/2011	39.60	0.25	70.40	77.78	83.95
1488	Lee & Man Handbags			0.70	27/6/2011	0.77	10.00	1.08	40.26	45.88
847	Kazakhmys PLC			165.00	29/6/2011	165.60	0.36	31.05	-81.25	-75.55
1241	Shuanghua			1.16	30/6/2011	1.46	25.86	0.34	-76.71	-69.59
1115	Tibet 5100 Water Resources			3.00	30/6/2011	3.69	23.00	2.95	-20.05	-12.93
1231	Newton Resources			1.75	4/7/2011	1.73	-1.14	0.59	-65.90	-63.60
1082	Modern Education			1.30	4/7/2011	1.39	6.92	0.28	-79.86	-77.56
1151	Elec & Eltek International			30.10	8/7/2011	30.80	2.33	16.10	-47.73	-44.02
8179	Gayety		Y	1.00	8/7/2011	1.50	50.00	1.20	-20.00	-16.29
6828	China Print Power			1.48	12/7/2011	1.36	-8.11	2.41	77.21	76.19
1165	Shunfeng Photovoltaic International			1.11	13/7/2011	0.99	-10.81	2.08	110.10	110.30
2098	Zall Development			2.89	13/7/2011	3.09	6.92	2.81	-9.06	-8.86
3777	China Fiber Optic Network System			1.20	14/7/2011	1.27	5.83	1.09	-14.17	-13.92
2123	Golden Shield			0.70	14/7/2011	0.60	-14.29	0.28	-53.33	-53.08
1259	Prince Frog International			2.60	15/7/2011	2.53	-2.69	5.08	100.79	100.75
6838	Winox			1.87	20/7/2011	1.91	2.14	0.91	-52.36	-51.81
1663	Sino Harbour Property			1.10	22/7/2011	1.13	2.73	0.75	-33.63	-31.13
1127	1010 Printing			0.70	25/7/2011	0.62	-11.43	1.00	61.45	63.29
6808	Sun Art Retail			7.20	27/7/2011	10.12	40.56	10.78	6.52	9.44
8112	Focus Media Network		Y	0.72	28/7/2011	0.76	5.56	0.60	-21.05	-18.01
1028	C.Banner			2.30	23/9/2011	1.96	-14.78	2.82	43.88	16.25
6868	Tenfu (Cayman)			6.00	26/9/2011	5.78	-3.67	3.90	-32.53	-63.85
1096	Active Group			1.20	28/9/2011	1.19	-0.83	0.81	-31.93	-58.85
1235	Travel Expert (Asia) Enterprises			0.63	29/9/2011	0.47	-25.40	0.65	38.30	11.38
3788	China Hanking			2.51	30/9/2011	2.45	-2.39	1.64	-33.06	-63.00
6030	Citic Securities	Y		13.30	6/10/2011	13.30	0.00	16.24	22.11	-13.03
8020	Chanceton Financial		Y	0.30	12/10/2011	0.32	5.00	2.96	839.68	813.08
6813	CapitaMalls Asia			7.76	18/10/2011	7.79	0.39	14.90	91.27	62.89
1206	Technovator International			1.00	27/10/2011	1.03	3.00	3.16	206.80	188.93
1152	Forton			0.50	28/10/2011	0.53	6.00	3.15	494.34	478.42
						Average	4.91		9.76	8.17

Notes: Y denotes yes.

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7 Can the forecasts generated from E/P ratio and bond yield be used to beat stock markets?

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Introduction

One of the earliest recorded uses of technical analysis was by Japanese rice traders in the 1700s. In the West, technical analysis started with the Dow Theory and has evolved to take on many forms since the 1900s. The fundamental principle of technical analysis is to identify and exploit market trends. This implicitly assumes that there is an uneven distribution of information, that `smart money' acts on information before it becomes public, and publicly available information like the price and volume will thus be affected. It is by applying technical analysis on such publicly available information that practitioners of technical analysis hope to follow the lead of `smart money' and in so doing earn profits. This is consistent with the idea of costly information addressed by Grossman & Stiglitz (1976) and Grossman (1976).

In fact, practitioners' reliance on technical analysis is well documented. Allen & Taylor (1989) show that for short horizons, about 90% of chief dealers use inputs from technical analysis to form expectations about price movements. Carter & Van Auken (1990) find that among investment managers, technical analysis is the second highest rated investment evaluation method. Frankel & Froot (1990) find that market professionals tend to include technical analysis when making market forecasts.

The popularity of technical analysis may stem from the notion that there is a tendency towards herding in the market, since a major use of technical analysis is for spotting and riding trends. DeLong, *et al.* (1990) develop the argument that rational investors may go along with the market herding behavior so as to achieve greater returns for themselves. Froot, *et al.* (1992) determines that this herding tendency is particularly noticeable for short-term traders. This could be why previous studies report positive autocorrelations for weekly returns, e.g. Lo & MacKinlay (1990) as well as Conrad & Kaul (1988).

On the other hand, many academics have long questioned the usefulness of such techniques, arguing that market efficiency leaves no room for technical analysis, which is based primarily on historical prices; e.g. Fama & Blume (1966), Jensen & Bennington (1970). In an efficient market, current prices reflect all publicly available information, and so historical prices convey nothing about future price movements. Also, efficient markets will discount the value of any recognized predictive tools because traders take advantage of them, and so even the best technical analysis may not be consistently reliable.

Nevertheless, many studies still stress the importance and usefulness of technical analysis to achieve an advantage in market timing. DeBondt, *et al.* (1985) find extreme loser stocks over a 3-5 year period tend to have strong returns relative to the market during the following years and vice-versa. Fama & French (1988) find that autocorrelation of returns becomes strongly negative for a 3-5 year horizon.

Sy (1990) demonstrates that market timing is increasingly rewarding when the difference in returns between cash and stocks is narrowed and when market volatility increases. Sweeney (1986) finds that small filters are profitable, after taking into account the interest expense, interest income and transaction costs. Muradoglu & Unal (1994) find that stock prices in the Turkish stock market are forecastable based on past price performance. Levich & Thomas (1993) find that simple technical trading rules often lead to excess profits. Finally, an important recent article by Lo *et al.* (2000) examines the prevalence of various technical patterns in American share prices during 1962-96 and finds the patterns to be unusually recurrent. The study does not prove that the patterns are predictable enough to make sufficient profit to justify the risk, but the authors conclude that this is likely[1].

Other studies have shown that some fundamental data like price-earnings ratios, dividend yields, business conditions and economic variables can predict to a large degree the returns on stocks, e.g. Campbell (1987), Breen *et al.* (1990) and Cochrane (1991). These studies conclude that traditional technical analysis could be combined with some economic or fundamental variables to produce some useful indicators. Wong (1993, 1994) introduced one such indicator, called the Standardized Yield Differential (*SYD*). It is based on the difference between the *E/P* ratio and the bond yield or the interbank interest rate. Ariff & Wong (1996) apply linear regression techniques to analyze the usefulness of the *SYD*, and find that there is a significant relationship between the *SYD* and share prices.

The present article extends Wong's (1993) work to study the predictive power of *SYD* to stock markets in two developed countries and one developing country. The finding is that applying the indicator enables investors to escape from most of the major crashes and catch most of the major bull runs in these countries. Two parametric test statistics are introduced to measure the performance of the *SYD* approach, and there is significant evidence that the trading signals provided by the indicator can generate significant profits. Also, the performance of the indicator is significantly better than the performance of the buy-and-hold strategy.

The article is summarized as follows: Section II below introduces the *SYD* indicator and discusses different scenarios for the market. Data, the hypotheses and the testing method are discussed in Section III while Section IV reveals the findings of applying Wong's *SYD* in monitoring the performance of the three stock markets. This article ends with a discussion in Section V of the usefulness and reliability of Wong's *SYD* model as a stock market index anticipator.

The standardized yield differential (SYD) indicator

Wong (1993, 1994) introduces a monthly indicator, the Standardized Yield Differential (*SYD*), which includes the *E/P* Ratio and the bond yield (*BY*) or interest rate. Note that the *E/P* ratio is the reciprocal of the *P/E* ratio.

This article examines the performance of applying Wong's *SYD* to the United States and Germany by using the ten-year treasury yield as the bond yield; and for Singapore using the three-month interbank rate since treasury yield figures are not available. The *E/P* ratio, EP_t at time t is a measure of market response to the earnings of all the firms in each stock market, calculated using the formula:

$$EP_t = \frac{E_t}{P_t} = \frac{\sum_{i=1}^{N} w_{i,t} E_{i,t}}{\sum_{i=1}^{N} w_{i,t} P_{i,t}} \quad (1)$$

where $E_{i,t}$ is the average earning per share for stock i at time t, $P_{i,t}$ is the average stock price for stock i at time t, $w_{i,t}$ is the weight of the stock i in the corresponding index, and N is the number of stocks in the stock market index used[2].

The monthly yield differential, YD_t, at time t is defined as

$$YD_t = EP_t - BY_t \quad (2)$$

where EP_t is defined in (1) and BY_t is the bond yield or interest rate at time t. The standardized yield differential at time t over k months, $SYD_{t,k}$ is calculated as:

$$SYD_{t,k} = \frac{YD_t - \overline{YD}_{t,k}}{SD(YD_{t,k})} \quad (3)$$

where $\overline{YD}_{t,k}$ and the standard deviation $SD(YD_{t,k})$ are defined as:

$$\overline{YD}_{t,k} = \frac{\sum_{i=t-k+1}^{t} YD_i}{k}$$

and

$$SD(YD_{t,k}) = \sqrt{\frac{\sum_{i=t-k+1}^{t} (YD_i - \overline{YD}_{t,k})^2}{k-1}}$$

For simplicity, the subscript k is dropped in subsequent sections. The value of k should be from 24 to 36 months as this will capture reasonably long periods to compute *SYD*. However, an investor who believes the bull market has been going too long (like Japan in 1989) may want to take a longer period, say 60 months, to capture the long run effect. The moving average technique is common in time series analysis and in technical analysis. $SYD_{t,k}$ is a standardized measure of a moving average.

Large values of SYD_t mean that (1) yield differential, *YD*, is large relative to the mean monthly differential $\overline{YD}_t$ and (2) the yield from equity is relatively higher than the yield from bonds.

In itself, the SYD_t does not explicitly signal a trend for the stock market, or predict what the economy will be like in the future. How the SYD_t indicator is applied and interpreted in the stock market depends largely on the decision of the investors under different market conditions. Below, two possible scenarios in how to use the SYD_t indicator are discussed.

Scenario A:

Large positive values of SYD_t are possible provided the current yield differential, YD_t, is large relative to the mean monthly differential $\overline{YD}_t$. This situation may be due to a stock market correction, an increase in corporate profit, or a fall in bond/cash yield. These conditions occur during bullish periods for equities. In this respect, large positive values for SYD_t

indicate that stock prices are likely to rise in the near future and hence it pays to invest in stocks. On the other hand, large negative SYD_t *values indicate that the stock prices are likely to fall in the near future. The present study tests the performance of* SYD_t *based on this interpretation.*

Scenario B:

Bull runs could be fueled by expectations of better economic prospects, which are reflected in a declining E/P ratio until the higher earnings are reported. A high E/P ratio may be indicative of poor economic prospects or a lack of confidence in the future earnings of an enterprise. Thus, a large positive SYD_t *value indicates that stock prices are likely to fall in the future; and a large negative* SYD_t *indicates that stock prices are likely to rise in the future.*

Market analysts can apply the SYD_t in different ways. As the market is a combination of many varied scenarios, one should be able to obtain better results through applying the SYD_t if one is able to clearly distinguish Scenario A, Scenario B, and the other scenarios in the market. However, for Scenario B, a wider range of economic variables is required before the SYD_t can be put to test. In this article, a simplistic approach is adopted without involving other economic variables except for the *E/P* ratios, bond yields and the interest rates; and the performance of the SYD_t is examined only for Scenario A. If SYD_t were found to be useful for Scenario A, it should also be useful for the market in general.[3]

Data, test method and hypotheses

The data collected are month-end stock index values, risk-free yields on 10-year Treasuries (three-month interbank rates for the Singapore market), and the *E/P* ratio in each of the three markets, namely the United States, Germany and Singapore. The period tested is from January 1975 to December 1994. The set of data covers as far back as three years before the test period, but testing has to begin from 1975 in view of the need to compute the initial *SYD* base figure using the first three years' data.

Stock indices are available from the Center for Research in Security Prices (CRSP) at the University of Chicago. The data on *E/P* ratios and the Singapore three-month interbank rates are collected from Morgan Stanley Capital International publications, while the bond yields on 10-year Treasury bonds are obtained from the Chicago Federal Reserve Board. From these two sets of yield data, a time series of standardized yield differential, SYD_t is calculated according to Equation (3). Monthly return (r_t) is calculated from the monthly close of the stock index as the log-return.

In order to utilize the SYD_t indicator, assume that investors will buy (sell) when the SYD_t indicates a buy (sell) signal, say at time t and sell (buy) when the SYD_t indicates a sell (buy) signal, say at time $t+n_t$. Then the aggregate return S_{t,n_t} will be

$$S_{t,n_t} = \sum_{i=1}^{n_t} r_{t+i} \tag{4}$$

For simplicity, S_{t,n_t} is denoted as S_t . The size of n_t depends on the buy and sell signals. For example, in Table 2A, the smallest size for n_t is 1 (month) and the largest size is 29 (months).

To check whether the *SYD* is (significantly) useful is equivalent to checking whether S_t is (significantly) greater than zero in a long position and is (significantly) less than zero in a short position. Assuming r_t is distributed as $N(\mu_t$, $\sigma_t^2)$, letting $cov(r_t, r_s) = \sigma_{t,s}$ with estimate $\hat{\sigma}_{t,s}$ and letting $\mu_{S_t} = \sum_{i=1}^{nt} \mu_{t+i}$, then the test statistic

$$T_t = \frac{S_t}{\sqrt{\sum_{i=1}^{n_t} \sum_{j=1}^{n_t} \hat{\sigma}_{t+i,t+j}}} \tag{5}$$

Will be approximately distributed as $N(0,1)$ if μ_{S_t} is 0. Testing the hypothesis $H_0 : \mu_{S_t} = 0$ against $H_1 : \mu_{S_t} > 0$ is to test whether the return is profitable and testing the hypothesis $H_0 : \mu_{S_t} = n_r \times \mu_r$ against $H_1 : \mu_{S_t} > n_r \times \mu_r$ is to test whether the *SYD* approach is better than the buy-and-hold strategy where r is the market return for the entire period with mean μ_r.

If n_t is large, it is not necessary to impose the normality assumption on r_t as T_t will still approach the standard normal distribution by virtue of the law of large numbers. Moreover, it is well-known that r_t is not iid (independent and identically distributed) normal, for example, see Fama (1965), Fama & French (1988) for the violation of the normality assumption and see Lo & MacKinlay (1990) and Conrad & Kaul (1988) for the violation of the independence assumption. In conclusion, the profit generated by using the *SYD* is significantly greater than zero if

$$\begin{cases} T_t > z_\alpha & \text{in a long position} \\ T_t < -z_\alpha & \text{in a short position} \end{cases}$$

where z_α is the value such that $\alpha = P(Z > z_\alpha)$ and Z follows a standardized Normal distribution.

To check whether the *SYD* approach (significantly) outperforms the buy-and-hold strategy, it is necessary to test whether the return from applying the *SYD* is (significantly) greater than the return from using the buy-and-hold strategy. First assume that $\overline{S_t}$ is independent of $\overline{r}$ without loss of generality and apply the following test statistic:

$$T'_t = \frac{\overline{S_t} - \overline{r}}{\sqrt{\sum_{i=1}^{n_t}\sum_{j=1}^{n_t}\hat{\sigma}_{t+i,t+j} \big/ n_r + \hat{\sigma}_r^2 \big/ N}} \tag{6}$$

where $\overline{S_t} = S_t / n_t$, r and $\hat{\sigma}_r$ are the sample mean and the sample standard deviation respectively of the return r derived by using the entire period. N is the number of observations in the entire period. The $\bar{r}$ is approximately equal to the actual mean return μ_r with very small standard deviation due to very large N. T'_t is approximately distributed as N(0, 1) when the return from *SYD* is the same as the return from the buy-and-hold strategy.

Using the *SYD* approach is significantly better than using the buy-and-hold strategy if

$$\begin{cases} T_t > z_\alpha & \text{in a long position} \\ T_t < -z_\alpha & \text{in a short position} \end{cases}$$

The test statistics in (5) and (6) take into consideration that r_t may be autocorrelated.

If r_t is not autocorrelated, (5) and (6) can be simplified. To check for autocorrelation, the sample autocorrelation function for the return r_t for each market should be significantly different from zero. If the return r_t is not autocorrelated, the sample autocorrelation function $\hat{\rho}_k$ of r_t will be distributed as N(0,1/n), see Box and Jenkins (1976). Hence, to test the hypothesis $H_0 : \rho_k = 0$ against $H_1 : \rho_k \neq 0$, the p-value of the test z = $\hat{\rho}_k / \sqrt{1/n}$ is calculated for each k from 1 to 24 and the p-value of Ljung-Box-Pierce Q-statistic for k = 6, 12, 18 and 24. The results are shown in Tables 1A-1C. Note that the sample means for r_t are 0.00762, 0.00690 and 0.0112 and the sample standard deviations for r_t are 0.0446, 0.0503 and 0.0736 respectively for the U.S., German and Singapore stock markets.

Table 1A. $\hat{\rho}_k$, *Q statistic, p-values for return in the U.S.*

K	1	2	3	4	5	6	Q-stats
$\hat{\rho}_k$	0.039	-0.043	-0.020	-0.061	-0.001	-0.075	2.66
p-val	0.548	0.512	0.761	0.347	0.982	0.249	0.85
K	7	8	9	10	11	12	Q-stats
$\hat{\rho}_k$	-0.050	-0.038	-0.082	0.066	0.055	0.005	6.30
p-val	0.442	0.563	0.206	0.311	0.400	0.941	0.90
K	13	14	15	16	17	18	Q-stats
$\hat{\rho}_k$	-0.026	-0.080	-0.025	0.025	-0.125	-0.036	9.18
p-val	0.689	0.217	0.704	0.705	0.053	0.577	0.96
K	19	20	21	22	23	24	Q-stats
$\hat{\rho}_k$	-0.145	0.017	-0.104	-0.020	-0.056	0.033	15.88
p-val	0.025	0.791	0.108	0.753	0.390	0.606	0.89

Table 1B. $\hat{\rho}_k$, *Q statistic, p-values for return in Germany*

K	1	2	3	4	5	6	Q-stats
$\hat{\rho}_k$	0.115	-0.065	0.050	0.011	-0.075	-0.090	7.83
p-val	0.074	0.316	0.436	0.856	0.244	0.161	0.251
K	7	8	9	10	11	12	Q-stats
$\hat{\rho}_k$	-0.039	-0.006	0.034	0.108	0.018	-0.034	12.14
p-val	0.545	0.917	0.592	0.092	0.777	0.592	0.434
K	13	14	15	16	17	18	Q-stats
$\hat{\rho}_k$	-0.043	-0.057	-0.075	-0.120	-0.025	0.120	19.77
p-val	0.506	0.372	0.244	0.062	0.689	0.063	0.346
K	19	20	21	22	23	24	Q-stats
$\hat{\rho}_k$	-0.121	-0.145	0.035	0.035	0.091	-0.002	29.53
p-val	0.059	0.024	0.581	0.580	0.159	0.969	0.201

Table 1C: $\hat{\rho}_k$ *, Q statistic, p-values for return in Singapore*

K	1	2	3	4	5	6	Q-stats
$\hat{\rho}_k$	0.123	-0.032	-0.120	-0.039	-0.111	-0.119	9.90
p-val	0.056	0.620	0.063	0.546	0.085	0.064	0.129
K	7	8	9	10	11	12	Q-stats
$\hat{\rho}_k$	-0.092	-0.027	0.009	0.030	0.142	0.022	18.87
p-val	0.152	0.673	0.884	0.633	0.027	0.725	0.092
K	13	14	15	16	17	18	Q-stats
$\hat{\rho}_k$	-0.006	-0.175	-0.076	-0.090	-0.091	-0.064	29.62
p-val	0.923	0.006	0.235	0.162	0.158	0.320	0.041
K	19	20	21	22	23	24	Q-stats
$\hat{\rho}_k$	-0.032	-0.059	-0.016	0.055	0.051	0.044	39.26
p-val	0.619	0.362	0.797	0.389	0.425	0.492	0.026

The results from the above tables verify the hypothesis that the return is not autocorrelated and hence the statistics in (5) and (6) can be simplified to:

$$T_t = \frac{\overline{S}_t}{\hat{\sigma}_r \sqrt{1/n_t}} \tag{7}$$

And

$$T'_t = \frac{\overline{S}_t - \overline{r}}{\hat{\sigma}_r \sqrt{1/n_t + 1/N}} \tag{8}$$

respectively where n_t is defined in (4) and $\hat{\sigma}_r$ and N are defined in (6). For simplicity T will be used in place of T_{tt} and T' in place of T'_t in the next section[4].

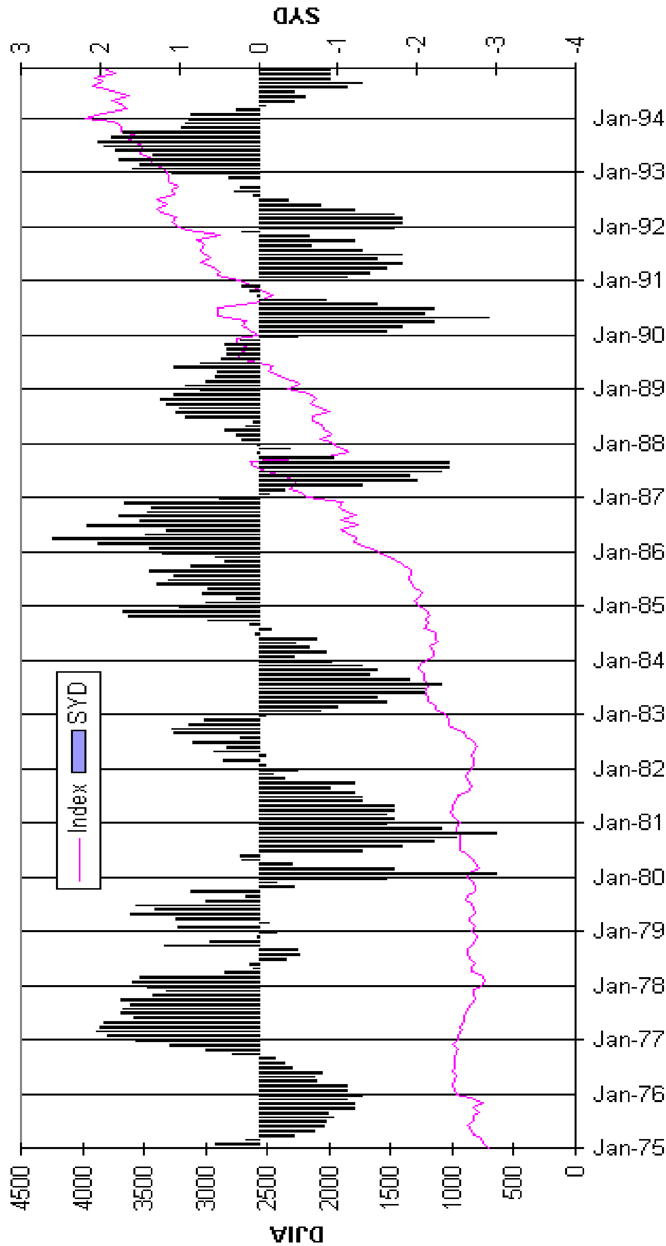
Recall that in this study the *SYD* is only applied under Scenario A, which assumes that a large positive value of *SYD* would be followed by upward price movement in the future, while large negative values would be followed by downward price movement in the future. Under this scenario, one may vary the values of *SYD* as market entry/exit points, or use it in different ways just like the other indicators. For example, one may buy when *SYD* reaches 2 from the south while another may buy when *SYD* reaches 2 from the north. To illustrate, the performance is analyzed by setting this rule: Categorical values greater than +2 (less than -2) indicate strong buy (sell) signals while values between 0 and 2 (between -2 and 0) indicate weak buy (sell) signals. Investors will buy when *SYD* reaches the predetermined value from the south and sell when *SYD* reaches the predetermined value from the north. If *SYD* works well under such a rule, it should be useful for the market if investors are able to apply it with different categorical values to determine entry/exit points.

For Scenario A, the *SYD* values of greater than +1/+2 indicate a strong buy signal, while *SYD* values of less than -1/-2 show strong sell signals (refer to the discussion and the charts in the next section). It is not necessary to impose the assumption of normality of the indicator *SYD*, but just use the concept of normality to select the pre-determined entry or exit point, e.g. knowing that $P(Z \geq 0) = .5$, $P(Z \geq 1) \approx .16$ and $P(Z \geq 2) \approx .025$. Hence, 0, ± 1 and ± 2 are used as predetermined values in the study.

For simplicity, only three sets of buy and sell points are tested (Strategies A to C). The first strategy, i.e. Strategy A, is to buy when the *SYD* reaches zero from the south and sell when it reaches zero from the north. The second strategy, i.e. Strategy B, with the distance between the points at 1 unit, is to buy when the *SYD* reaches zero from the south and sell when it reaches -1 from the north. Finally, the third Strategy C, where the distance between the points is at 2 units, is to buy/sell when *SYD* reaches 1/ -1 in a similar way. The sets of trading rules are summarized as follows:

Strategy	Buy Point	Sell Point	Distance Between Points
A	0	0	0
B	0	-1	1
C	1	-1	2

Figure 1: United States and 2-year SYD



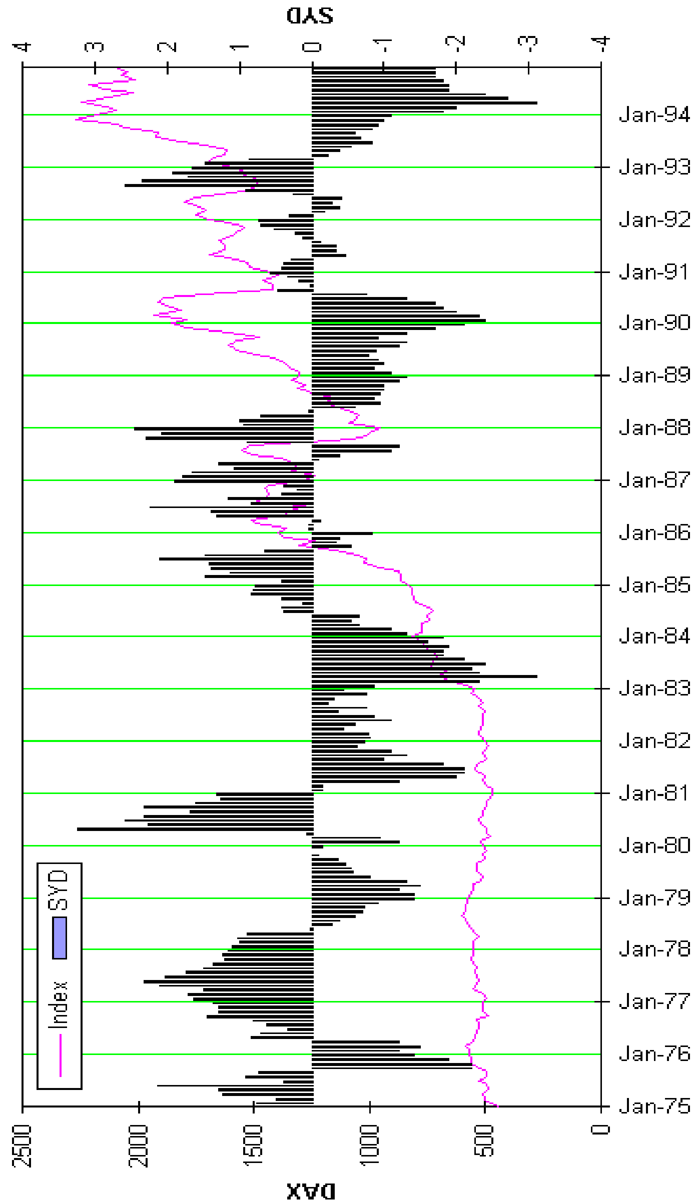
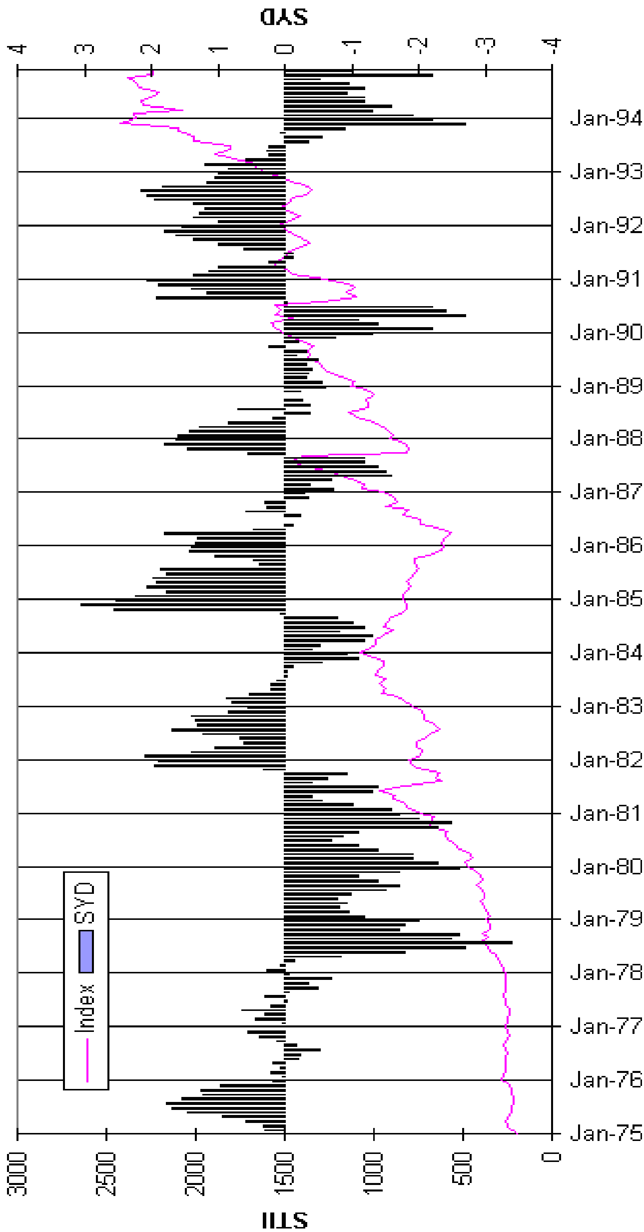


Figure 2 : Germany and 2-year SYD

Figure 3 : Singapore and 2-year SYD



Findings

To better illustrate the findings from the strategies discussed in the previous section, the 2-year (24-month) *SYD* and the stock indices (DJIA, DAX and STII) are plotted for the U.S., German and Singapore markets in Figures 1, 2 and 3 respectively.

In Figure 1 (for the U.S. market), using *SYD* = –1 (i.e. *SYD* reaches the value –1 from the north) or *SYD* = –2 (i.e. *SYD* reaches the value –2 from the north) as the sell strategy enables the investor to escape the stock market crashes of 1987 and 1990. In addition, better returns can be obtained by adopting *SYD* = –2 as the sell strategy. When *SYD* = 0 (i.e. *SYD* reaches 0 from the south) is adopted as the buy strategy, investors are able to ride on the bull runs between 1984 and 1988. The tools for technical analysis employed here undoubtedly bring better returns for the investors.

In Figure 2 (for the German market), using *SYD* = –1 as the sell strategy enables the investor to escape from the stock market crash in 1987. On the other hand, using *SYD* = –2 as the sell strategy not only results in better returns but also in the avoidance of the stock market crash in 1990. And if *SYD* = 0 is adopted as the buy strategy, investors are able to ride on the bull runs during the periods 1984-1986 and 1990-1994. Also, using *SYD* = 1 as the buy strategy results in better returns in the 1988-1990 bull market.

In Figure 3 (Singapore market), using any value of *SYD* between –1 and –2 as the sell strategy helps investors escape from the stock market crash in 1987. By waiting until the *SYD* rebounds from the bottom before taking further action, better returns can be achieved. Similarly, using any value of *SYD* between –1 and –2 as the sell strategy results in the avoidance of the stock market crash in 1990. In addition, using *SYD* $\geq$ 1 as buying strategy and *SYD* = –2 as sell strategy enables the bull runs in 1988-1990 and 1990-1994 to be captured completely.

From Figures 1 to 3, it is clear that an investor needs to set different values for *SYD* at different times to optimize the returns from the stock market. An investor may buy when

SYD reaches a predetermined value, or wait until it drops from the peak to a predetermined value, as he thinks acceptable.

Hence, there is no hard-and-fast rule for investors to set the *SYD* values. While it is evident that the above *SYD* approach does produce convincing and impressive results, *SYD* cannot be used as a foolproof tool for predicting the stock market movement. This can be seen from Figure 1, where incorrect sell signals occurred between 1991 & 1992. There are also incorrect sell signals between 1981 & 1983 in Figure 2; and between 1978 & 1980 in Figure 3. Nevertheless, so far nearly all the buy signals are correct. This could be attributed to the fact that the testing period under this study is, on the whole, a bull market.

The occurrence of incorrect signals could be attributed to the fact that only Scenario A is considered. Clearly, *SYD* should be a more effective tool to predict stock market movement if one could distinguish Scenario A from Scenario B and other scenarios.

For simplicity, only the effect of applying 2-year (24-month), 2½-year (30-month) and 3-year (36-month) *SYD* to the U.S., German and Singapore markets were studied, and only the following results reported:

- significant and insignificant trades arising from the use of 2-year *SYD* and Strategy A for the U.S. markets, as shown in Table 2A;
- significant trades arising from the use of 2-year *SYD* and Strategies B & C for the U.S. markets, as shown in Table 2B;
- significant trades arising from the use of 2-year *SYD* and Strategies A, B & C for the German and Singapore markets, as shown in Tables 3 and 4 respectively.

Refer to Chew (1997) for the detailed report. These tables contain information about entry date, entry price, entry *SYD* value, exit date, exit price, exit *SYD* value, total months of holding between entry and exit, aggregate return S for the trading, T and T', where S is defined in Equation (4), T is the value of the test statistic in (7) while T' is the value of the test statistic in (8). '***','**'and'*'are used to denote statistics which are significant at the 1%, 5% and 10% levels of significance respectively and the statistics are the right sign, and'###','##'and'#'are used to denote statistics which are significant at the 1%, 5% and 10% levels of significance respectively but the wrong sign.

Table 2A. *Using the 2-Yr SYD & Strategy A for the U.S. Market*

Pos.	Entry Date	entry price	entry SYD	exit Date	exit price	exit SYD	mths	agg. ret.	T	T'
Short	Apr-75	831.0	-0.45	Oct-76	966.1	0.32	18	0.15	0.80	0.07
Long	Oct-76	966.1	0.32	Jul-78	860.7	-0.34	21	-0.12	-0.57	-1.29#
Short	Jul-78	860.7	-0.34	Oct-78	827.8	1.19	3	-0.04	-0.50	-0.80
Long	Oct-78	827.8	1.19	Jan-79	840.9	-0.23	3	0.02	0.20	-0.09
Short	Jan-79	840.9	-0.23	Feb-79	815.8	1.02	1	-0.03	-0.68	-0.85
Long	Feb-79	815.8	1.02	Mar-79	855.3	-0.14	1	0.05	1.06	0.89
Short	Mar-79	855.3	-0.14	Apr-79	855.5	1.04	1	0.00	0.01	-0.17
Long	Apr-79	855.5	1.04	Nov-79	819.6	-0.43	7	-0.04	-0.36	-0.80
Short	Nov-79	819.6	-0.43	May-80	847.4	0.20	6	0.03	0.31	-0.11
Long	May-80	847.4	0.20	Jul-80	931.5	-1.30	2	0.09	1.50*	1.25
Short	Jul-80	931.5	-1.30	Mar-82	833.2	0.45	20	-0.11	-0.56	-1.27
Long	Mar-82	833.2	0.45	Apr-82	849.0	-0.08	1	0.02	0.42	0.25
Short	Apr-82	849.0	-0.08	May-82	815.0	0.56	1	-0.04	-0.92	-1.08
Long	May-82	815.0	0.56	Jan-83	1060.0	-0.07	8	0.26	2.08**	1.57*
Short	Jan-83	1060.0	-0.07	Jul-84	1135.0	0.04	18	0.07	0.36	-0.35
Long	Jul-84	1135.0	0.04	Aug-84	1224.0	-0.15	1	0.08	1.69**	1.52*
Short	Aug-84	1224.0	-0.15	Sep-84	1199.0	0.11	1	-0.02	-0.46	-0.63
Long	Sep-84	1199.0	0.11	Feb-87	2220.0	-0.13	29	0.62	2.56***	1.55*
Short	Feb-87	2220.0	-0.13	Nov-87	1842.0	0.02	9	-0.19	-1.40*	-1.87**
Long	Nov-87	1842.0	0.02	Dec-87	1939.0	-0.40	1	0.05	1.15	0.98
Short	Dec-87	1939.0	-0.40	Jan-88	1945.0	0.01	1	0.00	0.07	-0.10
Long	Jan-88	1945.0	0.01	Jan-90	2586.0	-0.48	24	0.28	1.30*	0.44
Short	Jan-90	2586.0	-0.48	Oct-90	2455.0	0.02	9	-0.05	-0.39	-0.88
Long	Oct-90	2455.0	0.02	Jan-91	2731.0	-0.01	3	0.11	1.38*	1.08
Short	Jan-91	2731.0	-0.01	Dec-91	3170.0	0.21	11	0.15	1.01	0.43
Long	Dec-91	3170.0	0.21	Jan-92	3223.0	-1.70	1	0.02	0.37	0.20
Short	Jan-92	3223.0	-1.70	Aug-92	3257.0	0.06	7	0.01	0.09	-0.36
Long	Aug-92	3257.0	0.06	Nov-92	3305.0	-0.02	3	0.01	0.19	-0.11
Short	Nov-92	3305.0	-0.02	Dec-92	3301.0	0.38	1	0.00	-0.03	-0.20
Long	Dec-92	3301.0	0.38	Apr-94	3682.0	-0.09	16	0.11	0.61	-0.07
Short	Apr-94	3682.0	-0.09	Nov-94	3739.0	0.00	7	0.02	0.13	-0.32

Table 2A tabulates the results arising from the use of 2-year *SYD* and Strategy A for the U.S. market. The following details are obtained from the table:

1. There are 31 trades. Among them, 15 are long and 16 are short.

(a) Of the 15 long trades, 13 show the correct sign for statistic T whereas out of the 16 short, 8 show the correct sign for T.

(b) Of the 15 long trades, 10 show the correct sign for statistic T' whereas of the 16 short trades, 14 show the correct sign for T'.

2. There are 6 significant and correctly-signed long trades, 1 at the 1% level, 2 at the 5% level and the other 3 at the 10% level for T.

3. There is 1 correctly signed short trade that is significant at the 10% level for T.

4. There are 3 long trades with correct signs, all are significant at the 10% level for T'.

5. There is 1 short trade with correct sign, significant at the 5% level for T'.

6. There is only 1 long trade with incorrect sign, significant at the 10% level for T'.

7. There is no significantly incorrectly signed trade for T.

From (1a), (2), (3) and (7), it can be concluded that applying the *SYD* can result in significantly better returns than holding cash. Chew (1997) had studied the situation with the inclusion of interest earned and drew the same conclusion. Hence, the interest earned while holding cash was not considered. From (1b), (4), (5) and (6), it can be concluded that applying the *SYD* is significantly better than using the buy-and-hold strategy.

The same conclusion can be drawn from Tables 2B to 4. Similarly, the hypotheses can be tested by using the 2½-year *SYD*, the 3-year *SYD* or *SYD*s of other periods. In this article, the results are presented for the 2-year, 2½-year and 3-year *SYD*. To be concise, the details of applying the 2½-year *SYD* and the 3-year *SYD* are omitted, with only a summary of the results provided here. Refer to Chew (1997) for further details.

Table 2B. *Using the 2-Year SYD for the U.S. Market*

Pos.	Entry Date	entry price	entry SYD	Exit Date	exit price	exit SYD	mth	aggregate return	T	T'
				Use Strategy B						
Long	Oct-76	966.1	0.32	Jan-80	881.5	-1.60	39	-0.09	-0.33	-1.29#
Long	May-80	847.4	0.20	Jul-80	931.5	-1.30	2	0.09	1.50*	1.25
Long	Mar-82	833.2	0.45	Mar-83	1130.0	-1.00	12	0.30	1.97**	1.35*
Long	Jul-84	1135.0	0.04	Apr-87	2280.0	-1.30	33	0.70	2.72***	1.63*
Sht.	Apr-87	2280.0	-1.30	Nov-87	1842.0	0.02	7	-0.21	-1.81**	-2.23**
Long	Nov-87	1842.0	0.02	Feb-90	2636.0	-1.60	27	0.36	1.55*	0.62
Long	Oct-90	2455.0	0.02	Feb-91	2910.0	-1.10	4	0.17	1.91**	1.55*
				Use Strategy C						
Long	Dec-76	999.8	1.12	Jan-80	881.5	-1.60	37	-0.13	-0.46	-1.40#
Long	Sep-82	907.7	1.07	Mar-83	1130.0	-1.00	6	0.22	2.01**	1.57*
Long	Nov-84	1182.0	1.65	Apr-87	2280.0	-1.30	29	0.66	2.74***	1.71**
Sht.	Apr-87	2280.0	-1.30	Aug-88	2002.0	1.05	16	-0.13	-0.73	-1.37*
Long	Aug-88	2002.0	1.05	Feb-90	2636.0	-1.60	18	0.28	1.45*	0.70

Table 3. *Results of Using the 2-Yr SYD for the German Market*

Pos.	Entry Date	entry price	entry SYD	Exit date	exit price	exit SYD	Mth	agg. Ret.	T	T'
				Use Strategy A						
Sht	Feb-81	473.7	-0.14	Jul-84	729.4	0.37	41	0.43	1.34#	0.43
Long	Jul-84	729.4	0.37	Oct-85	1301.0	-0.55	15	0.58	2.97***	2.37***
Long	Feb-86	1361.0	0.05	Apr-86	1507.0	-0.13	2	0.10	1.43*	1.23
Sht	Apr-86	1507.0	-0.13	May-86	1369.0	1.30	1	-0.10	-1.91**	-2.04**
Sht	Jun-87	1383.0	-0.09	Oct-87	1164.0	0.88	4	-0.17	-1.71**	-1.97**
				Use Strategy B						
Long	Jul-84	729.4	0.37	Aug-87	1548.0	-1.10	37	0.75	2.46***	1.51*
Sht	Aug-87	1548.0	-1.10	Oct-87	1164.0	0.88	2	-0.29	-4.01***	-4.18***
Long	Sep-90	1421.0	0.47	Dec-93	2268.0	-1.00	39	0.47	1.49*	0.59
				Use Strategy C						
Sht	Apr-81	510.4	-1.20	Mar-85	865.0	1.46	47	0.53	1.53#	0.54
Long	Mar-85	865.0	1.46	Aug-87	1548.0	1.10	29	0.58	2.15**	1.33*
Sht	Aug-87	1548.0	-1.10	Nov-87	1030.0	2.28	3	-0.41	-4.68***	-4.88***
Long	Nov-87	1030.0	2.28	Oct-88	1311.0	-1.00	11	0.24	1.45*	0.97
Long	Sep-92	1484.0	2.57	Dec-93	2268.0	-1.00	15	0.42	2.18**	1.60*

Table 4. *Using the 2-Year SYD for the Singapore Market*

Pos.	Entry Date	entry price	entry SYD	exit date	exit price	exit SYD	mth	agg. ret.	T	T'
				Use Strategy A						
Sht	Apr-78	304.5	-0.15	Nov-81	758.7	0.31	43	0.91	1.89##	0.82
Long	Jul-86	741.9	0.01	Aug-86	838.5	-0.23	1	0.12	1.66**	1.51*
Long	Oct-87	818.6	0.56	Jul-88	1143.0	-0.38	9	0.33	1.51*	1.04
Sht	Jul-88	1143.0	-0.38	Aug-88	1037.0	0.71	1	-0.10	-1.32*	-1.47*
Sht	Nov-89	1411.0	-0.21	Sep-90	1099.0	1.90	10	-0.25	-1.07	-1.52*
Long	Sep-90	1099.0	1.90	Jun-91	1490.0	-0.13	9	0.30	1.38*	0.91
				Use Strategy B						
Shrt	Jun-78	348.2	-1.80	Nov-81	758.7	0.31	41	0.78	1.65##	0.63
Sht	May-87	1220.0	-1.60	Oct-87	818.6	0.56	5	-0.40	-2.42***	-2.74***

Long	Oct-87 818.6 0.56	Jan-90 1515.0 -1.30	27 0.62	1.61* 0.78
Sht	Jan-90 1515.0 -1.30	Sep-90 1099.0 1.90	8 -0.32	-1.54* -1.94**
Long	Sep-90 1099.0 1.90	Dec-93 2426.0 -2.70	39 0.79	1.72** 0.72
		Use Strategy C		
Sht	Jun-78 348.2 -1.80	Dec-81 780.8 1.93	42 0.81	1.69## 0.65
Sht	Dec-83 1002.0 -1.10	Nov-84 817.6 2.56	11 −0.20	-0.83 -1.31*
Sht	May-87 1220.0 -1.60	Nov-87 800.0 1.44	6 −0.42	-2.34*** -2.68***
Long	Nov-87 800.0 1.44	Jan-90 1515.0 -1.30	26 0.64	1.70** 0.88
Sht	Jan-90 1515.0 -1.30	Sep-90 1099.0 1.90	8 −0.32	-1.54* -1.94**
Long	Sep-90 1099.0 1.90	Dec-93 2426.0 -2.70	39 0.79	1.72** 0.72

Table 5 tabulates the proportion of points with the correct sign. The results show that there are much more trades with the correct sign than with incorrect sign for both long and short positions as well as for both *T* and *T*′. Using selected results from Table 5 as an example; looking at the statistics *T* for long positions in the U.S. market, there are 15, 8 and 5 trades generated by the *SYD* for Strategies A, B and C respectively using the 2-Year *SYD*. Among these, there are 13, 7 and 4 correct trades respectively. Note that there are 2 (15–13), 1 (8–7) and 1 (5–4) incorrect trades generated by the *SYD* for Strategies A, B and C respectively.

The results in Table 5 support the hypotheses that:

1. Applying the *SYD* approach can generate better returns than holding cash.
2. The *SYD* approach is better than the buy-and-hold strategy.

Table 5. *Proportion of Periods with Correct Sign*

	SYD for T			SYD for T′		
Strategy	2-Yr	2½-Yr	3-Yr	2-Yr	2½-Yr	3-Yr
Long Position for the U.S. Market						
A	13/15	12/14	9/10	10/15	10/13	9/10
B	7/8	4/5	4/5	6/7	4/5	4/5
C	4/5	3/4	3/3	4/5	3/4	2/3
Short Position for the U.S. Market						
A	8/16	7/15	5/11	14/16	13/15	8/11
B	5/9	4/6	3/5	7/9	6/6	5/5
C	1/5	2/4	1/3	4/5	4/4	2/3
Long Position for the German Market						
A	7/8	8/10	6/7	4/9	5/11	2/8
B	5/5	5/5	4/5	3/5	3/5	3/5
C	6/6	6/6	4/6	4/6	4/6	4/6

Short Position for the German Market						
A	5/10	5/12	3/9	6/10	6/12	4/9
B	3/6	3/6	3/6	5/6	5/6	5/6
C	3/5	2/5	1/5	4/5	4/5	4/5
Long Position for the Singapore Market						
A	9/13	7/10	8/9	8/12	5/10	7/9
B	5/5	5/5	4/4	4/4	4/4	3/4
C	5/5	5/5	4/4	4/5	3/5	2/4
Short Position for the Singapore Market						
A	7/13	6/10	6/9	10/13	7/10	7/9
B	3/4	3/4	2/3	3/4	3/4	2/3
C	3/4	3/4	2/3	3/4	3/4	2/3

To further investigate the effects of applying the *SYD*, the significant statistics in Tables 6A-C are summarized. The results reflect many significant (1%, 5% as well as 10%) long and short trades with correct sign in all the markets. On the other hand, there are hardly any significant trades generated by the *SYD* with incorrect sign for both *T* and *T'*. For example, looking at the statistics *T*, Table 6A shows that when the 2-year *SYD* is used with Strategy A for the U.S. market, there are 6 significant long trades and 1 significant short trade with the correct sign but no trades generated with incorrect sign. These results further support the hypotheses 1 and 2 above that

1. applying the *SYD* approach can generate significantly better returns than holding cash, and
2. the *SYD* approach is significantly better than the buy and hold strategy.

Table 6A[5]**.** *Number of Significant Periods Generated from the SYD for the U.S. Market*

Strategy	2-Year SYD			2½-Year SYD			3-Year SYD			Total
	1%	5%	10%	1%	5%	10%	1%	5%	10%	
Long Position for T with Correct Sign										
A	1	3	6	1	3	4	1	1	3	
B	1	3	5	1	2	4	1	3	4	
C	1	2	3	1	2	2	0	2	2	63
Short Position for T with Correct Sign										

A	0	0	1	0	1	1	0	1	1	
B	0	1	1	0	1	1	0	2	2	
C	0	0	0	0	0	0	0	0	0	13
Short Position for T with Incorrect Sign										
A	0	0	0	0	0	0	0	0	0	
B	0	0	0	0	0	0	0	0	0	
C	0	0	0	0	0	0	0	0	1	1
Long Position for T' with Correct Sign										
A	0	0	3	0	2	3	0	1	1	
B	0	0	3	0	0	2	0	1	2	
C	0	1	2	0	1	2	0	0	1	25
Long Position for T' with Incorrect Sign										
A	0	0	1	0	0	1	0	0	1	
B	0	0	1	0	0	0	0	0	0	
C	0	0	1	0	0	0	0	0	0	6
Short Position for T' with Correct Sign										
A	0	1	1	0	1	1	0	1	1	
B	0	1	1	0	1	1	1	2	2	
C	0	0	1	0	0	0	0	0	1	17

Table 6B[6]. *Number of Significant Periods Generated from the SYD for the German Market*

Strategy	2-Year SYD			2½-Year SYD			3-Year SYD			Total
	1%	5%	10%	1%	5%	10%	1%	5%	10%	
Long Position for T with Correct Sign										
A	1	1	2	1	2	3	1	1	2	
B	1	1	2	1	1	2	0	1	2	
C	0	2	3	0	1	3	0	2	2	38
Short Position for T with Correct Sign										
A	0	2	2	1	1	1	1	1	1	
B	1	1	1	1	1	1	1	1	1	
C	1	1	1	1	1	1	1	1	1	28
Short Position for T with Incorrect Sign										
A	0	0	1	0	0	0	0	0	1	
B	0	0	0	0	0	0	0	0	1	
C	0	0	1	0	1	1	0	1	1	8
Long Position for T' with Correct Sign										
A	1	1	1	1	1	2	1	1	1	
B	0	0	1	0	0	1	0	0	1	
C	0	0	2	0	0	1	0	0	1	17
Short Position for T' with Correct Sign										
A	0	2	2	1	1	2	1	1	1	
B	1	1	1	1	1	1	1	1	1	
C	1	1	1	1	1	1	1	1	1	29

Table 6C7. *Number of Significant Periods Generated from the SYD for the Singapore Market*

Strategy	2-Year SYD			2½-Year SYD			3-Year SYD			Total
	1%	5%	10%	1%	5%	10%	1%	5%	10%	
Long Position for T with Correct Sign										
A	0	1	3	0	0	2	0	0	3	
B	0	1	2	0	1	2	0	2	3	
C	0	2	2	0	2	2	0	2	2	32
Short Position for T with Correct Sign										
A	0	0	1	0	0	2	1	1	3	
B	1	1	2	1	1	2	1	2	2	
C	1	1	2	1	1	2	1	1	1	32
Short Position for T with Incorrect Sign										
A	0	1	1	0	1	2	0	1	1	
B	0	1	1	0	1	1	0	1	1	
C	0	1	1	0	1	1	0	0	1	18
Long Position for T' with Correct Sign										
A	0	0	1	0	0	0	0	0	0	
B	0	0	0	0	0	0	0	0	1	
C	0	0	0	0	0	0	0	0	0	2
Short Position for T' with Correct Sign										
A	0	0	2	0	2	4	1	2	5	
B	1	2	2	1	2	3	1	2	2	
C	1	2	3	1	2	3	1	2	2	49

From the results shown in Tables 2 to 6 and Figures 1 to 3, it is evident that *SYD* does produce incorrect signals occasionally when Scenario A is considered only. This could be due to the possibility that Scenario B actually existed during that particular period, instead of Scenario A assumed earlier. Since the *SYD* indicator was tested only under the context of Scenario A, incorrect signals could thus arise. Supposing this is the real cause for generating incorrect signals in the tests; then if investors can distinguish Scenario A and Scenario B from the other scenarios, they should be able to use the *SYD* better and produce more convincing results.

The question arises as to whether there is more prevalence of Scenario A or more Scenario B in the market. The answer is not difficult to discern as the interpretation of *SYD* under Scenario B is exactly opposite to that under Scenario A. That is to say, if one believes the market as Scenario A and gets a buy signal by applying the *SYD*, then one will get a sell signal under the assumption of Scenario B. From Table 5, 74% (82% for long and 67% for short), 62% (70% for long and 55% for short) and 74% (79% for long and 69% for short) of the *SYD* signals generated under the assumption of Scenario A are of correct sign for the U.S., German and Singapore markets respectively. From Tables 6A-C, 94%, 93% and 86% of the *SYD* signals generated under the assumption of Scenario A are of significantly correct sign for the U.S., German and Singapore markets respectively. These findings support the performance test under the assumptions of Scenario A.

Discussion

The study leads to the following conclusions:

1. Using the *SYD* model could enable investors to escape from most of the crashes and catch most of the bull runs.

2. The trading signals provided by the *SYD* indicator can generate significant profits, and

3. The performance of the *SYD* indicator is significantly better than the performance of the buy-and-hold strategy.

The findings of this study sometimes show that the statistics are not significant, and sometimes *SYD* generates incorrect signals. There are several possible reasons for these shortcomings. Firstly, only Strategies A, B and C are adopted in this study. If more strategies are introduced, the outcome should be enhanced. Secondly, the markets only are considered under Scenario A. If Scenario B or other scenarios can be identified and examined, more complete results can be obtained. Thirdly, the market performance test consists of the *SYD* indicator alone. If other economic and fundamental indicators can be incorporated, or the *SYD* combined with other technical indicators, the results could be promising. In short, if more data were gathered from a wider spectrum of economic variables, more scenarios and more markets could be studied and examined comprehensively and the result of the *SYD* model would be more meaningful; and hopefully, it will produce more complete results to help predict market movements.

Also, the tests rely on the assumption that the returns are normally distributed. For future studies, this assumption can be relaxed to test the performance of the *SYD* indicator. One can use the following methods to do this:

(1) Three-moment or four-moment approximation to the statistics (Tiku & Wong 1998),

(2) Robust flat-tailed estimator (Tiku, *et. al.* 1999, 2000), or

(3) Robust Bayesian estimator (Matsumura, *et al.* 1990, Wong & Bian 2000).

A time series approach can also be used (for example, see Wong & Miller 1990) and Wong, *et al.*, (2000) to study the returns generated from using the *SYD* model. A cost of capital (Thompson & Wong 1991, 1996) approach can also be utilized to make better investment decisions. Another extension to improve the *SYD* model is to include the work of Li & Wong (2000) and Wong & Li (1999) which study the behavior of risk takers and risk averters in the stock market.

There are many other indicators besides the *SYD* for stock market movement (for example, see Chew & Wong 1996 and Wong, *et. al.* 1996). Each indicator has it own strengths and weaknesses. Similar testing procedure could be applied to analyze other indicators or the combinations of indicators. Another research on stock prices examined the performance of portfolio manager's probabilistic forecasts of stock prices (for example, see Muradoglu & Unal 1994).

Finally, this paper concludes that *SYD* indicator is indeed a useful technical analysis tool for stock market investment.

Notes

[1] The Lo study is cited in 'Economics focus: Using charts to predict share prices,' The Economist, 19 August 2000, p 78.

[2] Note that the E/P ratio (= E_t/P_t) at time t is different from the earning yield (= E_{t+1}/P_t) at time t. The former does not include the market anticipation of earnings growth while the latter does; see Brealey & Myers (1991) for reference. However, this study chooses to use the former E/P ratio to measure the actual earning from equity based on publicly available information. E_{t+1}/P_t data is actually not available to chartists so is not utilized for technical analysis here. The former ratio is commonly used to measure the earning of an enterprise relative to equity price and serves our purposes.

[3] It may seem inappropriate to construct an indicator from an aggregation of E/P ratio and bond yield because earnings are an accounting figure which varies depending on accounting conventions while bond yield is market-determined. However, both EY and BY are actually market-determined since E/P reflects the market response to earnings however measured. Furthermore, there are indeed some relationships among stock prices, E/P ratio and bond yield. For example, Wong & Manzur (2001) found that the logs of stock index, E/P ratio and bond yield are cointegrated for most bull runs.

[4] Refer to Chew (1997) for the situation in which the transaction costs are included. The holding period in applying SYD is usually long enough so that the transaction costs become negligible. Chew (1997) finds that the results including transaction costs are about the same as that without the transaction costs.

[5] **No** 'Long Position for T with Incorrect Sign' and **no** 'Short Position for T' with Incorrect Sign'

[6] **No** 'Long Position for both T and T' with Incorrect Sign' and **no** 'Short Position for T' with Incorrect Sign'

[7] **No** 'Long Position for both T and T' with Incorrect Sign' and **no** 'Short Position for T' with Incorrect Sign'

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Market Efficiency, Behavioural Finance, and Anomalies

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