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Role of Information Shocks in Predicting Equity Returns: A Comparison of Asian Developed and Asian Emerging Markets

by

Hassan Zada

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By

Hassan Zada

(DMS161009)

Dr. Hsin-I Daisy Chou, Associate Professor

RMIT University, Melbourne, Australia

Foreign Evaluator 1

Dr. Jessica West, Associate Professor

Stetson University, Florida, USA

Foreign Evaluator 2

Dr. Arshad Hassan

(Thesis Supervisor)

Dr. Lakhi Muhammad

(Head, Department of Management Sciences)

Dr. Arshad Hassan

(Dean, Faculty of Management & Social Sciences)

DEPARTMENT OF MANAGEMENT SCIENCES

CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY

ISLAMABAD

2022

This work is dedicated to my parents, late grandfather and grandmother, my parents, my family, and my supervisor Dr. Arshad Hassan. They are legends on the face of this transient earth. During my laborious life I receive massive inspirations and support. They are the best teacher I have ever had in my life, they are honest, trustworthy and above all enthusiastically unique human being on this planet. It is proudly stated that I am following their foot step and live the life as they have lived and live. Their way of living life has inspired my life. They are my best teachers, honest, trustworthy and enthusiastic human being for my life. I can say with proud that I am following their path and living the life as they have lived and living.

CAPITAL UNIVERSITY OF SCIENCE & TECHNOLOGY
ISLAMABAD
Expressway, Kahuta Road, Zone-V, Islamabad
Phone:+92-51-111-555-666 Fax: +92-51-4486705
Email: info@cust.edu.pk Website: https://www.cust.edu.pk

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This is to certify that the research work presented in the thesis, entitled "**Role of Information Shocks in Predicting Equity Returns: A Comparison of Asian Developed and Asian Emerging Markets**" was conducted under the supervision of **Dr. Arshad Hassan**. No part of this thesis has been submitted anywhere else for any other degree. This thesis is submitted to the **Department of Management Sciences, Capital University of Science and Technology** in partial fulfillment of the requirements for the degree of Doctor in Philosophy in the field of **Management Sciences.** The open defence of the thesis was conducted on **July 29, 2022**.

Student Name : Hassan Zada (DMS161009)

The Examination Committee unanimously agrees to award PhD degree in the mentioned field.

Examination Committee :

(a)	External Examiner 1:	Dr. Syed Muhammad Amir Shah Professor AIOU, Islamabad	
(b)	External Examiner 2:	Dr. Iftikhar Hussain Adil Assistant Professor NUST, Islamabad	Hussain
(c)	Internal Examiner :	Dr. Jaleel Ahmed Malik Associate Professor CUST, Islamabad	Jaleel Ahmed

Supervisor Name : Dr. Arshad Hassan
Professor
CUST, Islamabad

Name of HoD : Dr. Lakhi Muhammad
Associate Professor
CUST, Islamabad

Lakhi M.K

Name of Dean : Dr. Arshad Hassan
Professor
CUST, Islamabad

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Registration No : DMS161009

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Registration No : DMS161009

List of Publications

It is certified that following publication(s) have been made out of the research work that has been carried out for this thesis:-

1. Zada, H., Hassan, A., & Wong, W. K. (2021). Do Jumps Matter in Both Equity Market Returns and Integrated Volatility: A Comparison of Asian Developed and Emerging Markets. *Economies*, 9(2), 92.

(Hassan Zada)

Registration No: DMS161009

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Abstract

This study is initiated to identify the presence of jumps in Asian developed and Asian emerging markets and to examines the role of jumps specifically positive and negative jumps in predicting equity returns of Asian developed and Asian emerging markets. Furthermore, it explores the connection between factor premia and jumps returns for Asian developed and Asian emerging markets and finally, it provides insight into integrated volatility during periods of positive and negative jumps for Asian developed and Asian emerging markets. To accomplish the purpose, the swap variance (SwV) approach is used in this study to identify monthly price jumps and realized volatility is estimated using daily equity market data from February 2001 to February 2020 for both Asian developed and Asian emerging markets. Then returns during jump periods are calculated and compare with returns during non-jump periods for both Asian developed and Asian emerging markets and compare both markets. Furthermore, Fama and French five factors are regressed on jump returns to identify which factors of the Fama and French five-factor model are connected with jump returns in Asian developed and Asian emerging markets. Finally, integrated volatility during jump periods are estimated and compare with integrated volatility during non-jump periods for both Asian developed and Asian emerging markets and compare both markets. The finding shows that jumps play an important role in equity returns and integrated volatility of Asian developed and Asian emerging markets. Returns during the jump period are higher than non-jump periods. Furthermore, Jumps occur in all equity markets; however, in emerging markets, jumps are more frequent than in developed markets, whereas it is worth noted that positive jumps are more frequent than negative jumps in both markets. Furthermore, during jump periods, the markets with average volatility earn higher returns in emerging markets whereas, in developed markets, highly volatile markets earn higher returns during jumps periods. Moreover, markets with low returns and high volatility during normal periods are more adversely affected during periods of negative jumps in both markets. Furthermore, this study reveals that in the context of Asian developed markets, all the five factors of the Fama and French five factor model explain positive jump returns,

whereas in the context of Asian emerging markets, only market premium and investment premium explain positive jump returns. Similarly, market premium, profitability premium, and investment premium explain negative jump returns in Asian developed markets, whereas market premium, size premium, value premium, and investment premium explain negative jump returns in Asian emerging markets. Moreover, the study finds that TPV is a better estimation technique of continuous components of quadratic variation as compare with bipower (BPV). It is because that the BPV overstate the average integrated volatility whereas TPV has a minimum mean value and minimum standard deviation and this pattern is consistent across all Asian developed and Asian emerging markets. Furthermore, both Asian developed markets and Asian emerging markets have high volatility during 2001 and during the 2007-2009 global financial crises periods. Integrated volatility is high during periods of negative jumps compared with periods during positive jumps and the pattern is consistent across Asian developed and Asian emerging markets. The ratio of variation due to jump component to total realized variance shows a considerable amount of variations in both Asian developed and Asian emerging markets. The findings of this study have implications for asset pricing models, risk management, individual investors, and portfolio managers in developed and emerging markets.

Key words: Swap variance approach of jump identification; information shocks; realized volatility; integrated volatility; Asian developed markets; Asian emerging markets.

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Abbreviations

BPV	Bipower Variance
CAPM	Capital Asset Pricing model
EMH	Efficient Market Hypothesis
FF3F	Fama and French three-factor model
FF5F	Fama and French five-factor model
JP	Returns during jump periods
Jr	Jump return at the time
NJP	Returns during negative jumps periods
Njr	Negative jump return at time
PJP	Returns during positive jumps periods
Pjr	Positive jump return at time
R	Returns
RV	Realized variance
SwV	Swap Variance
TPV	Tripower Variance

Symbols

Ω	Omega
$\sum$	Summation
$\prod$	N- Ary Product
π	Pi
β	Beta
$C \propto$	Critical value
ε	Epsilon

Chapter 1

Introduction

1.1 Background of the Study

Over the past decade, integrated volatility and jumps in asset pricing have attracted particular attention in the literature of finance, and their importance is prominent (Brownlees et al., 2020; Buncic and Gisler, 2017). According to the efficient market hypothesis (EMH), the stock market responds to the arrival of new information, leading to changes in returns and volatility of the stock market prices (Duangin et al., 2018). However, sometimes there are abnormal movements or large discontinuous changes in stock prices, which are infrequent but large; these extreme movements are known as jumps or information shocks, associated with the arrival of unexpected new information (Ferriani and Zoi, 2020; Jiang and Zhu, 2017; Sun and Gao, 2020). Accordingly to Bajgrowicz et al. (2016), company-specific prescheduled announcements, macroeconomic news, and news reporting on unscheduled and uncategorized events all trigger the jumps in prices. Although, most of the news does not trigger price jump, but it might cause a market reaction that lead to volatility bursts.

Merton (1976) initiated the discussion on jumps in asset price, started a broad range of literature in the fields of financial econometrics and asset pricing. Jumps identification has profound implications in risk management, asset pricing, valuation of derivatives, and portfolio allocation. Lee and Mykland (2008) jumps identification helps us to determine the events that causes the jumps; therefore, identification of jumps help in understanding financial market movements. There are several advantages to using stock price jumps as a proxy for large information shocks; for example, studies on corporate events require event dates. The approach of using stock price jumps as a proxy for large information shocks, on the other hand, relaxes the requirements of event dates and is not limited to only publicly announced events. Private information, such as insider trading, can cause stock price changes. Jumps capture all types of information, whether it is public or private (Jiang and Oomen, 2008; Jiang and Yao, 2013; Jiang and Zhu, 2017).

The importance of jumps is illustrated in some early studies, including by (Aït-Sahalia, 2004; Aït-Sahalia and Hurd, 2015; Amaya and Vasquez, 2011; Bajgrowicz et al., 2016; Brownlees et al., 2020; Buncic and Gisler, 2017; Carr and Wu, 2003; Duangin et al., 2018; Dutta et al., 2021; Eraker et al., 2003; Ferriani and Zoi, 2020; Jiang and Oomen, 2008; Jiang and Yao, 2013; Jiang and Zhu, 2017; Binh et al., 2019; Odusami, 2021; Zhang et al., 2020; Pan, 2002; Wright and Zhou, 2009).

Pan (2002) shows evidence that investors demand a higher risk premium for taking the risk associated with price jumps. Eraker et al. (2003) provide strong evidence for jumps in returns and jumps in volatility. Jumps in the volatility model significantly increase implied volatility in the money and out of the money options than models having only jumps in returns. Carr and Wu (2003) state that to understand asset price behaviour, it is necessary to determine whether the best model is based on a purely continuous process, a pure jump process, or a combination of both of these two processes. Aït-Sahalia (2004) comments that jumps play an important role in asset returns, diminishing marginal returns, currencies, and interest rates. Moreover, the decomposition of total risk into Brownian and jump components is very useful for portfolio allocation and risk management.

Jiang and Oomen (2008) documented that Jumps are an important component of the price dynamics of financial assets. The arrival of unexpected news or liquidity shocks causes significant and instantaneous revisions in the value of financial securities. Wright and Zhou (2009) explain that there is significant evidence of predictability in excess returns on various assets, and some of the predictability may be attributed to time-variation in the distribution of jump risk. They observe that jump risk measures could accurately predict future excess returns of the bond. Furthermore, the coefficient on the jump means it is statistically significant, implying that including jumps can increase the predictability of bond risk premia. The analysis shows that root means square prediction error can be reduced to 40% by including the jump' mean in the model. Amaya and Vasquez (2011) suggest that positive jumps have a different effect on the future price of stocks than negative jumps. Positive jumps increase the prices of securities, and thus, a risk-averse investor prefers positive jumps over negative jumps. As a result, stocks with negative jumps should earn a higher premium than stocks with positive jumps.

According to Jiang and Yao (2013), there are two views about investors' rationality. The first view is that investors are rational and rational investors who form unbiased expectations about a company's future cash flows. If investors form rational expectations about future cash flows, then there exists a correlation among expected stock returns and the firm's specific characteristics such as size, book to market value of equity, profitability, investment, and momentum, etc. (which are considered as proxies of systematic risk). For rational investors, stock return is viewed as a function of systematic risk factors. The second view considers investors as normal human beings. Normal people do not always behave in a rational way; their choices are inclined by their behaviour. Normal investors form biased expectations about future cash flows associated with a company that leads to stock market inefficiency and mispricing of securities takes place. This mispricing of securities provides opportunities for investors to earn abnormal returns or unexpected components of stock returns. If mispricing is due to biased expectations of investors, then it will reverse in the future when new information about the company is updated, establishing a correlation between stock returns and the firm's specific characteristics. This relationship is due to investors' response to unexpected information shocks, not due to systematic risk factors. However, the argument of Jiang and Yao (2013) is that systematic risk factors may be associated with information shocks to explain the returns. Their study has concluded that size effect and value effect are associated with Jumps to explain returns.

Jiang and Zhu (2017), using jumps as a proxy of informational shocks, relaxed the requirements of planned event dates; therefore, they are not strictly related to events that are announced publicly. Jumps carry information that is beyond specific planned corporate events and bring large discontinued changes in the prices. Corradi et al. (2018) argue that considering the jump behaviour improves the conditional variance forecasts of returns. Ferriani and Zoi (2020) note that during phlegmatic market conditions, the relative contribution of jumps to total price variance is higher than during times of stress. Dutta et al. (2021) test the presence of jumps in OVX and explore their role in predicting crude oil price volatility. According to the findings, OVX has a jump behaviour that varies over time. They warrant investors, policymakers, and academics accounting for the presence of jumps to develop more accurate asset pricing models and volatility prediction methods.

Zhang et al. (2020) document that in China, most of the listed companies are owned by the state, and a limited portion of shares are available for trading in the stock market. Therefore, the Chinese stock market is highly susceptible to speculation. Furthermore, due to the increasing role of domestic and foreign institutions, stock market movements are still primarily driven by noise traders, that is, retail investors. Therefore, more jumps could be expected in emerging markets such as the Chinese stock market than in the developed stock markets.

Baker et al. (2020) explore the possible explanations for the stock market's unusual reaction to the COVID-19 pandemic. Previous pandemics have a very mild impact on the US stock market, whereas the COVID-19 pandemic has had a much more substantial impact on the stock market than previous pandemics such as the Spanish flu. According to the evidence, voluntary social distancing, government restrictions on commercial activity, and operating with powerful effects in a service-oriented economy are the primary reasons why the US stock market reacted so strongly to COVID-19 compared to the previous pandemic. Sharif et al. (2020) used the wavelet-based Granger causality and coherence wavelet to investigate the relationship between COVID-19, the stock market, oil price volatility shock, economic policy uncertainty, and geopolitical risk. According to the findings of the study, COVID-19 and oil price shocks influence the economic policy uncertainty, geopolitical risk and stock market volatility over low-frequency bands.

Apergis and Apergis (2020) analyze the impact of the COVID-19 pandemic on the returns and volatility of the Chinese stock market. For COVID-19, the study uses two proxies: the total confirmed cases and the total daily deaths. The analysis shows that COVID-19, as measured by two different proxies, has a significant negative impact on stock returns; however, when total deaths are used as a proxy, the negative impact on stock returns is more pronounced. COVID-19, on the other hand, has a positive and statistically significant effect on volatility. The findings are important for understanding the stock market implications of the COVID-19 pandemic. Empirical results of Kostrzewski and Kostrzewska (2021) indicate that a model with a time-varying jump intensity and a jump prediction mechanism is useful in forecasting.

Odusami (2021) states that it is essential to include jumps in financial models for managing the risk in the portfolio because jumps bring movements in asset prices; therefore, risk premia should be accounting for jumps along with continuous sample path variance. This study has observed asymmetry in the distribution of jumps, with a higher magnitude of negative jumps than positive jumps. The implication of their study is that jump risk is non-diversifiable. Therefore, when pricing assets, investors should account for risk premia, and when selecting policy weights in their portfolios, they should consider the determinants of jump risks.

Uddin et al. (2021) studies the impact of the COVID-19 pandemic on stock market volatility to see if economic strength could help mitigate the negative effects of the global pandemic. According to the findings, country-level economic characteristics and factors help to mitigate the volatility caused by the pandemic. Based on economic factors, policymakers may devise policies to combat stock market volatility and avoid financial crises in the future.

This study uses the theory of efficient capital market theory developed by Fama (1970) and others to explain three types of efficiency, namely, the weak form, the semi-strong form, and the strong form of efficiency known as the efficient market hypothesis (EMH). It states that security prices fully reflect all relevant information, eliminating arbitrage opportunities and bringing stock markets towards efficiency. The weak form of efficiency states that investors cannot earn an excess return based on past prices, returns, and trading volumes. In the semi-strong form of efficiency, the relevant information is publicly available information which states that investors cannot earn an excess return on information based on annual reports and news from media. In a strong form of efficiency, both past information and publicly available information are irrelevant for investors to earn excess returns.

There are, however, abnormal movements or large discontinuous changes in empirical stock analysis that are infrequent but large; these extreme movements are known as jumps or information shocks and are associated with the arrival of unexpected new information. Ferriani and Zoi (2020); Jiang and Zhu (2017); Sun and Gao (2020).Jiang and Zhu (2017) define stock price jumps as a proxy of large information shocks, and large discontinued changes in stock prices called jumps or stock price jumps. There are several advantages to using stock price jumps as a proxy for large information shocks; for example, studies on corporate events require event dates. The approach of using stock price jumps as a proxy for large information shocks, on the other hand, relaxes the requirements of event dates and is not limited to only publicly announced events. Private information, such as insider trading, can cause stock price changes. Jumps capture all types of information, whether it is public or private (Jiang and Oomen, 2008; Jiang and Yao, 2013; Jiang and Zhu, 2017).

The above discussion reveals that a comprehensive study is needed to cover the existing gap in the literature related to the jump studies. As stated by Kongsilp and Mateus (2017), existing studies on jump behaviour are based on the developed market, whereas Zhang et al. (2020) state that there are very few studies on jump behaviour in the emerging market. Moreover, earlier studies on asset pricing models like CAPM, Fama and French three-factor model (FF3F), Fama and French five-factor model (FF5F) have concluded that it is only the systematic risk that explains the returns. However, the argument of Jiang and Yao (2013) is that systematic risk factors are link with information shocks to explain the returns. Their study concludes that size effect and value effect link with Jumps to explain returns.

This study is initiated to cover the gap; First by identifying jumps in Asian developed and Asian emerging markets and comparing jumps in both markets. Second, to study the role of jumps and asymmetric effect that is positive and negative jumps in returns of Asian developed and Asian emerging markets and to compare both markets. The third is to identify the link of factor premia with jumps returns of Asian developed and Asian emerging markets and to compare both markets. Fourth is to study asymmetric behaviour that is positive and negative jumps in integrated volatility of Asian emerging and developed markets and to compare their results.

1.2 Research Questions

This study is aimed to answer five questions that need a thorough empirical investigation in the context of Asian developed and emerging markets.

1. Do jumps exist in Asian developed and Asian emerging markets?
2. What is the role of information shocks in explaining expected equity returns in Asian developed and Asian emerging markets?
3. Do information shocks have an asymmetrical effect i.e. positive and negative on equity returns in Asian developed and Asian emerging markets?
4. Is there a link between factor premia and jump returns in Asian developed and Asian emerging markets?
5. Do positive and negative information shocks matters in the integrated volatility of Asian developed and Asian emerging markets?

1.3 Objectives of the Study

The objectives of the study are:

1. To identify the presence of jumps in Asian developed and Asian emerging markets.
2. To provide insights about the role of information shocks in explaining equity returns in Asian developed and emerging markets.
3. To investigate the asymmetric effect of information shocks i.e. positive and negative shocks on equity returns in Asian developed and emerging markets.
4. To explore the connection between factor premia and jump returns for Asian developed and Asian emerging markets.
5. To provide insight into integrated volatility during periods of positive and negative jumps for Asian developed and Asian emerging markets.

1.4 Contribution of the Study

The contribution of this study is as follows. First, the literature on jump identification is limited to developed markets (Jiang et al., 2011; Jiang and Kim, 2016; Jiang and Yao, 2013; Jiang and Zhu, 2017). This study extends the existing literature on jump identification to Asian developed and Asian emerging markets by applying the swap variance (SwV) test developed by Jiang and Oomen (2008) to identify monthly jumps in Asian developed markets and Asian emerging markets. Second, this study examines the role of positive jumps and negative jumps in equity returns individually and collectively for both Asian developed and Asian emerging markets and compares the results. Third, this study identifies the role of positive and negative jumps in integrated volatility separately and jointly for both Asian developed and Asian emerging markets and compared the results. Fourth is that this study extends the work of Jiang and Yao (2013) by empirically studying the investment and profitability effect of the Fama and French five-factor model to identify that these two factors are connected with jump returns of Asian developed and Asian emerging equity markets.

The following findings are expected from the empirical results of this study; First, this study anticipates that the frequency of jumps may be higher in Asian emerging markets than in Asian developed markets. Because equity markets of developed countries are thought to be more informationally efficient than equity markets of emerging-market, this information asymmetry may cause a large number of jumps in equity markets of Asian emerging countries than Asian developed countries.

Second, this study further anticipates that during positive jumps periods, the equity markets of Asian-emerging countries may offer higher returns than those of Asian developed equity countries. This anticipation is built on the fact that returns are on the upside during positive jumps and on the downside during periods of negative jumps. Whereas a high level of information asymmetry increases the riskier and more volatile nature of equity markets of Asian countries, therefore, high returns are expected in Asian emerging countries than in Asian developed countries during periods of positive jumps.

Third, this study expects from that empirical results that there may exist a significant link between factor premia and jump returns in equity markets of both Asian developed and Asian emerging countries. The expectation is built on the fact that jumps capture all types of information, whether it is public or private (Jiang and Oomen, 2008; Jiang and Yao, 2013; Jiang and Zhu, 2017), and because of the information content capture through jumps, therefore, may exist a link between factor premia and jump returns.

Fourth, this study further expects from the empirical results that TPV may be a better estimation technique as compared to BPV for measuring integrated volatility of the jump component of total realized variance due to an upward bias of BPV in a finite sample. It further expects that integrated volatility may increase during periods of jumps as compared with non-jump periods in both Asian developed and Asian emerging markets.

1.5 Scope of the Study

The scope of this study is limited to Asian developed and Asian emerging markets. The Asian developed markets include Australia, Hong Kong, Japan, and New Zealand, whereas Asian emerging markets include China, India, Indonesia, Pakistan, Thailand, and Sri Lanka. Moreover, the focus of this study is not company-specific; rather, it only focuses on the market as a whole. The major market of each country is considered for analysis. The markets include S&P ASX for Australia, Hang Seng index of Hong Kong, Nikkei225 index of Japan, and NZX 50 index of New Zealand for Asian Developed markets. Whereas for Asian emerging markets, this study has considered (Shanghai Composite index of China, Nifty 50 index of India, JKSE index of Indonesia, KSE-100 index of Pakistan, SET Index of Thailand, and CSE All index of Sri Lanka. These are the oldest and mature indices of their regions that is why this study has considered these markets.

1.6 Significance of the Study

In finance, one of the most important and prominent areas in financial literature is asset pricing. A significant number of studies have been conducted in developed as well as in emerging equity markets in this domain. Since the start of the twenty-first century, the role of the financial market has rapidly increased globally. It has brought the attention of the investors to efficiently allocate their financial resources. Over the last two decades, jumps in asset pricing have attracted particular attention in the literature of finance.

This study extends the identification of jumps in a number of Asian developed and Asian emerging equity markets. Earlier, most of the jumps related studies are limited to only developed markets, specifically US markets. Future studies in emerging markets related to jumps identification can compare their studies with the findings of this study. Furthermore, this study has compared returns of equity markets during jump periods with returns during non-jump periods. The outcomes of returns during jumps periods and returns during a non-jumps period provide essential investment strategies for Asian developed and Asian emerging markets. Moreover, it identifies the link of factor premia with jumps returns for both Asian developed and Asian emerging markets. It may start a new discussion in the area of asset pricing for future researchers to further explore the association of risk factors and returns within Asian developed, Asian emerging markets, and other markets around the globe. This study warrant investors, policymakers, and academicians to accounting for the presence of jumps to develop more accurate asset pricing models and volatility prediction methods.

The results of this study are helpful for all types of Investors; individual investors, corporate investors, investment banks, financial analysts, and mutual funds managers of Asian developed and Asian emerging markets. This study provides important insights to the investors in Asian developed and Asian emerging markets to earn higher returns during jump periods. The implication is also very important for asset pricing theory as investors prefer positive jumps to negative jumps. Therefore, stocks with negative jumps should earn a premium compared to stocks with positive jumps. This is also an important factor in consideration of investment. This study provides insights to academics, practitioners, and policymakers on the asymmetric effect of jumps in equity market returns and integrated volatility in the context of Asian developed and Asian emerging markets.

1.7 Plan of the Study

The rest of the study is organized as follows. Chapter 2 is literature review that cover studies on jumps identification techniques, integrated volatility, and jumps and returns. Chapter 3 is research methodology that describes the data use in the study and methodologies related to jumps identification, and analysis conducted in this study. Chapter 4 is the results and analysis that provides empirical results and findings of the study and discusses the findings with previous studies. Whereas Chapter 5 is conclusion, limitation, and future direction that concludes the study, provide limitations of the study and gives future research directions.

Chapter 2

Literature Review

The review of literature covers studies that have been conducted on Jumps identification techniques and their application around the globe.

Aït-Sahalia (2002) states that most of the time, based on discrete data, inferences can be taken about a hypothesized continuous time model. Most specifications of the continuous-time model are diffusive. The diffusive process is a Markov process having continuous sample paths. From a discrete subsample of a continuous-time model, can it be told that the underlying model is a diffusive model or jumps are present in the model? Intuition says that no, it can't be told. Discrete data is purely discontinuous even though the sample path is a continuous time. A finer look exposes that there are different degrees of discontinuity in the discrete data, some discontinuities follows diffusive process while some discontinuities have jumps. The study uses an approach that relies on the identification of a necessary and adequate restriction on the transition densities of diffusions at the sampling interval of the observed data. The argument is based on the fact that on the real line if a diffusion starts below from another, diffusion can't be finished above the second one without their sample path having at least one cross. As the discrete data can reveal the transition density at any sampling interval so based on discrete subsamples, the Markov process can discriminate into diffusive and jumps parts.

Andersen et al. (2003b) devise a nonparametric method for measuring continuous sample-path variation as well as discontinuous jump variation in a quadratic variation process separately. In this study, they have made advancements to the study of Andersen et al. (2003a) that use simple reduced form time series models for realized volatility. The approach is based on the theoretical results of Barndorff-Nielsen and Shephard (2004) and Barndorff-Nielsen and Shephard (2006), which is a bi-power variation technique. The study uses high frequency data, such as five-minute returns on the 30-year US Treasury bond yield, the S&P 500 index, and exchange rates, to test the model. The continuous component path of the sample is found to be more persistent than the jump component. This new model also incorporates the jump component (jumps are measured by HAR-(RV) model; a reduced form heterogeneous autoregressive model) as an independent variable. The coefficient of the jump component is a highly significant quarterly, weekly, and daily forecasting period. This study demonstrates that by separating the model for continuous and jump components, derivatives pricing, risk management, and allocation of financial assets can be improved.

Carr and Wu (2003) argue that in order to understand asset pricing behaviour, it is necessary to know whether the best model is based on a strictly jump process or merely a continuous process or a combination of these two processes. The study proposes a method to differentiate between these processes and examine these processes as the option maturity date approached the valuation date by using market prices of at the money and out of the money options. The speed of convergence varies across these possibilities when the prices of at the money and out of the money options converge to zero when the date of maturity approaches zero. The identifies the type of asset pricing process by examining the convergence speed of the option prices. In a continuous process, there is very little chance that the underlying asset's price will change significantly in a short period of time. So there is a low possibility that the OM option will move in the money. Whereas, in the jump process, there are high chances that the prices of the underlying asset can jump into the money in a short period. The behaviour of these two types of processes is different for option prices in the short term because these two processes are hard to separate from a discrete sample. This study provides contrasts to the test proposed by (Aït-Sahalia, 2002). Carr and Wu (2003) provide a mechanism for identifying the presence of a jumping component and a continuous component and are not limited to a single factor. Whereas, Aït-Sahalia (2002) only tests whether or not the underlying asset follows a single-factor Markovian diffusion process. Furthermore, Carr and Wu (2003) look to the behaviour of option prices across maturities at fixed moneyness states, whereas, Aït-Sahalia (2002) examines the transition density across all possible states. So these two methods are complementary to one another through a focus on the information set of different dimensions.

Huang and Tauchen (2005) evaluate the properties of the jumps detection techniques developed by (Barndorff-Nielsen and Shephard, 2004, 2006; Andersen et al., 2003a). The study uses a single-factor log-linear stochastic volatility model with jumps for the Monte Carlo data generating process. It also analyzes two factor model of (Chernov et al., 2003). The study investigates the size, power, and ability of the tests to correctly identify trading days on which a jump has occurred, as well as the confusion matrix, which contains the probabilities of correct and incorrect classification. Furthermore, it considers tests that are designed to answer the question of whether an entire dataset is generated by a pure diffusion or jump diffusion model, which has never been considered or analyzed before. The study uses high-frequency financial price data for the detection of jumps with market microstructure noise. The robustness of the generic jump test is examined theoretically for microstructure noise by considering the appropriateness of a correction strategy from (Andersen et al., 2003a). The theory generates precise predictions, which are then tested using Monte Carlo simulations.

Barndorff-Nielsen and Shephard (2006) construct a non-parametric test for the presence of jumps in stock prices by using high-frequency data. The study proposes two tests of jumps identification. One is the difference, and the second measure is the ratio of realized BPV and realized quadratic variation. The study builds the jump test on the idea of bipower variation (BPV) provided by Barndorff-Nielsen and Shephard (2004) and Back (1991) that sum of squared returns- a measure of variations on asset prices is based on the quadratic variation process. Moreover, they also derive the asymptotic distributional theory for these tests under quite weak conditions. The study demonstrates these jump tests through simulations and as well as using data on exchange rates. According to the findings of the study, some of the jumps are due to macroeconomic news.

Lee and Mykland (2008) develop a non-parametric test to identify jumps in financial assets by using high-frequency data. The proposed jump detection technique resolves the difficulty of the jumps identification issue. Once jumps are detected, then it can be examined that what sort of information is related to it to improve asset pricing models. Moreover, the test also determines the direction as well as the size of the detected jumps, which lets to characterize the distribution of jumps size and stochastic jump intensity. Based on these outcomes, hedging strategies are developed. Lee and Mykland (2008) compare the proposed test with that of (Barndorff-Nielsen and Shephard, 2006; Jiang and Oomen, 2008). According to Lee and Mykland (2008), the proposed test outperforms others in terms of size and power. An empirical study is conducted on US equity markets. It is found that jumps do not occur regularly, so that stochastic jump intensity should be considered in equity markets. Moreover, more frequent jumps are observed in individual equity, and its size is larger than the index returns. In individual stocks, jumps are associated with company-specific news, i.e., scheduled earnings announcements and as well as unscheduled news. Therefore, with earnings announcements, other firm-specific news is to be incorporated for option pricing. Whereas in the index, jumps occur because of general market news, i.e., Federal Open Market Committee (FOMC) meetings and macroeconomic reports. Therefore, general market news is to be incorporated for index options.

Jiang and Oomen (2008) devise a nonparametric technique by using high frequency data to identify jumps in stock prices, known as the swap-variance approach (SwV). The study develop the test based on Neuberger (1994) variance swap replication strategy - a short position in “log contract; A futures contract with a settlement price equal to the logarithmic price of the underlying assets.” plus a continuously re-balanced long position in the asset underlying the swap contract. The profit or loss from such a replication strategy is proportional to the realized variance (RV), allowing for perfect replication of the swap contract. However, when there are jumps, this strategy fails, and the replication error is entirely determined by the realized jumps. The Swap Variance, which is the accumulated difference between simple and log returns, is calculated and compared to realized variance in the study. When there are no jumps, the difference is zero, but when there are jumps, it reflects the variance swap's replication error, which gives it the ability to detect jumps. The purpose of this test is similar to the bipower variation test of Barndorff-Nielsen and Shephard (2006) but the underlying logic and properties are different. The BPV test detects jumps by comparing RV to a jump robust variance measure, whereas the SwV test detects jumps by comparing RV to a jump sensitive variance that includes higher-order moments of return, making it more effective in many situations. The study conducts extensive simulations and compares results with the bi-power variation test to examine the performance of the SwV test. The findings show that the SwV jump test performs well and is a good substitute for the bipower variation test.

Mancini (2009) devise a non-parametric threshold estimation technique for jumps identification. The threshold estimator is more efficient than power variations, multipower variations, or kernel estimators. Simulations show that the methodology can be used with finite samples and that it outperforms multipower variations, particularly when high-frequency data is available.

Aït-Sahalia and Jacod (2009a) propose a parametric test by using high-frequency financial data to answer the characteristics of the process which derive asset returns. They modelled the log-price X of an asset as a one-dimensional process over a fixed interval of time at discrete times. This process is assumed to be an Itˆo semimartingale. So it has a drift, a continuous martingale part, and has a jump process with a stochastic Levy measure. For modelling, the characteristics can be inferred from observation of X, which is drift, volatility, and levy measure. When the time interval (the difference between two consecutive periods) goes to zero, then volatility can be constantly inferred under weak assumptions, but if the time interval is fixed, then constant inferences are not possible for drift and levy measures. The characteristics of levy measure near zero are that if it does not explode near zero, it means that there is a finite number of jumps. But when this number is infinite, it tells about the concentration of small jumps. The main objective is to provide the specification of financial models that accept the possibility or the presence of large jumps.

Aït-Sahalia and Jacod (2009b) propose Truncated Realized Volatility (TRV) which is a threshold method to determine and truncate jumps in a discretely observed process. It is a direct and very simple test to identify jumps by providing a family of test statistics. TRV estimates integrated volatility by detecting when price jumps are greater than the threshold level. The value of test statistics converges as 0 to1 if there are jumps and converges to a value of 2 if there are no jumps. The test provides by them is non-parametric and requires high-frequency data points.

Podolskij and Ziggel (2010) propose a threshold test for jumps based on the truncated power variation of (Mancini, 2009). The truncated power variation is used to construct test statistics for semimartingale models with and without noise. If there are jumps, the test statistics diverge to infinity, but in the absence of jumps, they have a normal distribution. The proposed test is applicable to all Itô semimartingales and has good finite sample properties. When compared to alternative tests documented in the literature, the proposed tests have a higher power.

Aït-Sahalia and Jacod (2010) continue their discussion on the development of statistical methods to provide the specification of continuous-time models by using high-frequency data. The basic assumption taken here is that the variable of interest X, the log price of an asset, follows an Itˆo semimartingale. The semimartingale is observed on some fixed interval of time, at discrete regularly spaced times with a small time lag. Semimartingale has three parts which include a drift, a continuous Brownian- driven part, and a discontinuous or jump part. Jumps part can be further decomposed into small and big jumps. This process generates a finite number of big jumps, whereas it may also generate a finite and infinite number of small jumps, which is a case of finite and infinite jump activity situations. In their early work, based on the observed sample path, they propose a test to determine whether the jumps part is present or not and whether the jumps have finite or infinite activity. Here in this study, they further tackled one more question, which is: Does the semimartingale need to have a continuous part? More precisely, Do Brownian motion exists at all? There is a natural statistical interest from the model specification point of view to separate the continuous part and discontinuous part. If there are no jumps at all or a limited number of jumps and no Brownian motion, The value of X decreases to a pure drift plus infrequent jumps, a model like this unrealistic in most financial data series. In finance, models have a jump component and drift part. Mathematical financial models having jumps are jump-diffusion models, which include a drift term, a Brownian-driven continuous part, and a finite activity jumps part. An infinite number of jumps dispense with the Brownian motion altogether. In this way, the process of log-price is a discontinuous levy process. The mathematical treatment of a model that relies purely on the jump process is quite different from the treatment of models where Brownian motion is present. There is a need to construct a procedure by which it can be decided that either the Brownian motion is present or it is forgone in favour of a pure jump process. This study aims to provide two tests permitting for asymmetric treatment of the two situations. At first, the presence of Brownian motion is the null hypothesis, whereas in the second null hypothesis is its absence. The approach of testing for the existence of Brownian motion is an alternative but a related approach (Todorov and Tauchen, 2010). The study employs the test statistics for jumps of (Aït-Sahalia and Jacod, 2009b).

Aït-Sahalia and Jacod (2011) propose a non-parametric statistical method to empirically classify the finite and infinite number of jumps using high-frequency data. Before this study, there is no statistical procedure to differentiate among various types of jumps. They consider a univariate process X which log of an asset price, on a fixed time interval ranges from one day to one year, at discretely and regularly spaced times measured in seconds. It is assumed that if the observed path has a jump process, then it is tested that whether there are finite jumps or infinite jumps known as “finite activity” or “infinite activity” for the jump component of X. The aim is to provide an asymptotic testing method, having an asymptotic significance level where asymptotic going to 1 to test the null hypothesis that univariate process or series has finite jumps. Whereas symmetric null hypothesis that series has infinite jumps. The assumption taken is that the process is an Itˆo semimartingale. The idea behind the two test statistics presented here is the same as (Aït-Sahalia and Jacod, 2009b). The study computes various power variations of the increments like truncated using different data frequencies. The aim is to construct a test statistic that is easy to calculate and having model-free properties. It is easy to up to the level that the implementation of these two tests does not require anything more than the computation of various truncated power truncations. For testing the null hypothesis that univariate process or series has a finite number of jumps, the test statistics proposed here as the same as Aït-Sahalia and Jacod (2009b), which is used for the presence of jumps with an additional truncation step. Whereas testing the null hypothesis that series has an infinite number of jumps is entirely new. When these test statistics are implemented on high-frequency stock returns, the results of both tests have provided evidence of infinite jumps in the data. It is also in line with the empirical results of (Aït-Sahalia and Jacod, 2009a). The assumptions taken here are much weaker than in Aït-Sahalia and Jacod (2009a) in the sense that the estimator proposed here is non-parametric, whereas the estimator proposed earlier is parametric.

Aït-Sahalia and Jacod (2012) provide spectrogram methodology, which is a non-parametric technique and relies on high-frequency data observations. This methodology decomposes asset returns into the continuous part, small jumps, and large jumps. The study also analyzes the magnitude and characteristics of each component.

Lee et al. (2013) propose an optimal test for comparing the null hypothesis of a continuous diffusion model to the alternative hypothesis of jump-diffusion models while accounting for market microstructure noise in the data. Under the general assumptions of the data generation process, the study derives a rate-optimal test that is valid. It also compares the proposed test's power to that of other competing tests, finding that the test's size and power properties are comparable to those of competing tests.

Corradi et al. (2014) introduce tests for jump intensity. The tests are developed as a pretest for jumps before estimating jump diffusions. It solves the test consistency and the sequential testing bias problems to facilitate consistent estimation of jump-diffusion models. A "self-excitement" test is also being designed to have power against path-dependent intensity. Monte Carlo simulations have shown that the proposed tests perform adequately in finite samples.

Jing et al. (2014) propose a non-parametric Preaveraging threshold (PAT) procedure to estimate the integrated volatility in the simultaneous presence of microstructure noise and jumps. The method is based on two steps, namely the step of pre-averaging to reduce microstructure noise and the step of threshold to eliminate jumps. For both finite and infinite activity jumps, the estimator is shown to work. Further, asymptotic properties, such as consistency and a central limit theorem, of the proposed estimator are established. Compared with some alternative methods in the literature, simulation studies show the excellent performance of the proposed estimators. The survey of covariation (matrix) estimation, a significant quantity in econometrics, under the simultaneous presence of noise and infinity activity jumps, includes some possible extensions of the present work.

Corradi et al. (2018) develop a jump test based on the earlier work of (Aït-Sahalia, 2002). The test uses data collected over a longer period of time and is based on realized third moments. The introduction of a model free jump test for the null hypothesis of zero jump intensity is the first contribution of the study. Second, it introduces a self-excitement test for the null of constant jump intensity versus the alternative of path dependent intensity under the maintained assumption of strictly positive jump intensity. These tests have power against autocorrelation in the jump component and are direct tests for Hawkes diffusions of (Aït-Sahalia et al., 2015). The occurrence of jumps and self-excitation is shown in an empirical illustration based on the analysis of 11 stock price series.

Cheng and Swanson (2019) used the Monte Carlo method to compare long-span jump tests to a variety of fixed-span jump tests. It finds that the long time span tests have good finite sample properties. Further, the study finds that fixed time span tests suffer not only from sequential bias but also severely oversized when jumps with a long time span are directly tested.

Kong et al. (2020) predict intraday stock price jumps using high frequency data from 1271 stocks listed on the Shenzhen Stock Exchange. According to the study, jumps in intraday stock prices, as well as their direction, can be predicted using technical indicators and liquidity measures. The finding suggests that combining the two measures outperforms either one alone in predicting stock price jumps.

Wu and Shi (2021) use a new effective and robust jump detection test based on the MaxEWMA chart methodology, which is useful to detect jumps at different frequencies of large as well as small changes in prices. The study observes that the simulation test provides better results with the increase of the value of lambda; that is why they recommend using a large value of lambda to identify jumps at small and large sampling frequencies.

The above Literature is concluded that a comprehensive study is needed to cover the existing gap in the literature related to the jump studies. As stated by Kongsilp and Mateus (2017), most existing studies on jump behaviour are based on the developed market, whereas Zhang et al. (2020) state that there are very few studies on jump behaviour in the emerging market. In the literature, much of the work is on jumps identification and is mostly limited to developed markets, and emerging markets are not much explored most specifically Asian markets.

Therefore, a comprehensive study is needed to identify jumps specifically in Asian developed and Asian emerging markets and compare the frequency of jump occurrences in both markets. Because developed-country equity markets are thought to be more informationally efficient than emerging equity markets. As a result, this study anticipates that the frequency of jumps may be higher in Asian emerging markets than in Asian developed markets. The first hypothesis that is developed for this study is:

Hypothesis 1: Jumps occur more frequently in Asian emerging markets as compared to Asian developed markets.

Andersen et al. (2002) provide a set of jump diffusion models for estimating the dynamics of returns and can be applied to continuous-time asset pricing. The study improves stochastic volatility diffusion by allowing for time-varying poison jumps in return. The study also investigates alternative models both within and outside the affine class. The study uses the Gallant and Tauchen (1996) efficient method of moments (EMM) procedure for estimation, which provides powerful model diagnostics and specification tests. The study uses this method to analyze daily data from the S&P 500 index as the daily frequency captures high-frequency fluctuations in the returns process, which are important for detecting jumps. The findings of the paper are that without jumps, all variant of stochastic volatility fails to considers all characteristics of returns. Similarly, any model without a strong negative correlation between returns and diffusion volatility fails. However, the main features of daily returns are taken into account by two stochastic volatility jump-diffusion (SVJD) specifications that have a strong negative correlation between returns and stochastic volatility.

Chernov et al. (2003) study the role of stochastic volatility (SV) factors that is additional volatility and jumps in the modelling of equity returns. There are two SV factors; one is stochastic volatility of volatility factor or long memory component, whereas the second factor, on the other hand, is solely focused on modelling tail behaviour. Volatility moves quickly in the first factor specification; this movement is forbidden in a single SV specification. The study has estimated ten models that are either affine or logarithmic in nature. For extending the model, in the affine class, two factors are considered: first, a jump to returns, and second, a simultaneous jump to both returns as well as volatility (Eraker et al., 2003). Whereas, the model is extended in the logarithmic class by adding a second SV factor by taking into account the feedback of the model. The study has used an efficient method of moment (EMM) as an estimation method. There are several advantages of using EMM, which include; it offers formal model fit statistical tests, formal diagnostics of model inadequacies, and comparison of non-nested specifications in a meaningful way.

An alternative to the test proposed by Aït-Sahalia (2002) is provided by Johannes

(2004). The test depends on a given null model, while the test of Aït-Sahalia is model-independent.Johannes (2004) explores the statistical and economic role of jumps in continuous-time interest rate models. The results show that jumps are substantial both economically and statistically. Statistically, the presence of jumps means that models of diffusion are misspecified. Diffusion models ignore jumps and are incorrectly specified in the sense that the tail behaviour of interest rate changes cannot be capture accurately. It uses a new jump-induced misspecification testing procedure, and the results provide strong evidence of jump presence. Estimations suggest that jumps remove the misspecification of the tail and produce more than half the conditional variance of changes in the interest rate. Next, to quantify the statistical role of jumps in interest rates, the study proposes a non-parametric jump-diffusion model and finally analyze the connection between jumps and macroeconomic news arrivals to measure the economic impact. Jumps have an essential effect on interest rate option prices, but they play a minor role in determining the cross-section of the prices of bonds.

Jiang et al. (2011) examine jumps in the prices of U.S. treasury bonds. In this study, the focus is on how the announcement of macroeconomic news and variation in market liquidity explains the jumps in U.S. treasury bonds. In this study, the Informativeness of order flow is scrutinized instantly after jumps in bond prices to know that how price discovery is affected by jumps. The variance swap approach of Jiang and Oomen (2008)is used to identify jumps in U.S. treasury bonds. The data of 5 minutes from Jan 2004 to Jun 2007 is collected for 2,3,5, and 10-year notes and 30-year bonds from the interdealer electronic trading platform i.e., BrokerTec. A large number of jumps are identified for all maturities. From the identified jumps, Economic news or events are recognized by (Bollerslev et al., 2000). A large number of prescheduled macroeconomic news and events are identified, which have the potential to causes jumps in bond prices. It is found that during the prescheduled announcement of macroeconomic news, a large number of jumps has occurred.

Amaya and Vasquez (2011) conduct a study to explore the relationship between jumps and stock returns. First, the study estimates weekly jumps in intraday data through the jumps estimation procedure of (Barndorff-Nielsen and Shephard, 2004). Using univariate sorting and Fama-Macbeth regressions, it is found that realized jumps significantly predict one-week stock returns. The bivariate sorting methodology shows a negative relationship between realized jumps and stock returns. Returns of large negative jumps are found larger than large positive jumps. The robustness tests also confirm this negative relationship. It is also found that returns of the long-short strategy increase in the time period of two weeks and three weeks. Furthermore, in the window of four weeks, reversal of returns is not observed.

Yan (2011) demonstrates that the stock return decreases with the average size of the jump in a stochastic discount factor framework. As a result, stocks with negative jumps must be compensated with higher returns than stocks with positive jumps.

Jiang and Yao (2013) state that in behavioural finance, investors form biased expectations about future cash flows associated with a company. These biases may also be related to company-specific characteristics. These biased expectations lead to stock market inefficiency, and mispricing of securities takes place. This mispricing of securities provides opportunities for investors to earn abnormal returns or unexpected components of stock returns. If mispricing is due to biased expectations of investors, then it will reverse in the future when new information about the company is updated, establishing a correlation of firm-specific characteristics with stock returns. This relationship is due to investors' response to unexpected information shocks, not due to systematic risk factors. They use a model-free approach in their study to identify jumps. Simulations have confirmed that this procedure of jump identification provides accurate estimations for the jumps returns. Data of daily stock returns for a period of 82 years, i.e., July 1927 to June 2009, collected from the CRSP database is used for jumps identification. The study focuses on five anomalies, i.e., Size, value, momentum, net share issuance, and liquidity, to measure the relationship between predictability of stock returns and jumps in stock prices. Annual returns are decomposed into jump returns and continuous returns and found that size, value, and liquidity effects are determined by jumps. When stocks are sorted into equally weighted size quintiles, it is found that the return of the jump of small firms is significantly exceeded by large firms relative to total returns. While the difference between continuous returns components of small and large stocks are statistically insignificant. The same is the case with stock illiquidity for jumps returns and continuous returns. However, for equally weighted quintile portfolios, both jump returns, as well as continuous returns for value stocks, are found significantly larger relative to growth stocks. Both the momentum effect and net share issuance effects are not determined by jumps. In momentum effects, all the past losers have higher jump returns instead of past winners. The empirical evidence of this study suggests that size, illiquidity, and significant part of value premium is a challenge to risk base explanation of cross-sectional stock returns predictability. The study has also shown that size and stock liquidity have no longer predictive power of stock returns after controlling for jumps.

Jiang and Kim (2016) examines the informational content hidden in analyst revisions. It uses jumps in stock prices as a proxy of large informational events. The objective of the study is to test that whether analysts provide incremental information over and above the information is contained in shadowy corporate events. Therefore, the focus is on the revision of before and after stock price jumps. It is found that short-term market reactions before and after revision of jumps is statistically significant. It means that these revisions have significant informational contents, but revision before and after jumps have different informational contents. Moreover, multivariate regression is used to control for potential differences in characteristics at the revision level, analyst level, and stock level. Three days "buy and hold" market-adjusted return is used as a dependent variable, whereas dummies of concurrent revisions, prejump revision, and post jump revisions are used as independent variables. It is evident from the results that revisions that are made concurrently with jumps in stock prices strengthened the reaction of the market. While the revisions after jumps diminish the reaction of the market. It is also shown by the results that revision before jumps are more informative than revision after jumps. In the end, it concludes that revisions of analyst recommendations occurred most of the time on the days with jumps in stock prices and explain a big portion of early market reaction. But still, revisions have significant information content, specifically before jumps in stock prices.

Jiang and Zhu (2017) uses large discontinued changes in prices of equity stock as proxy informational shocks, also called jumps. Jumps are the change in prices of stocks that are not frequent and large as well. First of all, jumps are identified in daily stock prices and intraday prices of equity stocks by using the statistical method given by (Jiang and Oomen, 2008; Jiang and Yao, 2013). Then the market reaction of large information shocks is examined by measuring the relationship between large information shocks and stock returns after shocks. The sample period for this study is from Jul 1975 to Dec 2012, while for intraday analysis, the time period is limited from Jan 1995 to Dec 2012. For the analysis, when stocks are sorted on the basis of preceding one month and past three-month cumulative jump returns. Stocks in the uppermost decile having positive information shocks outperform stocks in the bottom decile with negative information shocks in monthly returns in the next one month as well as in the next three months' investment period. So strategies such as long stocks (buying) having positive lagged jump returns and selling stocks (short) having negative lagged returns earn abnormal returns significantly. The analysis of intraday returns also shows the confirmation of short-term underreaction. The stocks with large jumps in the previous day earn larger returns movement in the same direction as the jump for the next day and three days than stocks with small intraday jumps in the previous day's investment periods. Furthermore, stock portfolios of positive jumps and negative jumps are constructed. Its predictive power is then compared with stocks having no jumps. Results show stronger underreaction in negative jumps in comparison with positive jumps. Stock returns after jumps are divided into jumps and non-jumps components. The results show more persistent positive jumps as compared with that negative jumps. Moreover, the analysis is replicated by excluding the jumps having a relationship with announcements of earnings to that how much underreaction in the short-run is driven by the earnings momentum. The results provide evidence of significant short-term underreaction, which means jumps are capturing information shock beyond earnings surprises. Furthermore, the limited investor attention hypothesis is tested for the existence of short-term underreaction. The result shows that the hypothesis of investor attention has limited contribution towards underreaction in the short run.

Chao et al. (2017) estimate Fama-French portfolio realized jumps and investigate whether the estimated positive, negative, and sign realized jumps can forecast or explain cross-sectional stock returns. According to the study, risk premium compensates not only realized jump components and continuous volatility, but also negative and positive jump risk, as well as sign jump risk, to some extent explain portfolio stock returns.

Mizrach et al. (2018) explore the significance of jumps in predicting future returns. First, it decomposes realized jumps into upside (positive) and downside (negative) jumps. Secondly, upside and downside jumps are separated into large and small jumps. It is found that both large and small upside jumps negatively predict next week's returns, whereas both large and small downside jump positively predicts next week's returns. On the basis of single and double portfolio sorting procedures and Fama Macbeth cross-sectional regression, it is found that signed small jumps predict future weekly returns significantly and negatively. Furthermore, a signed small jump is also a driver of signed jump risk and relatively earns higher returns. It is revealed from findings that pricing "upside" and "downside" jumps improve predictions cross-sectional return. Additionally, the breakdown of positive and negative jumps into large and small jumps brings further improvements in the prediction of returns. Moreover, the finding shows that small jumps derive the marginal predictive content of jumps, whereas large jumps have appeared as a proxy of realized skewness.

Nguyen et al. (2020) examine the extent to which firm size, book-to-market, past performance and/or jumps can explain long-term return volatility. According to the study, long memory volatility is common in the US, and the degree of memory is more closely linked to firm-specific characteristics, implying that long memory volatility is negatively priced in the cross section.

Megaritis et al. (2020) investigate whether rising macroeconomic uncertainty in the US equity market can predict increased volatility and stock price jumps. According to the findings, macroeconomic uncertainty has a significant and long term impact on volatility and jumps in the US equity market. It further argues that macroeconomic uncertainty is a common predictor of volatility and jumps in intraday returns of the S&P 500 index, and it has a higher predictive power on equity market volatility and jumps.

The above literature on jumps and returns is concluded that jumps can be divided into positive and negative jumps and returns during periods of jumps can also be compared with returns during non-jump periods to explore the role of jumps in equity returns of Asian developed and Asian emerging markets. As equity markets of emerging countries are considered as less informationally efficient than equity markets of developed countries therefore due to information asymmetry this study anticipates that during positive jumps periods the emerging equity markets may offer higher returns as compared with developed equity markets. Therefore, this study develops the second hypothesis as:

Hypothesis 2: Returns during positive jumps periods are larger than returns during non-jump periods and this pattern is more pronounced in Asian emerging markets as compared to Asian developed markets.

Moreover, earlier studies on asset pricing models like CAPM, Fama and French three-factor model (FF3F), Fama and French five-factor model (FF5F) conclude that it is only the systematic risk that explains the returns. However, the argument of Jiang and Yao (2013) is that systematic risk factors are link with information shocks to explain the returns. The study concludes that size effect and value effect are associated with jumps to explain returns. Therefore, Jiang and Yao (2013) study can be extended to study the profitability effect and investment effect of the Fama and French five factors model that whether these effects are connected with jumps returns in Asian developed and Asian emerging markets.

As jumps capture all types of information, whether it is public or private (Jiang and Oomen, 2008; Jiang and Yao, 2013; Jiang and Zhu, 2017), therefore If the factor premia is link with jump returns, this study argue that the premium associated with these factors are due information shocks or information content that is capture through jumps. Therefore, this study develops the third hypothesis as:

Hypothesis 3: There exists a significant link between factor premia and jump returns.

Andersen et al. (2001) introduce the realized volatility (RV), a non-parametric measure of volatility calculated by adding intraday squared returns. Their findings are based on high-frequency data, specifically 5-minute returns on two major currencies, the Deutschemark and the yen against the dollar, over a ten-year period. In the absence of noise and jumps, the study demonstrates that RV is a model-free and error-free estimator of integrated volatility. The findings include the fact that volatility movements across the two exchange rates are highly correlated, and the correlation increases as volatility rise. In daily returns, there are also strong volatility clustering effects. Furthermore, when compared to previous work, monthly RV remains highly persistent, indicating that volatility persistence decreases rapidly with the horizon.

Andersen et al. (2003b) develop a model to forecast realized volatility and correlation based on the theory of continuous-time arbitrage-free price processes. The proposed model is very simple to apply practically. It is empirically tested on the data of the foreign exchange market by estimating long-memory Gaussian vector autoregression (GVAR) on daily data of logarithmic realized volatilities. The results of this study (daily volatility models) are compared with high-frequency models. It is found that the volatility forecast of the developed model (Gaussian VAR) is very successful and dominate over other related approaches, including the GARCH approach. Moreover, lognormal-normal mixture forecast distribution provides conditionally well-calibrated density forecasts of returns, from which estimates of conditional return quantiles can be obtained accurately.

Eraker et al. (2003) analyze jumps in returns and jumps in volatility in the S&P 500 and Nasdaq 100 index. For this purpose, they develop a likelihood-based estimation method and estimated parameters, spot volatility, jump times, and jump sizes. Empirics shows that models having no jumps in volatility, diffusive stochastic volatility models without jumps, and jumps in returns are misspecified. The misspecification is because that there is no component that drives the conditional volatility of returns, which increases quickly. However, strong evidence is found for jumps in returns and jumps in volatility. Jumps in returns and jumps in volatility have a strong impact on option prices. Jumps in the volatility model significantly increase implied volatility for in-the-money and out-of-the-money options than models having only jumps in returns.

Barndorff-Nielsen and Shephard (2003) introduce a generalized form of realized volatility known as realized power variation (RPV). The study derives limit theorems of realized volatility and RPV that strengthen the results of consistency and help in the understanding of realized power variation and actual power volatility.

Corsi (2004) employs high-frequency realized volatility estimators to forecast the time series behaviour of foreign exchange volatility and develop a conditional volatility model based on realized volatility that could account for all of the empirical features found in the data (including memory persistence) while remaining parsimonious and easy to estimate. It also proposes an additive volatility cascade, which leads to a simple AR-type model in realized volatility with features that take into account realized volatility over various time horizons. This new model is termed the Heterogeneous Autoregressive model of Realized Volatility or HAR-RV. Simulation confirms that the HAR-RV produces empirical financial data characteristics such as long memories, fat tails, and self-similarity in a very easy and parsimonious manner. Estimation results and forecast of HAR-RV has shown exceptionally good out of sample forecasting performance, which consistently and significantly outperforms other standard models.

Barndorff-Nielsen and Shephard (2004) use realized power variation (RPV) in the context of Stochastic Volatility (SV) models, which inspired them to introduce realized bipower variation (BPV), which is a partial generalization of quadratic variation. BPV is a non-parametric technique and requires high-frequency data. Both RPV and BPV have the same robustness property, but the latter can also estimate the integrated variance in stochastic volatility models. In this way, BPV provides a model-free and consistent alternative to realized variance. Barndorff-Nielsen and Shephard (2004) also introduce the generalized form of bipower variation called Tripower Variation (TPV). BPV is an unbiased estimator of integrated volatility in the presence of jumps, but it is subject to an upward bias in a finite sample. TPV is more efficient than BPV but also more vulnerable to market microstructure noise of high-frequency data.

Aït-Sahalia (2004) uses maximum likelihood statistical-based methods to disentangle volatility from jumps accurately. The study decomposes total noise into a continuous Brownian part and a discontinuous jump part. This study answers a simple, rather important question of how the presence of jumps impacts the estimation of diffusion parameters. Maximum likelihood can be used to perfectly separate Brownian noise and a jump part. The Levy process is made up of three distinct processes: a continuous component, a big jump component in the form of a compound Poisson process with jumps larger than one, and a small jumps component in the form of a pure jump martingale with only smaller jumps. In this study, Aït-Sahalia (2004) separates the Brownian component from the big jumps component and disentangle the Brownian component from the small jumps components.

According to Barndorff-Nielsen and Shephard (2004), adding jumps to the SV model does not change the probability limit of the bipower estimator, which means that realized variance can be combined with realized bipower variation to estimate the quadratic variation of the jump component. This method divides quadratic variation into continuous and jumps components.

One of the challenges with realized volatility using high frequency data is that market microstructure noise becomes more prominent when the sampling frequency is less than 10 minutes, and the realized volatility estimates do not remain robust. Zhang et al. (2005) propose a model-free two-scale estimator (TSRV) that works for any size of noise. It uses tick data to correct for the adverse effects of microstructure noise on volatility estimation. During the estimation process, it becomes clear why and where the volatility estimator fails when returns are sampled at high frequencies.

A major problem with volatility estimation is how to estimate it consistently and efficiently in microstructure noise. The issue of consistency is addressed by Zhang et al. (2005), but in the TSRV approach, the volatility estimates are not efficient because the rate of convergence is not satisfactory. In their work, the best estimator converges to the true volatility only at the rate of n1/6. Zhang (2006) propose a new non-parametric estimation technique, multi-scale realized volatility (MSRV), which converges to the true volatility at the rate of n1/4, which is the best attainable.

Fan and Wang (2007) propose nonparametric methods for estimating integrated volatility and jump variation in the presence of market microstructure noise. The study uses noise resistant methods to estimate the integrated volatility after removing jumps from the data. It adjusts the data for jumps using the estimated jumps and then proposes using TSRV and MSRV to estimate integrated volatility using the jump adjusted data. It also estimates integrated volatility by constructing wavelet realized volatility from the jump adjusted data. The asymptotic analysis and simulation study shows that the proposed wavelet methods successfully remove jumps and accurately estimate the integrated volatility.

Kalnina and Linton (2008) propose Adjusted Two Scale Realized Volatility (ATSRV) which is a modified version of TSRV. Zhang et al. (2005) and Zhang (2006) assume that the microstructure noise is i.i.d. and independent of the latent price. Kalnina and Linton (2008) generalize the standard additive noise model in three directions. Allowing for a correlation between MS noise and latent returns is the first generalization. The magnitude of MS noise is the second generalization. The estimator's rate of convergence varies depending on the magnitude of the noise, ranging from n1/6 to n1/3, with n1/6 corresponding to the "big" noise. The third generalization is that it allows MS noise to have diurnal heteroscedasticity. Allowing for diurnal heteroscedasticity in the model changes the TSRV in such a way that the original TSRV estimator may become inconsistent due to end effects. In some cases, instead of estimating the quadratic variation, some function of the noise would be estimated. The ATSRV estimator is consistent without requiring the selection of new parameters.

Barndorff-Nielsen et al. (2008) develop realized kernels (RKs) as an estimate of quadratic variation in the presence of market microstructure noise. RKs are efficient and converges at the fastest rate. Moreover, the asymptotic variance of RKs is smaller than TSRV and MSRV estimators. RKs are robust in the presence of noise process, endogenous market frictions, and endogenous spacing in the timing of the data. RKs are also related to heteroscedastic autocorrelation estimators. RKs are more accurate than realized variance when compared on the basis of 20 minutes returns data.

Podolskij and Vetter (2009) propose Modulated Bipower Variation (MBPV) for diffusion models with microstructure noise for finite jumps activity. For this purpose, the study uses sub-sampling to obtain more efficient estimators of the integrated volatility and the integrated quarticity. The conversion of the proposed model is proved stable with a conversion rate of n1/4.

Corsi et al. (2010) introduce the concept of threshold bipower variation based on bipower variation and threshold estimation. The objective is to study the role of jumps in volatility forecasting. They divide the volatility into its continuous and discontinuous components using consistent estimators (threshold bipower variation). The results show that threshold multipower variation, which is a generalized form of threshold bipower variation, concedes a reasonable central limit theorem in the presence of jumps as that of standard multipower variation. The proposed techniques, based on empirical evidence, significantly improve the accuracy of volatility forecasts, particularly after jumps periods.

Barndorff-Nielsen et al. (2011) construct subsampled realized kernels (SRK). They construct SRK by combing the subsampling technique of Zhang et al. (2005) and Barndorff-Nielsen et al. (2008) realized kernels. Subsampling is beneficial for estimating discontinuous kernels like truncated kernels. It also does not affect the asymptotic distribution of kinked kernels like Bartlett kernels. However, subsampling is harmful to efficient smooth kernels such as parent kernels because it increases the asymptotic variance. The subsampled estimator is consistent and converges at a rate of n1/6. It also overcomes the inefficiency of the poor choice of kernel weights.

Andersen et al. (2012) introduced two new estimators of integrated variance (MinRV and MedRV) alternatives to bipower and tripower variation. These estimators rely on nearest neighbour truncation to achieve jump robustness while sharing several essential features with existing estimators. Todorov and Tauchen (2012) introduce the realized Laplace transform of volatility (RLT). It is a nonparametric approach that is robust to the presence of jumps. According to asymptotic analysis and Monte Carlo simulations, the method can be used to reliably estimate the integrated joint Laplace transform of the volatility over different points in time.

Jacod and Todorov (2014) propose a non-parametric efficient estimation technique of integrated volatility in the presence of infinite jumps variation. The study estimates volatility locally from the characteristic empirical function of the increments of the process over blocks of shrinking length and then add these estimates to form initial estimators of the integrated volatility. The study removes the bias of infinite jumps variations by using integrated volatility estimators formed from the empirical characteristic function of the high-frequency increments for different values of its argument.

Brownlee et al. (2016) introduce a new estimator of the integrated volatility of asset prices, called truncated two-scales realized volatility estimator (TTSRV). It introduces the new technique by combining the truncation technique of Mancini (2009) to deal with the jumps and TSRV of Zhang et al. (2005) to deal with the market microstructure noise. The New TTSRV estimator is consistent in the presence of finite or infinity price jumps and market microstructure noise. The simulation shows that the TTSRV performs satisfactorily in finite samples and outperforms many alternative estimators.

The above literature on integrated volatility measures is concluded that there exist various techniques of measuring integrated volatility. Realized volatility of Andersen et al. (2001) is the most widely used method for measuring total integrated volatility. RV estimates both continuous and discontinuous (jump) components of quadratic variation. Whereas realized bipower variation (BPV) and tri-power variation (TPV) methods of Barndorff-Nielsen and Shephard (2004) and Barndorff-Nielsen and Shephard (2006) capture only the continuous component of quadratic variations. Therefore, the jump component can be identified simply by the difference of RV and BPV Barndorff-Nielsen and Shephard (2004) and Barndorff-Nielsen and Shephard (2006), or by the difference of RV and TPV (Andersen et al., 2007). However, In the presence of jumps, BPV is an unbiased estimator of integrated volatility, but it has an upward bias in a finite sample. As a result, TPV is more effective than BPV.

Therefore, this study first expects that TPV may be a better estimation technique to capture continuous component of quadratic variations and integrated volatility of the jump component can be better estimated by using method of (Andersen et al., 2007). It further expects that integrated volatility may increase during periods of jumps as compare with non-jump periods. Hence, this study develops the fourth hypothesis as:

Hypothesis 4: Integrated volatility during jumps periods is larger than integrated volatility during non-jumps periods in both Asian emerging markets than in Asian developed markets.

2.1 Summary of the Hypotheses

The summary of the hypotheses are as follows:

Hypothesis 1: Jumps occur more frequently in Asian emerging markets as compared to Asian developed markets.

Hypothesis 2: Returns during positive jumps periods are larger than returns during non-jump periods and this pattern is more pronounced in Asian emerging markets as compared to Asian developed markets.

Hypothesis 3: There exists a significant link between factor premia and jump returns.

Hypothesis 4: Integrated volatility during jumps periods is larger than integrated volatility during non-jumps periods in both Asian emerging markets than in Asian developed markets.

Chapter 3

Research Methodology

This chapter describes the markets for which data is collected, as well as the methodology used in this study. Section 3.1 provides the detail of the data used in the analysis of this study and discusses the sampling procedure for selecting indices from each Asian developed and Asian emerging region. Section 3.2 discusses the swap variance methodology used to identify jumps in Asian-developed and Asian-emerging markets. Section 3.3 provides an overview of the stock indices selected from Asian developed and Asian emerging equity market. Section 3.4 gives descriptive statistics of daily data index returns for each Asian developed and Asian emerging market for the selected period.

3.1 Data Frame and Sampling Technique

This study uses the daily index prices data to identify monthly jumps in the index prices of Asian developed and Asian emerging equity markets from February 2001 to February 2020. The study uses the Morgan Stanley Capital International (MSCI) classification to separate the Asian developed and Asian emerging markets. The developed market as classified by MSCI includes five Asian-developed markets and ten Asian-emerging markets. These markets are considered as population of the study.

In this study, a two-tier sample selection procedure is used. The first-tier decides that which class of financial markets is to be included in the sample. In this study, it is decided to include both Asian-developed and Asian-emerging markets. The main reason to include both markets is that it covers both the stable markets and rapidly growing markets of Asia. Asian emerging markets are riskier and highly volatile as compared to Asian developed markets. The Asian emerging markets have political instability, whereas Asian developed markets are politically stable. The corporate governance in Asian emerging markets is comparatively poor than in Asian developed markets. Furthermore, Asian emerging markets have a thin structure, low liquidity, and high inflation rates than Asian developed markets. Moreover, the currency of Asian emerging markets devalues most of the time and has high-interest rate risk, and cross-border cash flows are high compared to Asian developed markets. These factors hurt the Asian emerging markets and make the Asian emerging markets highly volatile. Because of these differences in both markets, a current study compares the identification of jumps, returns in the presence and absence of jumps, and integrated volatility during jumps and non-jump periods.

The second-tier decides that which countries from each class are to be included in the sample. Therefore, in this study, all of the markets from Asian developed and Asian emerging markets are considered for analysis except those markets whose indices are established after 2001. The reason to select the time period from Feb 2001 to Feb 2020 is to consider the same time frame for all markets to prove a common base for comparison of Asian-developed and Asian-emerging markets. Four markets out of five Asian developed markets meet the criteria whereas six out of ten Asian emerging markets meet the criteria to be considered in the sample for analysis. Therefore, the study has taken four countries from Asian developed markets and six countries from Asian emerging markets.

The Asian developed markets include Australia (S&P ASX 200 index), Hong Kong (Hang Seng index), Japan (Nikkei 225 index), and New Zealand (NZX 50 index). Whereas Asian emerging equity markets include China (Shanghai Composite index), India (Nifty 50 index), Indonesia (JKSE index), Pakistan (KSE-100 index), Thailand (SET Index), and Sri Lanka (CSE All Share index). The data of these equity indices are taken from the Thomson Reuters DataStream.

3.2 Methodology

There are various methods to identify statistically significant jumps. The methods can be grouped into five categories: first, jump tests based on bi-power variation include the tests developed by Andersen et al. (2007), Andersen et al. (2012), Barndorff-Nielsen and Shephard (2004), Barndorff-Nielsen and Shephard (2006), Corsi et al. (2010), and Huang and Tauchen (2005); second, techniques based on higher-order variation include the techniques developed by Aït-Sahalia and Jacod (2009a) and Podolskij and Ziggel (2010); third, jump tests based on returns include the tests developed by Lee and Mykland (2008) and Lee and Hannig (2010); fourth, tests based on swap variance include tests developed by Jiang and Oomen (2008); fifth, jump tests that mitigate the impact of microstructure noise include the tests developed by (Aït-Sahalia and Jacod, 2012; Lee and Mykland, 2012).

In this study, the jumps are estimated through the swap variance (SwV) jump identification method proposed by Jiang and Oomen (2008) to identify monthly jumps in Asian developed markets and Asian emerging markets. The SwV test is similar in purpose to the bi- power variation (BPV) test developed by Barndorff-Nielsen and Shephard (2006) but with different logic and properties. The BPV test identifies jumps by comparing RV to a jump robust variance measure. In contrast, the SwV test identifies jumps by comparing RV to a jump-sensitive variance measure involving higher-order moments of returns, making it more powerful in many circumstances. Moreover, the SwV jump test explicitly considers market microstructure noise and can be applied to daily data (Jiang and Oomen, 2008; Jiang and Zhu, 2017)

3.2.1 Swap Variance Approach of Jumps Identification

The swap variance jump test statistic, J_t, at time t is given in the following equation under the null hypothesis of no jump:

$$\mathrm{J_t}{=}\frac{\mathrm{BPV_t}}{\mathrm{M^{-1}}\sqrt{\widehat{\Omega}_{\mathrm{SwV}}}}\left(\frac{1{-}\mathrm{RV_t}}{\mathrm{SwV_t}}\right) \tag{3.1}$$

Where J_t is Jiang and Oomen (2008) Swab Variance jump test statistics. RV_t is the realized variance Andersen et al. (2001), a measure of total volatility in asset prices calculated by summing daily squared returns filtered through an MA (1) process, that can be estimated by the following equation:

$$\mathrm{RV_t}{=}\sum_{\mathrm{t=1}}^{\mathrm{M-1}}(\mathrm{r_t})^2 \tag{3.2}$$

where RV_t is monthly realized volatility and r_t is the daily logarithmic return, and BPV_t isthe realized bi-power variation developed by Barndorff-Nielsen and Shephard (2004) tocapture the continuous component of the total variation, and is calculated as:

$$\mathrm{BPV_t}{=}\frac{\pi}{2}\left(\frac{\mathrm{M}}{\mathrm{M}-1}\right)\sum_{\mathrm{t=2}}^{\mathrm{M}}|\mathrm{r_t}|\quad|\mathrm{r_{t-1}}| \tag{3.3}$$

where BPV_t is the monthly bipower variation, SwV_t is swap variance, and calculate as follows:

$$\mathrm{SwV_t}{=}\ 2\sum_{\mathrm{t=1}}^{\mathrm{M}}(\mathrm{R_t}{-}\mathrm{r_t}) \tag{3.4}$$

where SwVt is the monthly swap variance, R_t is simple to return, and $\widehat{\Omega}_{\mathrm{SwV}}$ is estimated bythe following equation:

$$\widehat{\Omega}_{\mathrm{SwV}}{=}\frac{\mu_6}{9}\ {\mu_{6/4}}^{-4}\frac{\mathrm{M}^3}{\mathrm{M}-3}\sum_{\mathrm{t=1}}^{\mathrm{M}}\prod_{\mathrm{k=0}}^{3}|\mathrm{r_{t-k}}|^{3/2} \tag{3.5}$$

in which the value of $\frac{\mu_6}{9}\ {\mu_{6/4}}^{-4} = 3.05$ (Maneesoonthorn et al., 2020), M is the number of equity market price observations per month with 22 observations per month and $\mathrm{r_t}$ denotes the logarithmic returns of equity market prices.

In addition, the total numbers of months having jumps, positive jumps, and negative jumps are given as follow:

$$\text{Number of months having jumps } = \sum_{\mathrm{t=1}}^{\mathrm{T}} (|\mathrm{Jt}| > \mathrm{c}_{\propto}) \tag{3.6}$$

$$\text{Number of positive jumps months } = \sum_{\mathrm{t=1}}^{\mathrm{T}} (\ \mathrm{Jt} > \mathrm{c}_{\propto}) \tag{3.7}$$

$$\text{Number of negative jumps months } = \sum_{\mathrm{t=1}}^{\mathrm{T}} (\mathrm{Jt} < -\mathrm{c}_{\propto}) \tag{3.8}$$

where $\mathrm{c}\propto$ is the critical value at the 5% significance level, which is 1.645, and the percentage of the month having jumps relative to the total number of the months is computed as under:

$$\text{Percentage of months having jumps } = \frac{\text{Number of jump months}}{\text{Total number of months}} * (100) \tag{3.9}$$

3.2.2 Equity Market Returns During Jump Periods: A Dummy Variable Regression Model

The dummy variable regression model is used to measure the impact of the presence of jumps on equity returns of Asian developed markets and Asian emerging markets.

$$\mathrm{R}_t\ = \beta_0 + \beta_1 \mathrm{JP}_t + \ \varepsilon_t \tag{3.10}$$

Whereas in equation 3.10, R_t indicates monthly index returns and JP is a dummy variable representing returns during jump periods (JP). If there is a jump in the index prices for the month, the dummy variable is assigned a value of one, and if there is no jump, the dummy variable is assigned a value of zero.

$$\mathrm{R}_t = \beta_0 + \beta_1 \mathrm{PJP}_t + \beta_2 \mathrm{NJP}_t + \varepsilon_t \tag{3.11}$$

In equation 3.11, PJP is a dummy variable that indicates index returns during positive jumps periods, it takes the value of one if the month has a positive jump, and otherwise, it takes the value of zero. Whereas NJP is a dummy variable that indicates index reruns during negative jumps periods, it takes the value of one if the month has a negative jump; otherwise, it takes the value of zero. In equation 3.10 the index returns are regressed over JP whereas in equation 3.11 index returns are regressed over PJP and NJP to examine the role of the presence of positive and negative jumps on index returns in each Asian developed equity market separately.

3.2.3 Association of Fama and French's Five Factors and Jump Returns

In order to determine which factor of Fama and French's five factors are link with jump returns in Asian developed and Asian emerging markets. The Jump returns, positive jump returns, and negative jump returns are regressed against Fama and French's five factors risk premium for Asian developed and Asian emerging markets.

For this purpose, monthly jump returns are calculated for each Asian developed market and each Asian emerging market. Then monthly jump returns are further segregated into positive and negative jump returns. After segregation, a composite jump returns, a composite positive jump return, and a composite negative jump return are calculated for the developed Asian pacific region and emerging Asia Pacific region by taking the average of the significant jumps returns, positive jump returns, and negative jump returns of all Asian developed markets and all Asian emerging markets. Whereas data of Fama and French's five-factor risk premium for Asian pacific developed and emerging markets is downloaded from Kenneth R.

French - Data Library. The regression equations take the following forms:

$$\mathrm{JR_t} = \mathrm{b_0} + \mathrm{b_1}\,(\mathrm{MKT_t}) + \mathrm{b_2}\,(\mathrm{SMB_t}) + \mathrm{b_3}\,(\mathrm{HML_t}) + \mathrm{b_4}\,(\mathrm{RMW_t}) + \mathrm{b_5}\,(\mathrm{CMA_t}) + \varepsilon_t \tag{3.12}$$

$$\mathrm{PjR_t} = \alpha_0 + \alpha_1\,(\mathrm{MKT_t}) + \alpha_2\,(\mathrm{SMB_t}) + \alpha_3\,(\mathrm{HML_t}) + \alpha_4\,(\mathrm{RMW_t}) + \alpha_5\,(\mathrm{CMA_t}) + \varepsilon_t \tag{3.13}$$

$$\mathrm{NJR_t} = \gamma_0 + \gamma_1\,(\mathrm{MKT_t}) + \gamma_2\,(\mathrm{SMB_t}) + \gamma_3\,(\mathrm{HML_t}) + \gamma_4\,(\mathrm{RMW_t}) + \gamma_5\,(\mathrm{CMA_t}) + \varepsilon_t \tag{3.14}$$

Whereas

$\mathrm{JR_t}$ = Jump return at the time t

$\mathrm{PjR_t}$ = Positive jump return at time t

$\mathrm{NjR_t}$ = Negative jump return at time t

$\mathrm{MKT_t}$ = Market premium at the time t

$\mathrm{SMB_t}$= Size Premium at time t

$\mathrm{HML_t}$= Value Premium at the time t

$\mathrm{RMW_t}$= Profitability Premium at the time t

$\mathrm{CMA_t}$= Investment Premium at time t

3.2.4 Integrated Volatility Measures and Integrated Volatility During Jump Periods

Barndorff-Nielsen and Shephard (2004) and Barndorff-Nielsen and Shephard (2006) developed robust jump estimators to capture only the continuous component of quadratic variation known as realized bipower variation (BPV) as in equation (3.3) and tri-power variation (TPV) as in equation (3.16). BPV is an unbiased estimator of integrated volatility in the presence of jumps, but it is subject to an upward bias in a finite sample. Thereby, TPV is more efficient than BPV. Since RV estimates both continuous and discontinuous (jump) components of quadratic variation, while BPV and TPV capture only the continuous component, the jump component can be identified simply by the difference of RV and BPV Barndorff-Nielsen and Shephard (2004) and Barndorff-Nielsen and Shephard (2006), or by the difference of RV and TPV (Andersen et al., 2007).

This study uses the method developed by (Andersen et al., 2007) to separate the variation due to the monthly jump component and the continuous components by using realized volatility (RV) as in equation (3.2) and tri-power variation (TPV) as in equation (3.16). Variations due to the jump component are estimated as follows:

$$\mathrm{JV_t{=}RV_t{-}TPV_t} \tag{3.15}$$

where tri-power variation (TPV) is given as follows:

$$\mathrm{TPV_t}{=}\left(2^{\frac{1}{3}}\frac{\gamma(\frac{5}{6})}{\gamma(\frac{1}{2})}\right)^{-3}\sum_{\mathrm{t=3}}^{\mathrm{M-1}}|\mathrm{r_t}|^{2/3}\;|\mathrm{r_{t-1}}|^{2/3}|\mathrm{r_{t-2}}|^{\frac{2}{3}} \tag{3.16}$$

The ratio of jump variation to total variation is calculated as:

$$\text{The ratio of jump variation to total variations} = \frac{\mathrm{JV_t}}{\mathrm{RV_t}} \tag{3.17}$$

The ratio of jump to total variation measures the percentage of varations of the due to jump component in total variations. Realized variation (RV) measure the total variations in index prices for each eqiuty market.

3.3 Overview of Indices Selected From Asian Developed and Asian Emerging Markets

The indices selected from Asia's developed and emerging markets are discussed in order to provide a brief overview of each index.

3.3.1 Overview of Indices Selected From Asian Developed Markets

The indices selected from the Asian developed market are discussed briefly to get an insight of each Asian developed index.

3.3.1.1 S&P-ASX- 200 Index

The S&P-ASX (Standard & Poor-Australian Stock Exchange) index was established on March 31, 2000, representing 82% of Australia's total share market capitalization and comprises 200 largest listed companies. It is considered as a benchmark for equities' performance in the Australian market. The S&P-ASX-200 uses a capitalization-weighted-index, which implies that the contribution of a company is proportional to its market value of shares relative to total market capitalization. It is also a float-adjusted-index as the contribution of a company to the ASX-200 index is proportional to the value of the company at the time of float. The number of companies does not always remain fixed at 200; it fluctuates after quarterly rebalancing.

3.3.1.2 Hang Seng Index

The HSI (Hang-Seng-Index) started its operations as an index in 1969 and it is under the supervision of Hang-Seng-Indexes-Company-Limited (HSICL). The responsibility of HSICl is to compile, manage and publish the HSI. The HSI is also float adjusted and market-capitalization-weighted index comprising 50 companies with the largest market capitalization list on the Hong Kong Stock exchange. It shows the overall performance of the Hong Kong market. It keeps track and monitors changes of daily stock prices For a company to be included in the HSI, it should have had two years history of listing and should be one of the companies that account for the top 90% of total market capitalization. Moreover, that company should be one of those companies, which account for the top 90% of the total turnover of shares on the HSI.

3.3.1.3 Nikkei 225 Index

The Nikkei-225-index is the Tokyo Stock Exchange index, which started functioning in 1950. It is an index of 225 companies based on price weightage. It trades shares on the Japanese Yen. The selected 225 companies on the index represent various sectors of Japan's industries. It evaluates the share performance of listed companies and acts as a benchmark for all public companies listed on the TSE.

3.3.1.4 NZX 50 Index

The NZX 50 Index is New Zealand's main stock exchange index representing the 50 biggest stocks. It is a free-float and market-capitalization index and accounts for around 90% of equity market capitalization in New Zealand. It was renamed as S&P/NZX 50 in 2015 as a mark of 'strategic partnership' between the S&P Dow Jones Index and NZX Index. Following the partnership, S&P DJI has taken up the responsibility for recording, publishing, and distributing all NZX indices to the interested parties.

3.3.2 Overview of Indices Selected From Asian Emerging Markets

The indices considered from Asian developing markets are briefly discussed to have an insight of each Asian developed index.

3.3.2.1 Shanghai Composite Index

The Shanghai stock exchange composite Index (SSE-composite Index) is a stock market index of all types of stocks (A stocks and B stocks) that are traded at the SSE (Shanghai-Stock-Exchange) and was started on July 15, 1991. SSE Indices are calculated on the basis of a Paasche weighted composite price index formula. It means that the index takes into account a base period on a specific day for its calculation. December 19, 1990 is the base day for SSE Composite Index and that constitutes the total market capitalization for all stocks. The Base Value for calculation of SSE-composite Index is 100.

3.3.2.2 Nifty 50 Index

The Nifty 50 index, launched on 22 April 1996, is a benchmark index of the Indian stock market that shows the weighted average of the largest 50 listed on the National Stock Exchange. It is owned and managed by NSE Indices and is the subsidiary (wholly owned) of the NSE Strategic Investment Corporation Limited. It is a free float weighted index with a base value of 1000. On June 26, 2009, the computation was changed to free-float methodology from the previous weighted method.

3.3.2.3 JKSE Index

The JKSE (Jakarta Stock Exchange Composite Index) started its operations in 1977. It is an index for all stocks of companies listed on the Indonesia Stock Exchange. JKSE was a stock exchange based on Jakarta, Indonesia before it was merged with the SSE (Surabaya Stock Exchange) to become the Indonesia Stock Exchange.

3.3.2.4 KSE-100 Index

The KSE-100 Index (Karachi Stock Exchange) was launched in November 1991as a stock index with a base of 1000 points and acts as a benchmark for the performance of stock prices on the Pakistan Stock Exchange (PSX) over a given period. The KSE-100 is a weighted index capitalization- and comprises 100 companies that represent about 90% of the total market capitalization. Companies with the highest market capitalization are selected as representatives for index computation. To make sure full representation on the index, companies with the highest market capitalization from each key sector is also included.

3.3.2.5 SET Index

The Stock Exchange of Thailand (SET) Index is a Thai composite stock market which uses the base date of April 30, 1975 (when it was first established) with a base of 100 points. It is calculated on the basis of the prices of all common stocks trades on SET. It is a market capitalization-weighted price index and it compares the current market value of all listed common shares with the base period. The SET Index is adjusted in line with changes in the prices of stocks as a result of changes in the number of stocks due to exercised warrants, public offerings, or conversions of preferred stock to common shares.

3.3.2.6 CSE All Share Index

The CSE (Colombo Stock Exchange All-Share Index) is the main stock market index that evaluates the performance of stocks of all companies listed on the CSE in Sri Lanka. It is a market capitalization weighted-index. The CSE has the base year of 1985 with a base value of 100. It represents companies from across 20 business sectors and operates through a Central Depository System—an automated system for clearing the buying and selling process. The company was renamed as the Colombo Stock Exchange in 1990.

3.3.3 Investment in Foreign Indices

Most equity investors who want to diversify their investment portfolio may opt to go for investment in foreign indices. However, investors face some constraints while investing in the foreign index, making it difficult to invest in foreign stocks. The most important constraints that almost all investors face includes the high transaction cost (such as brokerage commissions) in foreign equity markets as compare with investing local markets, volatility of exchange rates over times, and the risk of liquidity associated with investment in foreign stocks. Therefore, investors must consider these constraints before investing in foreign indices. Investors may use hedging techniques like (options, futures, and or forward contract) for reducing exchange rate risk. Investors may observe the bid-ask spread and trading volume of foreign stocks. Stocks that have low bid-ask spread and high trading volume are generally more liquid.

3.4 Descriptive Statistics of Monthly Index Returns for Each Asian Developed and Asian Emerging Market

This section provides descriptive statistics of monthly return data for Asian developed and Asian emerging markets in order to get an understanding of returns and variations in returns across all Asian developed and Asian emerging markets. First it provides descriptive statistics of monthly index returns, and then the monthly returns of each index are plotted on a line graph to obtain a graphic representation of monthly index returns and their variation for each developed and emerging market.

3.4.1 Descriptive Statistics of Monthly Index Returns for Asian Developed Markets

The descriptive statistics of monthly index returns for Asian developed markets are reported in table 3.1. It shows the mean monthly returns, standard-deviation of returns, minimum value, maximum value, kurtosis (kur), and skewness (skew) for all indices of Asian developed region.

Table 3.1: Descriptive Statistics of Monthly Index Returns for Asian Developed Markets

Indices	Mean	SD	Min	Max	Kur	Skew
S&P ASX 200	0.358%	3.649%	-12.662%	7.310%	0.428	-0.717
Hang Seng	0.423%	5.854%	-22.466%	17.074%	1.128	-0.357
Nikkei 225	0.366%	5.408%	-23.827%	12.850%	1.080	-0.597
NZX 50	0.869%	3.321%	-11.851%	8.731%	1.374	-0.687

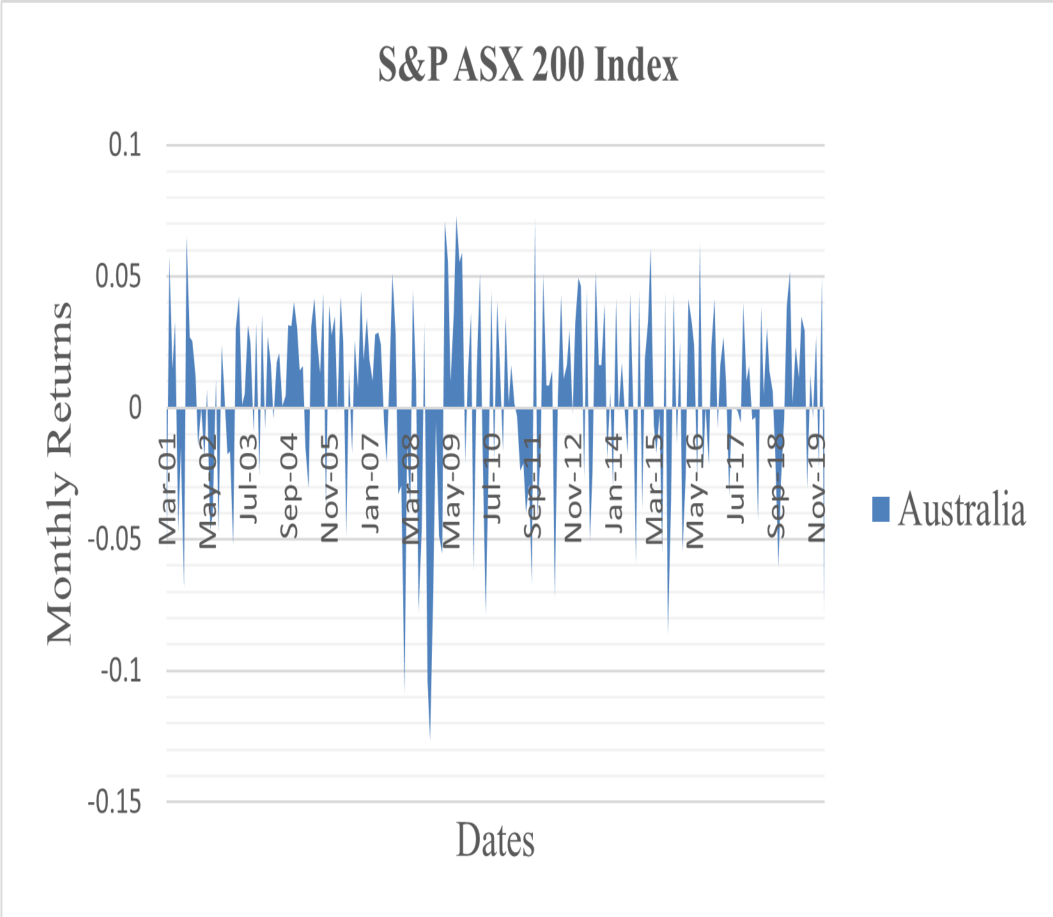
Table 3.1 describes descriptive statistics of monthly returns for Asian developed markets. The NZX 50 index has the highest average monthly return of 0.869 percent per monthly, while the S&P ASX 200 index has the lowest average monthly return of 0.358 percent per month. The value of standard deviation for the Hang Seng index is 5.854 percent, which means that the average deviation of the Hang Seng index from its average returns is 5.854 percent per month, implying that the Hang Seng index monthly returns are highly risky when compared to monthly returns of other Asian developed markets. While the standard deviation lowest for the NZX 50 index which is 3.321 percent, this means that the index's average monthly returns deviate from its mean returns by 3.321 percent.

The maximum value is highest for Hang Seng index that is 17.074 percent, whereas the minimum value is the lowest for the Nikkei 225 index that is -23.827 percent. The returns of Asian developed markets are leptokurtic, particularly the returns of the NZX 50 when compared to others as value of excess kurtosis for NZX 50 index is highest among Asian developed markets. Furthermore, the monthly returns of all Asian developed markets are negatively skewed. The minimum-maximum values are significantly higher for every equity market in the Asian developed region, indicating the possibility of jump occurrences in Asian developed markets. The line graph of monthly return may clearly show the higher returns moment for each of these markets.

3.4.1.1 S&P-ASX- 200 Index

Figure 3.1 displays line graph of the monthy returns for S&P ASX 200 index for the sample period of February 2001 – February 2020. It is observed from figure 3.1 that for most of the months the range of monthly returns for S&P ASX 200 is almost between -1% to +1%. However, there are also many months in which returns are abnormally high and lie between negative 8% to positive 6%, so there is high possibility of jumps occurrences in these days.

FIGURE 3.1: Monthly Returns Line Graph: S&P-ASX- 200 Index



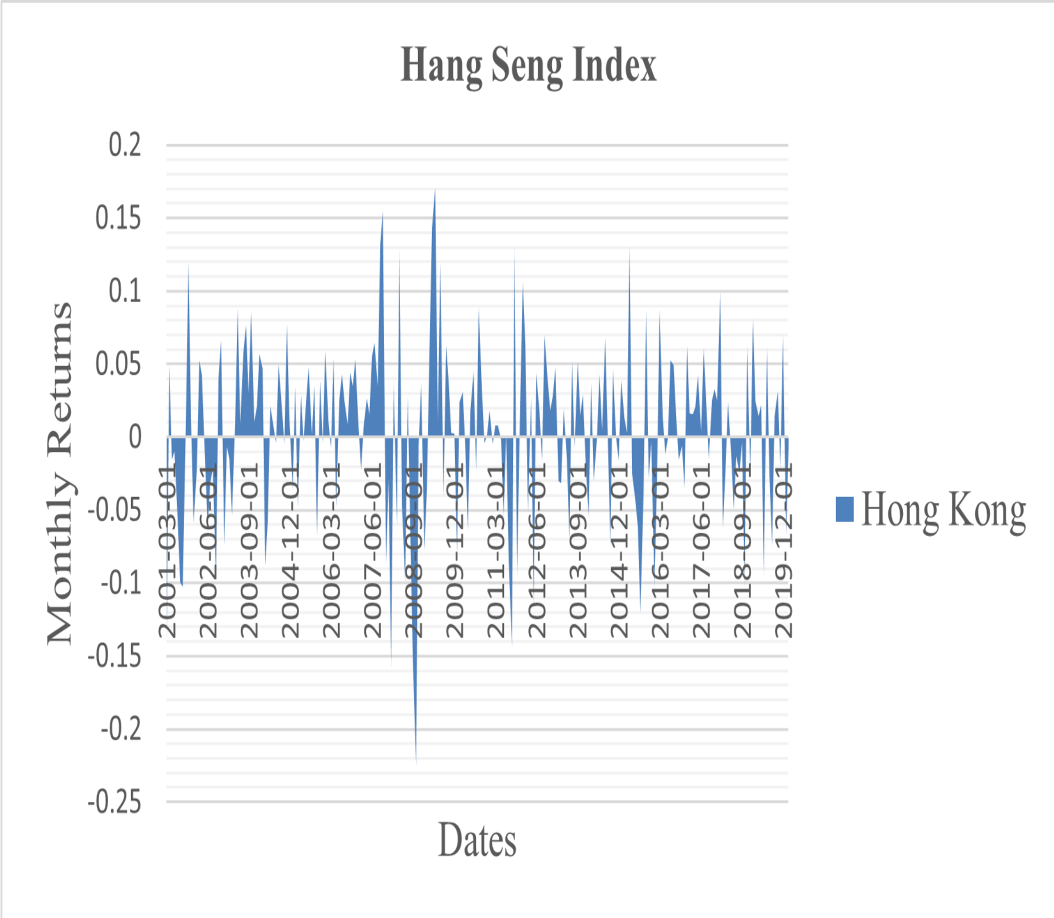
3.4.1.2 Hang Seng Index

Figure 3.2 depicts a line graph of the monthly returns for the Hang Seng index from February 2001 to February 2020. Figure 3.2 shows that the range of monthly returns for the Hang Seng index is usually between -2 percent and +2 percent for many of the months. However, there are many months when returns are abnormally high, ranging from -12 to +14 percent, indicating a high likelihood of jumps occurring during these monthly.

3.4.1.3 Nikkei 225 Index

Figure 3.3 depicts a line graph of the Nikkei 225 index index's monthly returns from February 2001 to February 2020. The range of monthly returns for the Nikkei 225 index is almost between negative 2.5 percent and positive 2.5 percent for the

FIGURE 3.2: Monthly Returns Line Graph: Hang Seng index

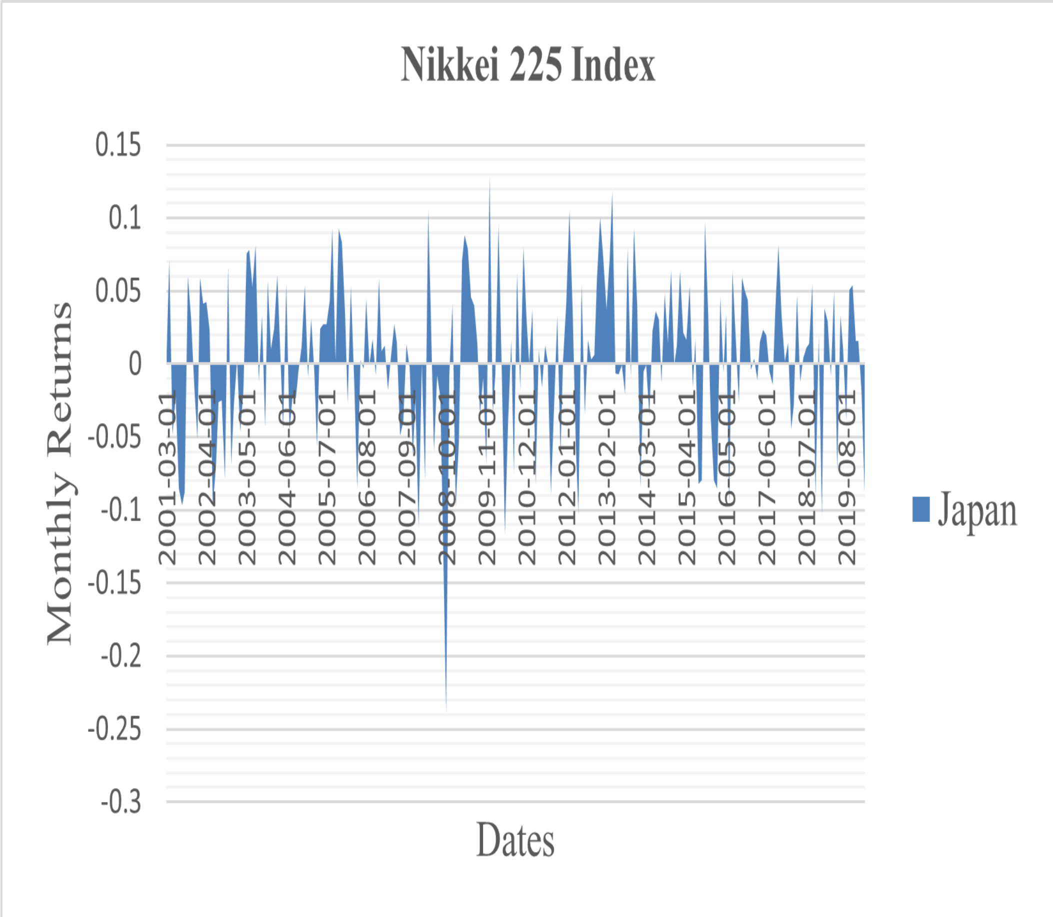


majority of the months, as shown in Figure 3.3. However, there are many days when returns are abnormally high, ranging from negative 15% to positive 10%, indicating that there is a high chance of jumps on these months.

3.4.1.4 NZX 50 Index

For the sample period of February 2001 to February 2020, Figure 3.4 shows a line graph of the monthly returns for the NZX 50 index. Figure 3.4 shows that the range of monthly returns for the NZX 50 index is almost between negative 2 percent and positive 3.5 percent for the majority of the months. However still, there are many months when returns are unusually high, ranging from negative 08 percent to positive 06 percent, implying that there is a high likelihood of jumps in these months.

FIGURE 3.3: Monthly Returns Line Graph: Nikkei 225 Index



3.4.2 Descriptive Statistics of Monthly Index Returns for Asian Emerging Markets

Table 3.2 presents descriptive statistics of monthly index returns for Asian emerging markets. It shows the mean monthly returns, standard deviation of returns, minimum and maximum values, kurtosis (kur), and skewness (skew) for all indices of Asian emerging region.

Table 3.2 illustrates monthly return statistics for Asian emerging markets. The KSE-100 index has the highest average monthly return (1.720 percent per month), while the Shanghai Composite index has the lowest return (0.463 percent per month). The Shanghai Composite has highest standard deviation of 7.632 percent, which means that the average monthly returns of the Shanghai Composite index deviate from the mean returns by 7.632 percent. However, standard deviation is lowest for SET Index. The Nifty 50 index has the highest maximum value

FIGURE 3.4: Monthly Returns Line Graph: NZX 50 Index

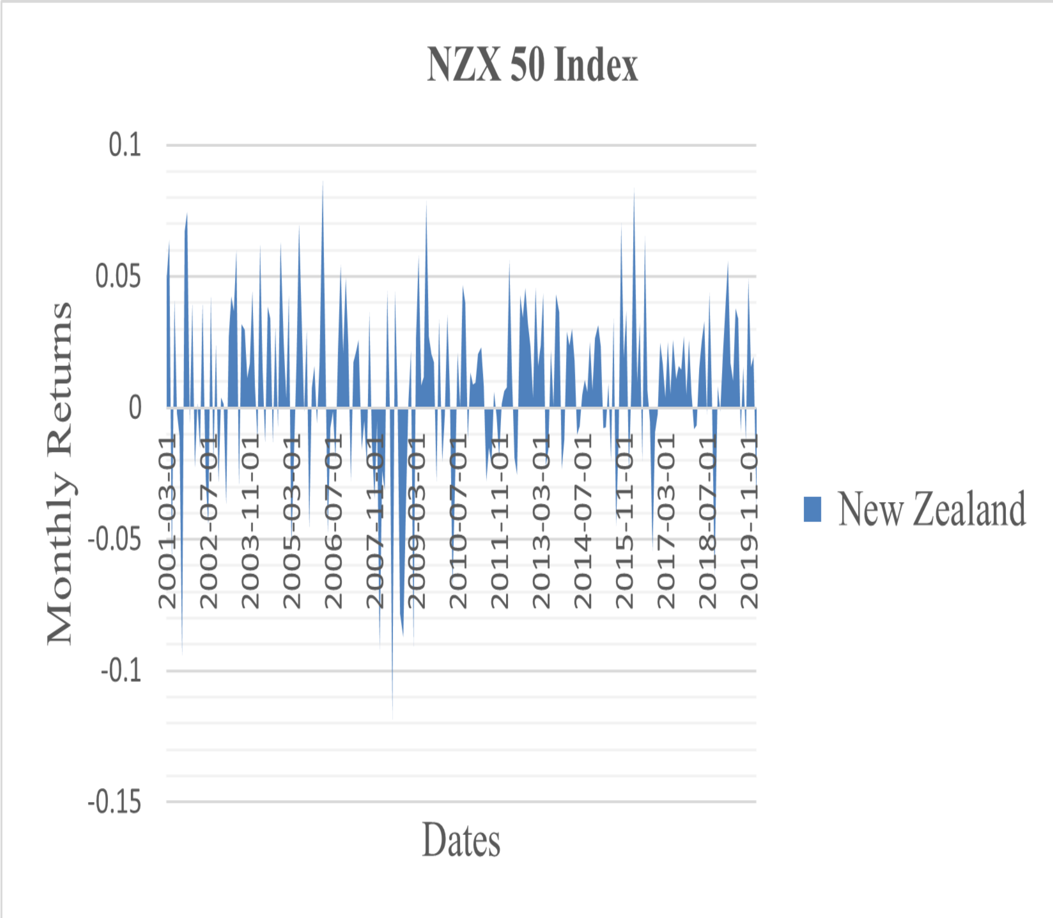
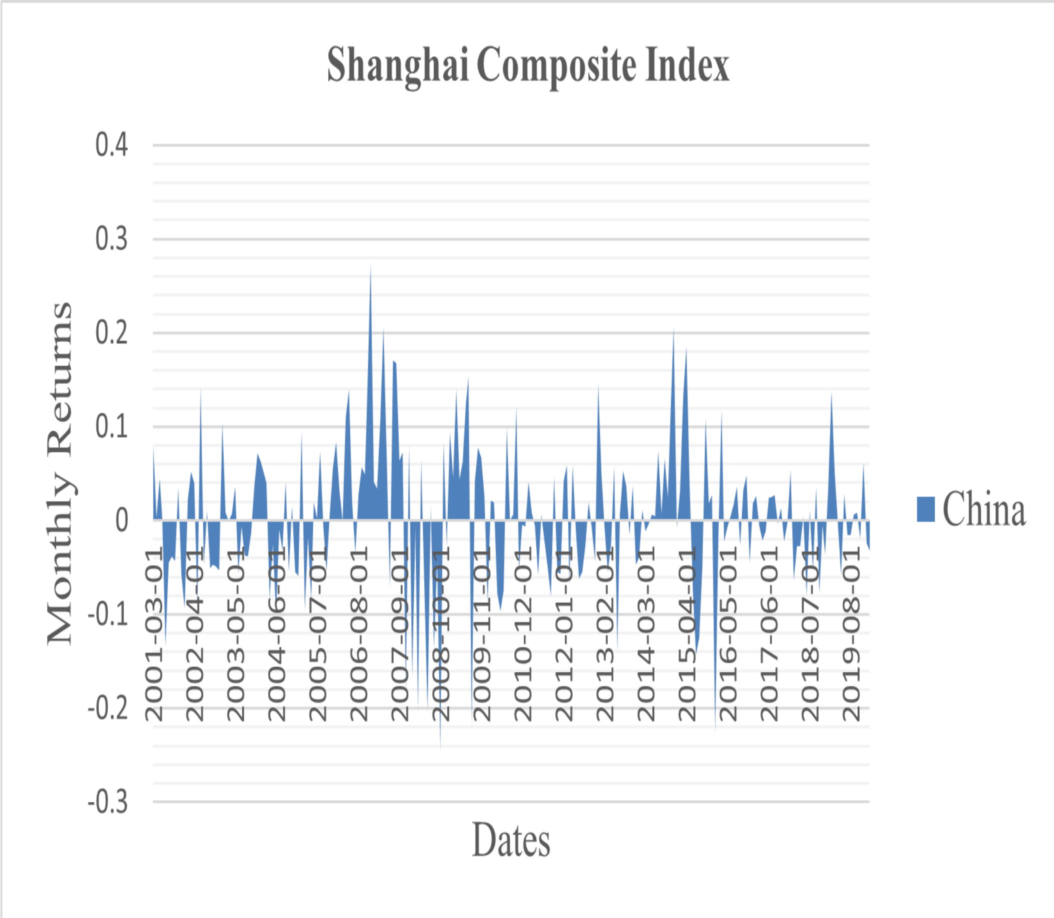


TABLE 3.2: Descriptive Statistics of Monthly Index Returns for Asian Emerging Markets

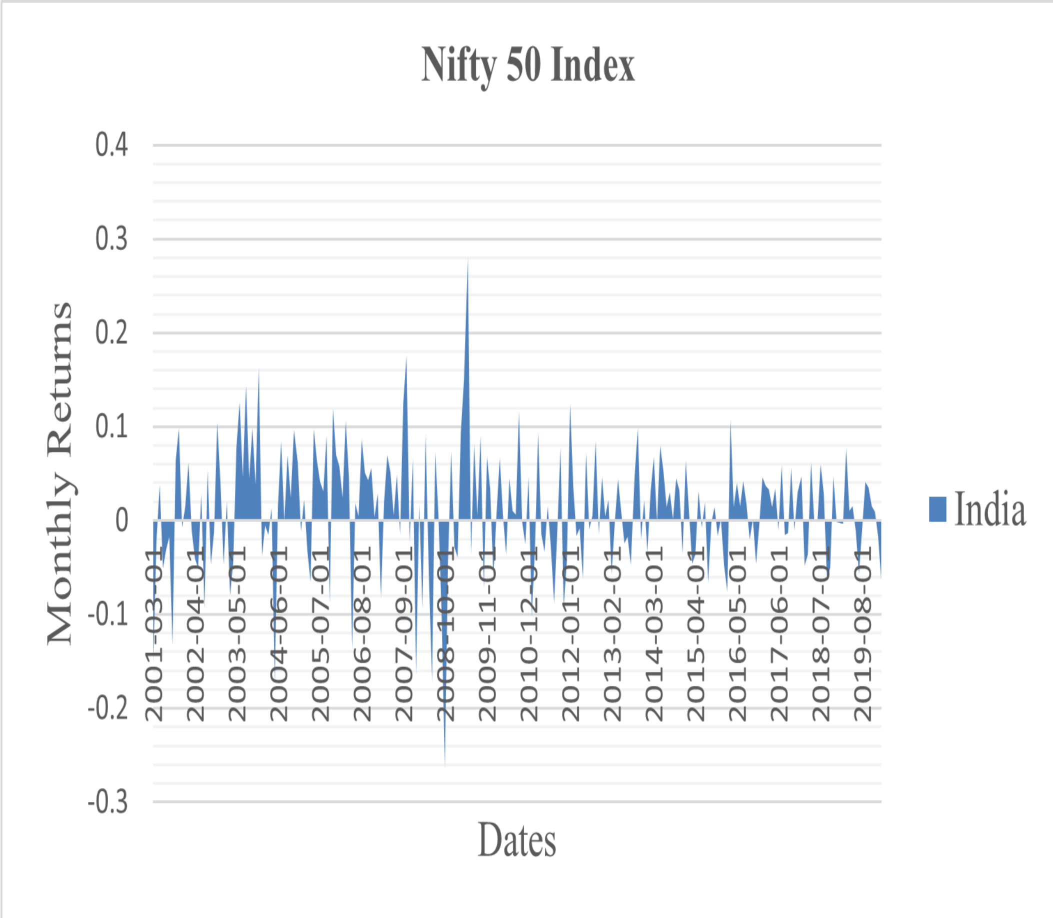
Indices	Mean	SD	Min	Max	Kur	Skew
Shanghai Composite	0.463%	7.632%	-24.631%	27.446%	1.513	-0.089
Nifty 50	1.143%	6.482%	-26.410%	28.066%	2.414	-0.225
JKSE	1.301%	5.919%	-31.422%	20.132%	3.924	-0.654
KSE-100	1.720%	7.281%	-36.160%	27.267%	3.578	-0.375
SET	0.797%	5.824%	-30.176%	19.522%	3.537	-0.682
CSE All	1.327%	6.594%	-16.151%	25.273%	1.731	0.767

FIGURE 3.5: Monthly Returns Line Graph: Shanghai Composite Index



of 28.066 percent, while the KSE-100 index has the lowest minimum value of -36.160 percent. When compared to other emerging markets, the returns of Asian emerging markets are leptokurtic, particularly the returns of the KSE-100 index as the value of excess kurtosis is highest for KSE-100 index. Furthermore, the CSE All index's monthly returns are positively skewed, whereas other Asian emerging markets' returns are negatively skewed. The minimum-maximum values for every Asian emerging market are significantly higher than their average monthly returns, indicating the possibility of jumps in Asian emerging markets. For each of these markets, the line graph of monthly returns may clearly show the higher returns moment.

FIGURE 3.6: Monthly Returns Line Graph: Nifty 50 Index



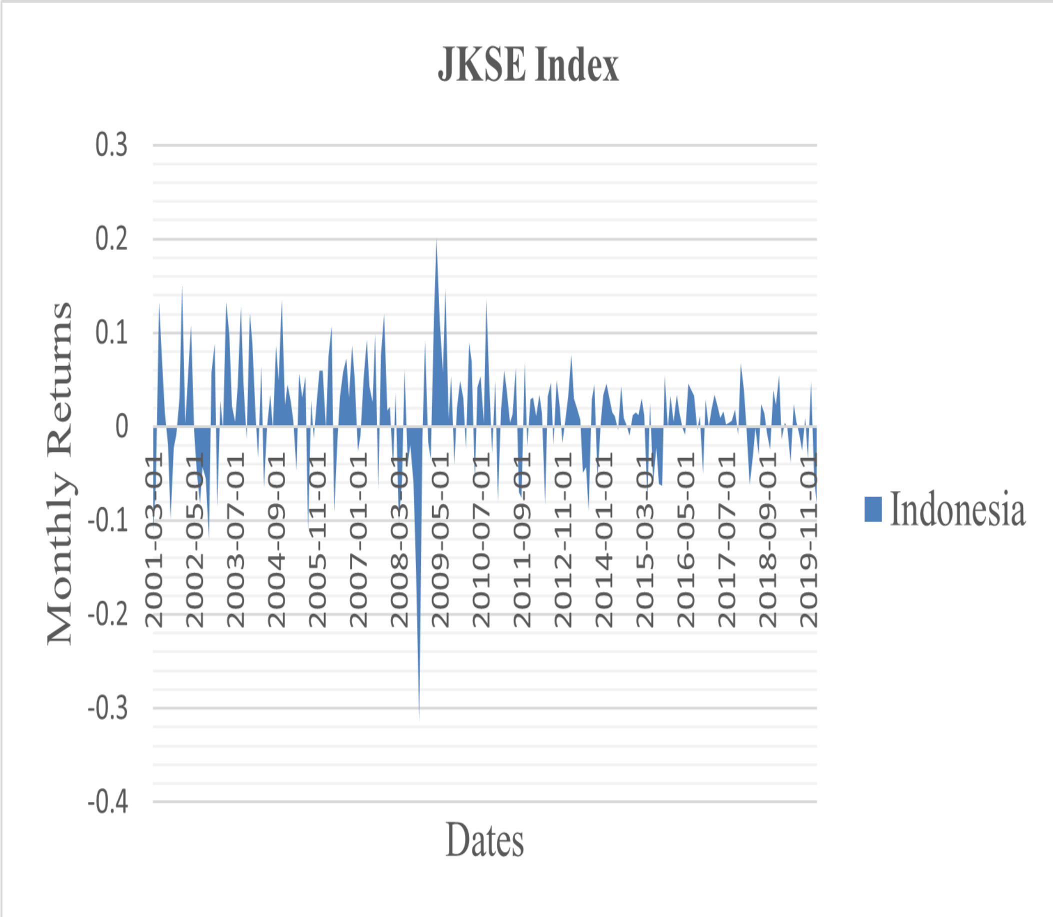
3.4.2.1 Shanghai Composite Index

Figure 3.5 illustrates a line graph of monthly returns for the Shanghai Composite index from February 2001 to February 2020. Figure 3.5 reveals that the range of monthly returns for the Shanghai Composite index is almost between negative 2% and positive 2% on most of the months. However, there are many months as well when returns are excessively high, varying from negative 15% to positive 20%, so there is more chances of occurrences of jumps during these periods of abnormally high returns.

3.4.2.2 Nifty 50 Index

Figure 3.6 represents a line graph of the monthly returns for the Nifty 50 index from February 2001 to February 2020. Figure 3.6 shows that for the majority of

Figure 3.7: Monthly Returns Line Graph: JKSE Index

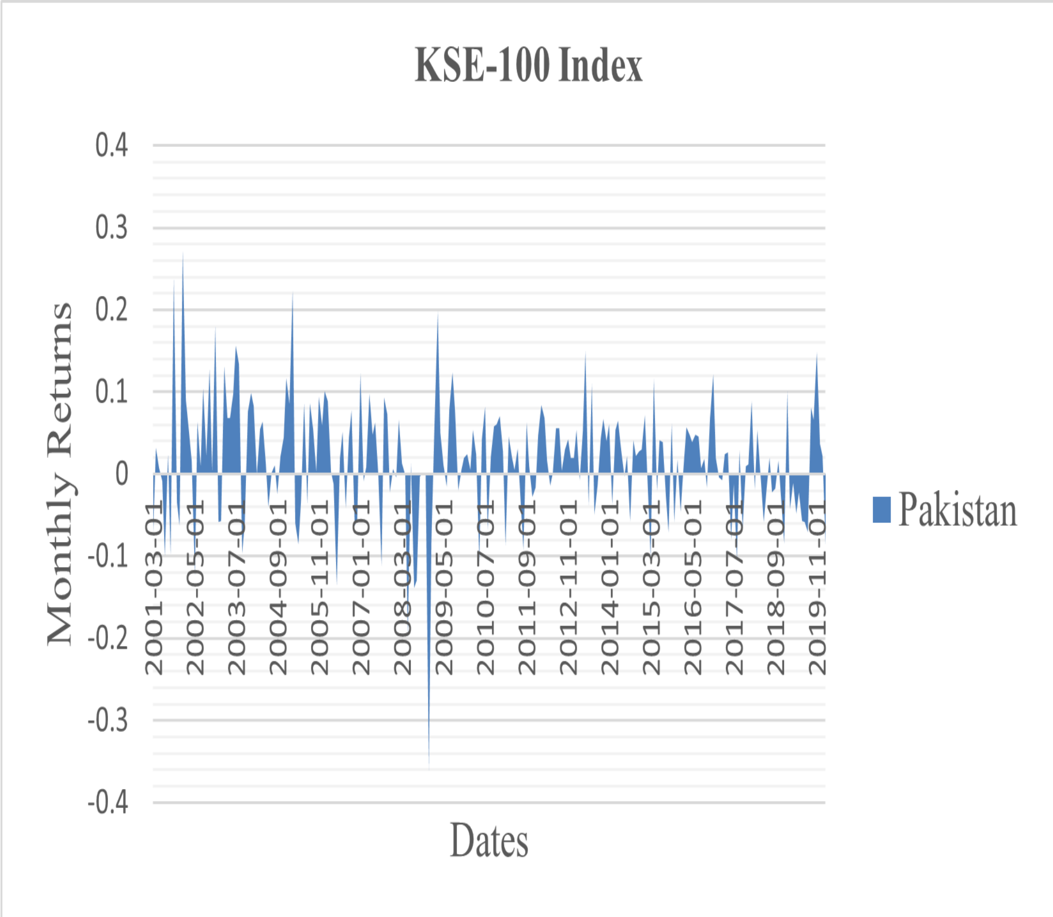


the months, the range of months returns for the Nifty 50 index is almost between negative 2% and positive 1%. However, there are many months when index returns are abnormally high that ranges from -12% to +17%, showing high chances of jumps arising during all these months.

3.4.2.3 JKSE Index

Figure 3.7 shows a line graph of the JKSE index's monthly returns for the period February 2001 to February 2020. Figure 3.7 shows that the range of monthly returns for the JKSE index is almost between negative 2 percent and positive 1.5 percent for the majority of the months. However, there are many months when returns are abnormally high that ranges from negative 10% to positive 10%, indicating that there is a high probability of jumps on these months.

Figure 3.8: Monthly Returns Line Graph: KSE-100 Index



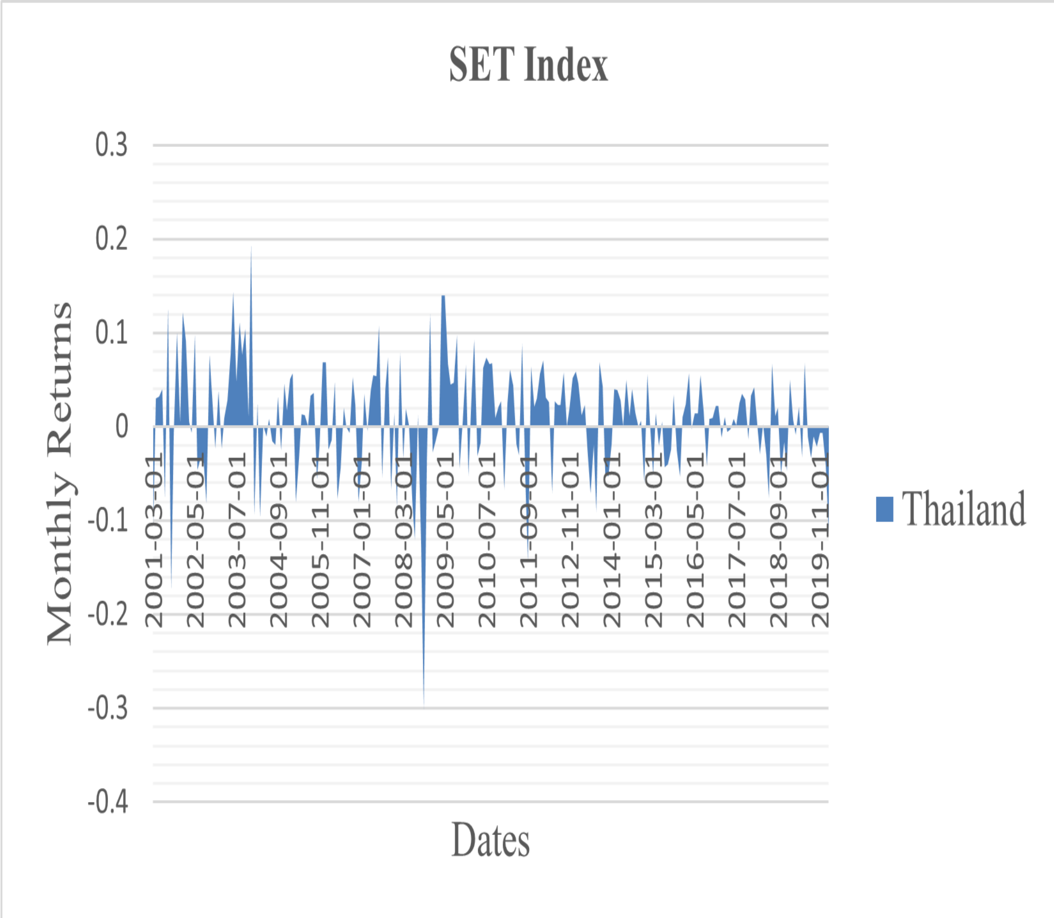
3.4.2.4 KSE-100 Index

Figure 3.8 depicts a line graph of the monthly returns for the KSE-100 index from February 2001 to February 2020. Figure 3.8 shows that for the majority of the months, the range of monthly returns for the KSE-100 index seems to be almost between -2% and +1.5%. However also, there are many months in which returns of KSE-100 index is abnormally high ranging from -8% to +9%, suggesting that there is a high likelihood that jumps may occurs during these months.

3.4.2.5 SET Index

Figure 3.9 depicts a line graph of the monthly returns for the SET Index from February 2001 to February 2020. Figure 3.9 shows that for the majority of the

Figure 3.9: Monthly Returns Line Graph: SET Index

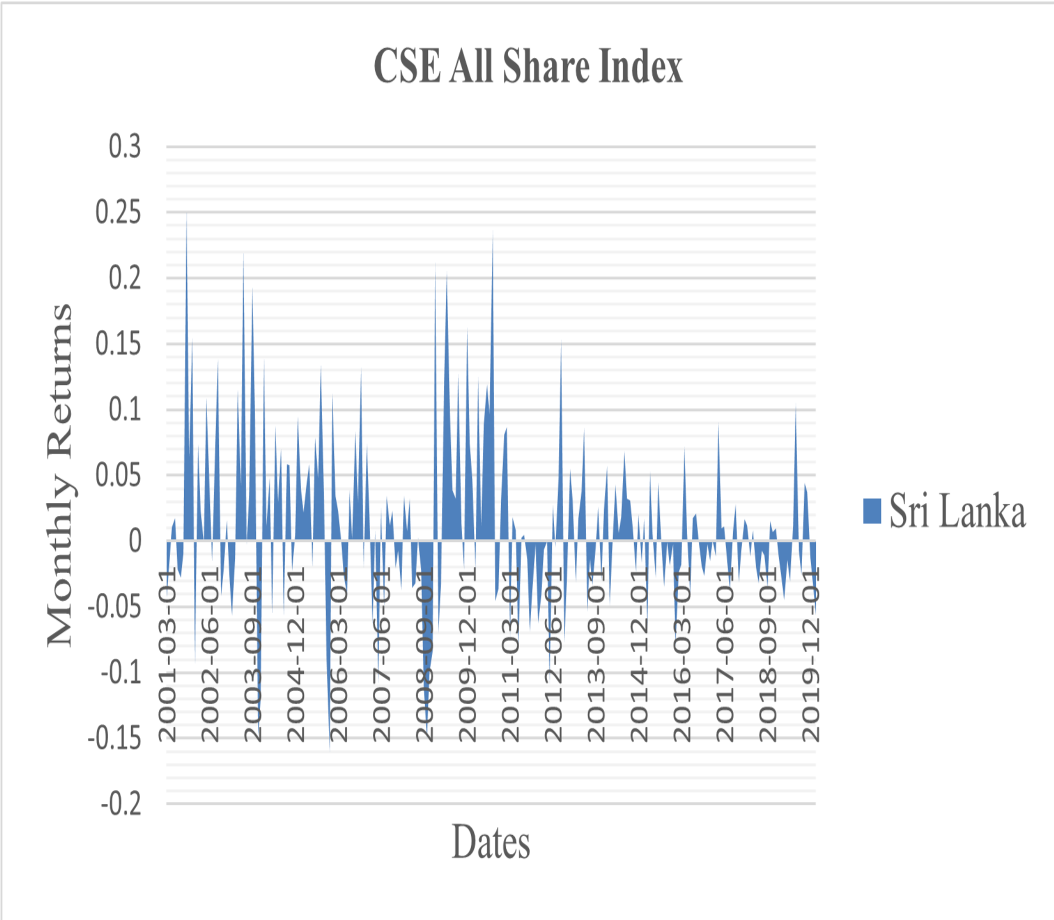


months, the range of monthly returns for the SET Index is almost between negative 2% and positive 2%. However, there are many months when returns are abnormally high, ranging from negative 5% to positive 10%, and there is a high possibility of jump occurrences on these months.

3.4.2.6 CSE All Index

Figure 3.10 displays a line graph of the monthly returns for the CSE All index from February 2001 to February 2020. Figure 3.10 shows that for the most of months, the range of monthly returns for the CSE All index is almost between negative 1% and positive 1%. However, there are many days when returns are extremely high, that range from negative 14% to positive 20%, indicating a significant likelihood of jumps occurring on these months.

Figure 3.10: Monthly Returns Line Graph: CSE All Index



Chapter 4

Results and Discussion

This chapter covers all the empirical analyses conducted in the study. The analysis started from the identification of jumps in both Asian developed and Asian emerging markets and a comparison of both markets. Then returns during jump periods are compared with returns during non-jump periods of both markets and compared their results. Then Fama and French five factors are regressed on jump returns of both markets to identify that which factors of the Fama and French five factor model is associated with jump returns. Finally, integrated volatility during jump periods is calculated for Asian developed markets and Asian emerging markets and compared the results.

4.1 Identification of Jumps in Asian Developed and Asian Emerging Markets

Table 4.1 and Table 4.2 report estimated results to achieve the first objective of the study to identify the presence of jumps in Asian developed and Asian emerging markets. Table 4.1 shows the number of months identified as having jumps in the context of Asian developed markets whereas Table 4.2 shows the number of months identified as having jumps in the context of Asian emerging markets. The number of months identified as having jumps are then exhibited in the scatter plot (Figure 4.1), which shows the total number of jumps, positive jumps, and negative jumps for all of the Asian developed and Asian emerging markets for the period of 229 months from February 2001 to February 2020.

Table 4.1: Number of Monthly Jumps for Asian Developed Markets

	Overall jumps		**Positive jumps**		**Negative jumps**	
Indices	Number of Jumps	Percentage of Jumps	Number of Jumps	Percentage of Jumps	Number of Jumps	Percentage of Jumps
S&P ASX 200	62	27.07%	33	14.41%	29	12.66%
Hang Seng	71	31.00%	43	18.78%	28	12.23%
Nikkei225	56	24.45%	33	14.41%	23	10.04%
NZX 50	58	25.33%	32	13.97%	26	11.35%

Table 4.1 shows the number of months in which jumps have been identified for Asian developed markets. It provides the percentage of months in which jumps are identified for Asian developed markets and the number of months having Swap Variance (SwV) jump at a 5% significance level. In the Asian developed markets, it is observed from Table 4.1 that the Hang Seng index has the maximum number of jumps. The jumps have been identified in 71 months out of 229 months being studied which means that 27% of the total months have jumps. These jumps include 43 positive jumps that are 14.41% of the total number of months and 28 negative jumps that are 12.66% of the total number of months. Furthermore, the minimum number of jumps in the Asian developed markets are identified in NZX50, which are in 56 months out of a total of 229 months. In these 56 months, 33 months have positive jumps, whereas 23 months have negative jumps.

Table 4.2 shows the number of months in which jumps have been identified for Asian emerging markets. It provides the percentage of months in which jumps are identified for Asian emerging markets and the number of months having Swap Variance (SwV) jump at a 5% significance level. In the Asian emerging markets, the maximum number of jumps are identified in the CSE All index, which has jumps in 100 months that is 40.61% of the total number of months with 63 positive jumps which means that 17.90% of the total number of months have jumps, in which there are 37 negative jumps that are 22.71% of the total number of months. However, the minimum number of jumps is 63 for the Nifty 50 index which is

Table 4.2: Number of Monthly Jumps for Asian Emerging Markets

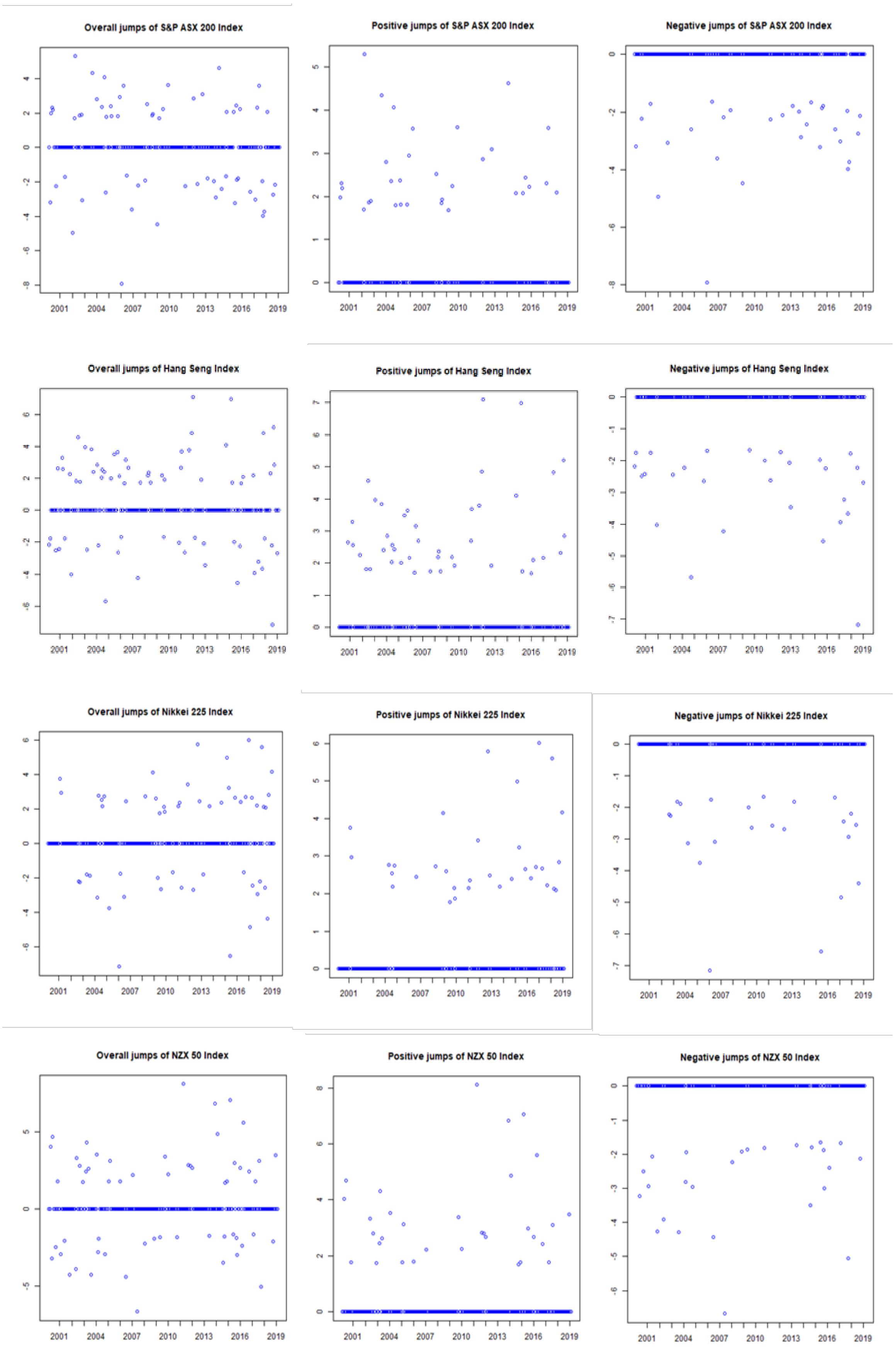
	Overall jumps		**Positive jumps**		**Negative jumps**	
Indices	Number of Jumps	Percentage of Jumps	Number of Jumps	Percentage of Jumps	Number of Jumps	Percentage of Jumps
Shanghai Composite	93	40.61%	41	17.90%	52	22.71%
Nifty 50	63	27.51%	40	17.47%	23	10.04%
JKSE	67	29.26%	41	17.90%	26	11.35%
KSE-100	73	31.88%	56	24.45%	17	7.42%
SET Index	77	33.62%	49	21.40%	28	12.23%
CSE All	100	43.67%	63	27.51%	37	16.16%

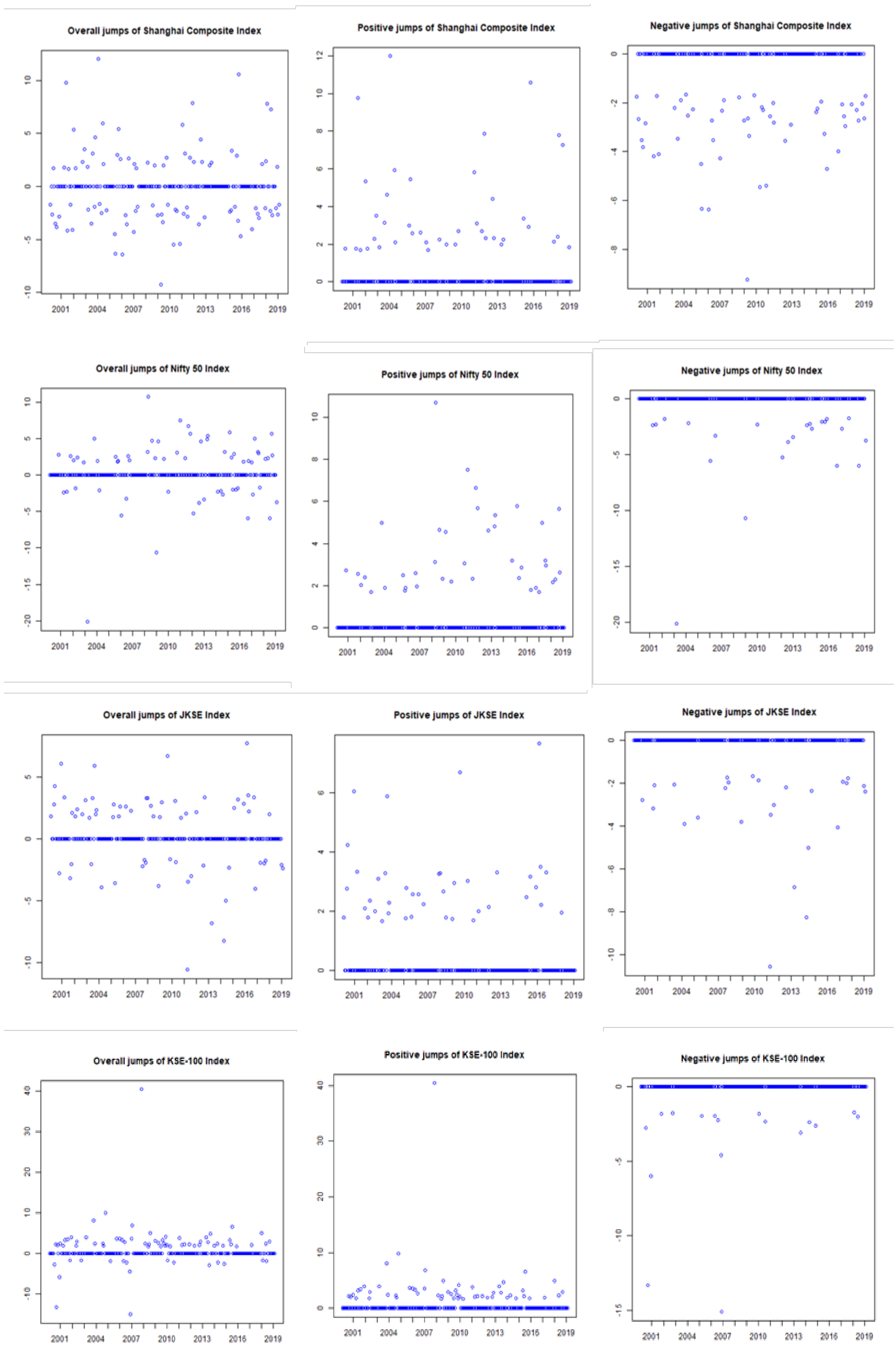
27.51% of the total number of months, including 40 positive jumps that are 17.47% of the total months and 23 negative jumps which are 10% of the total number of months.

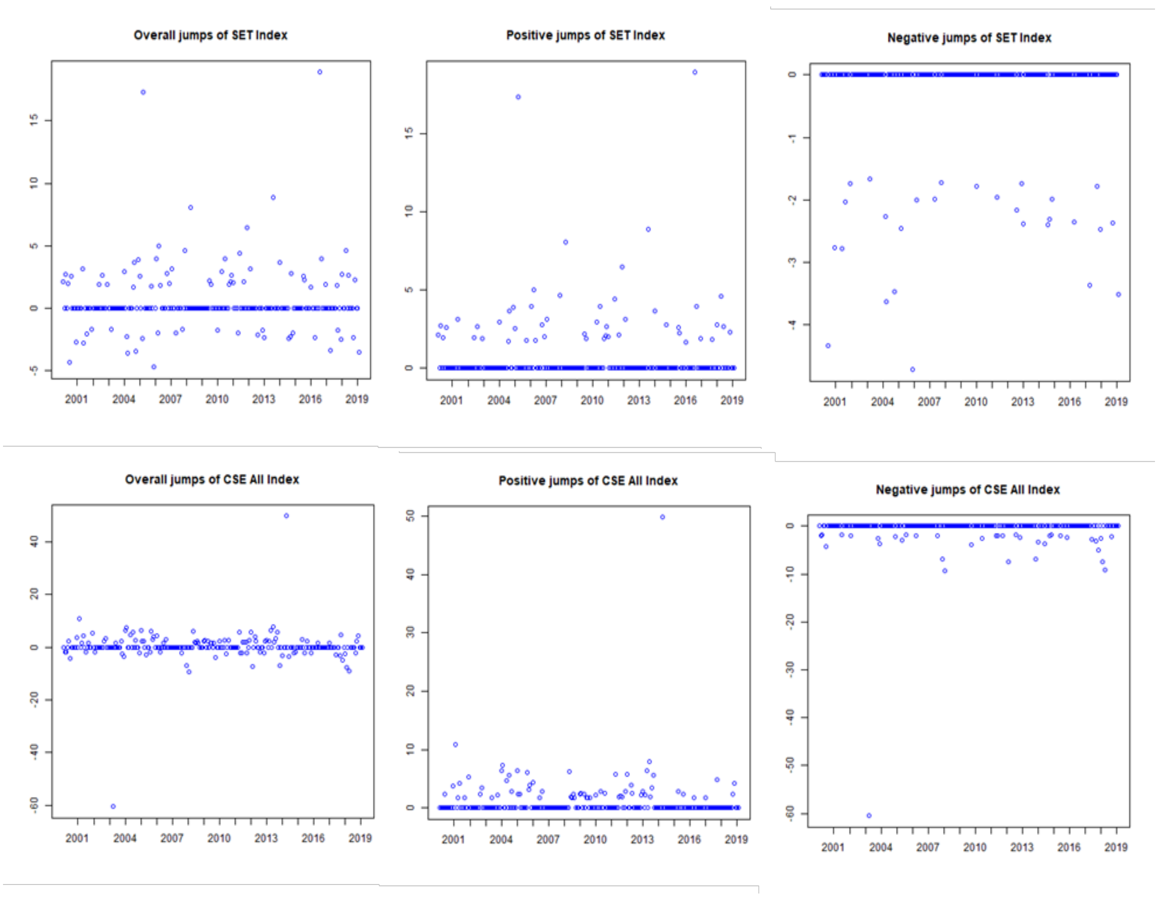
It is concluded from Table 4.1 and Table 4.2 that, on average, the Asian developed markets have fewer jumps as compared with the Asian emerging markets. Similarly, positive and negative jumps also arise more frequently in the Asian emerging markets in comparison with the Asian developed markets. Furthermore, on average, the tendency of a larger number of positive jumps relative to negative jumps occurs in both Asian developed and Asian emerging markets. The possible justifications of the occurrence of more jumps in the Asian emerging markets relative to the Asian developed markets could be the riskier and more volatile nature of the Asian emerging markets due to political instability, poor corporate governance, thin structure of the markets, lack of liquidity, high inflation rate, deflation or currency devaluations, interest rate risk, and high cross-border cash flows. All these factors hurt the economy and make the stock markets highly volatile, which leads to an increase in the tendency of jumps.

The number of months with jumps, as identified in Table 4.1 and Table 4.2 are exhibited in the scatter plot (Figure 1), showing the total number of jumps, positive jumps, and negative jumps for all of the equity markets in the sample period from February 2001 to February 2020.

FIGURE 4.1: Number of Months Identified as having Jumps




Overall jumps of Shanghai Composite Index
Positive jumps of Shanghai Composite Index
Negative jumps of Shanghai Composite Index
Overall jumps of Nifty 50 Index
Positive jumps of Nifty 50 Index
Negative jumps of Nifty 50 Index
Overall jumps of JKSE Index
Positive jumps of JKSE Index
Negative jumps of JKSE Index
Overall jumps of KSE-100 Index
Positive jumps of KSE-100 Index
Negative jumps of KSE-100 Index
2001 2004 2007 2010 2013 2016 2019



It is reflected in Figure 4.1 that the magnitude of some jumps is big whereas small for others. A cutoff point of +3 standard deviation and -3 standard deviation is set to distinguish small or average size jumps from big jumps. A jump with a magnitude greater than +3 standard deviation is considered a big positive jump. A jump with a magnitude between zero and +3 is considered a positive small or average size jump. Similarly, a jump with a magnitude less than -3 standard deviation is considered a big negative jump whereas a jump with a magnitude between zero and -3 is considered a negative average size or small jump.

It is observed from Figure 4.1 that in the context of Asian developed markets, on average, the magnitude of big negative jumps is larger than the magnitude of big positive jumps. The same pattern is also observed for emerging markets as well. However, this pattern is much higher in Asian emerging markets as compared with Asian developed markets. When considering small-size jumps, a big difference is not observed in the magnitude of negative and positive jumps in the context of Asian developed markets. However, on average, the magnitude of small negative jumps is slightly on the higher side as compare to small positive jumps in Asian emerging markets. This means that investors considered negative information more deeply than positive information. However, the depth of feeling is on the higher side in emerging markets. It may be due to the lack of confidence of investors in the information that may cause an overreaction to negative information.

4.2 Jumps and Equity Returns of Asian Developed and Asian Emerging Markets

To achieve the second objective of the study which is to discuss the role of jumps in equity returns of Asian developed and Asian emerging markets and the third objective which is to discuss the role of positive jumps and negative jumps in equity returns of Asian developed and Asian emerging markets, first of all, descriptive statistics are calculated for returns during normal periods (r), descriptive statistics of returns during jump periods (Jr), descriptive statistics of returns during positive jumps periods (Pjr), and descriptive statistics of returns during negative jumps periods (Njr) for each of the Asian developed markets and Asian emerging markets. Table 4.3 reports descriptive statistics of returns for Asian developed markets whereas Table 4.4 reports descriptive statistics of returns for Asian emerging markets. Then dummy variable regression model is used to measure the impact of the presence of jumps on equity returns of Asian developed markets and Asian emerging markets. Table 4.5 to Table 4.8 reports the estimated results of the dummy variable regression model for Asian developed markets whereas Table 4.9 to Table 4.14 reports the estimated results of the dummy variable regression model for Asian emerging markets.

4.2.1 Descriptive Statistics of Returns for Asian Developed Markets

Table 4.3 presents descriptive statistics of returns during normal periods (r), descriptive statistics of returns during jump periods (Jr), descriptive statistics of returns during positive jumps periods (Pjr), and descriptive statistics of returns during negative jumps periods (Njr) for Asian developed markets. The returns during jump periods are based on the SwV Jump Test for 229 months, from February 2001 - February 2020.

Table 4.3: Descriptive Statistics of Returns for Asian Developed Markets

Indices	**Jumps**	**Returns**	**Mean**	**SD**	**Min**	**Max**	**Kurt**	**Skew**
S&P ASX 200	229	r	0.25%	3.76%	-18.09%	9.80%	2.23	-0.93
	62	Jr	0.60%	4.21%	-8.22%	9.73%	-0.78	-0.40
	33	Pjr	3.99%	1.58%	1.39%	9.73%	4.25	1.45
	25	Njr	-3.86%	2.30%	-8.22%	-0.64%	-1.09	-0.37
Hang Seng	229	r	0.16%	5.84%	-25.45%	16.63%	1.57	-0.54
	71	Jr	1.00%	6.89%	-14.88%	15.76%	-0.58	-0.34
	41	Pjr	5.92%	3.27%	1.54%	15.76%	1.27	1.13
	24	Njr	-6.74%	3.01%	-12.10%	-2.29%	-0.86	-0.45
Nikkei 225	229	r	0.15%	5.45%	-28.17%	13.30%	2.43	-0.89
	56	Jr	0.86%	6.00%	-12.39%	9.87%	-0.64	-0.54
	32	Pjr	5.10%	2.65%	0.54%	9.87%	-0.87	0.24
	20	Njr	-5.79%	3.78%	-12.39%	-0.18%	-1.10	-0.16
NZX 50	229	r	0.70%	3.38%	-14.31%	8.31%	3.02	-1.11
	58	Jr	0.39%	4.61%	-12.62%	8.31%	0.48	-0.79
	31	Pjr	3.69%	1.95%	0.89%	8.31%	-0.22	0.72
	23	Njr	-4.05%	3.53%	-12.62%	-0.12%	0.62	-1.11

Notes: There were some months in which positive jumps were incurred, but the average monthly returns are negative, and some months in which negative jumps incurred but the average monthly returns are positive. All those jumps are excluded in descriptive stats. The descriptive in Table 4.3 shows only positive returns due to the positive jumps and negative returns due to the negative jumps.

Table 4.3 shows in Asian developed markets, the NZX 50 index has earned higher returns per month during normal periods with minimum spread indicated by standard deviation, minimum, and maximum values followed by the S&P ASX 200, so these markets are the most attractive for risk-averse investors. In comparison, the Nikkei 225 has the lowest monthly returns during normal periods, followed by the Hang Seng with maximum spread indicated by standard deviation, minimum, and maximum values. Therefore, these markets are more volatile. For average returns during jump periods and average returns during positive jump periods, the Hang Seng index and the Nikkei 225 index have the highest average returns per month, with maximum spread shown by standard deviation, minimum, and maximum values. Therefore, these markets are the most attractive markets for risk-taking investors. Whereas the NZX 50 index and the S&P ASX 200 index have the lowest returns during jump periods and lowest returns during positive jump periods with maximum spread indicated by standard deviation, minimum, and maximum values. It is observed from Table 4.3 that more volatile markets tend to earn larger returns during jump periods relative to less volatile markets. Furthermore, returns during positive jump periods are higher for a more volatile market than less volatile markets. Therefore, forecasting positive jumps plays an essential role for investors to earn larger returns. However, returns of more volatile markets like the Hang Seng index and Nikkei 225 index are also more affected during negative jump periods relative to less volatile markets like the NZX 50 index and S&P ASX index. It is worth noting that among volatile markets, a market having low returns is much more vulnerable to negative jumps e.g Hang Seng and Nikkei 225 index.

4.2.2 Descriptive Statistics of Returns for Asian Emerging Markets

Table 4.4 presents descriptive statistics of returns during normal periods (r), descriptive statistics of returns during jump periods (Jr), descriptive statistics of returns during positive jumps periods (Pjr), and descriptive statistics of returns during negative jumps periods (Njr) for Asian emerging markets. The returns during jump periods are based on the SwV Jump Test for 229 months, from February 2001 - February 2020.

Table 4.4 shows that in the context of Asian emerging markets the KSE-100 and Shanghai composite index are more volatile markets (as measured by the standard deviation of continuous returns) relative to others. The Shanghai composite has the lowest return during normal periods, and the KSE-100 has the largest return

Table 4.4: Descriptive Statistics of Returns for Asian Emerging Markets

Indices	Jumps	Returns	Mean	SD	Min	Max	Kur	Skew
Shanghai Composite	229	r	0.08%	7.70%	-28.28%	24.12%	1.86	-0.55
	93	Jr	-0.62%	8.61%	-25.68%	24.12%	1.23	-0.28
	38	Pjr	6.90%	5.10%	0.63%	24.12%	2.43	1.43
	47	Njr	-7.09%	5.95%	-25.68%	-0.03%	3.51	-1.86
Nifty 50	229	r	0.66%	6.51%	-31.42%	24.74%	3.20	-0.69
	63	Jr	2.70%	7.14%	-10.81%	24.74%	0.14	0.15
	39	Pjr	7.19%	4.52%	1.43%	24.74%	4.70	1.60
	21	Njr	-5.52%	2.89%	-10.81%	-0.77%	-0.26	-0.22
JKSE	229	r	0.99%	5.81%	-37.72%	16.43%	8.27	-1.27
	67	Jr	1.65%	8.01%	-37.72%	16.43%	7.58	-1.76
	39	Pjr	6.47%	3.93%	0.93%	16.43%	-0.58	0.61
	23	Njr	-6.24%	7.66%	-37.72%	-0.25%	13.74	-3.35
KSE-100	229	r	1.31%	7.06%	-44.88%	26.83%	8.38	-1.19
	73	Jr	3.90%	7.00%	-13.76%	26.83%	1.44	0.12
	54	Pjr	6.90%	4.95%	0.05%	26.83%	4.65	1.83
	15	Njr	-5.95%	3.97%	-13.76%	-0.38%	-0.59	-0.56
SET Index	229	r	0.48%	5.98%	-35.57%	18.59%	5.92	-1.10
	77	Jr	1.41%	7.44%	-35.57%	18.59%	7.03	-1.55
	47	Pjr	5.77%	3.69%	0.60%	18.59%	2.45	1.52
	26	Njr	-6.22%	6.80%	-35.57%	-0.12%	14.45	-3.40
CSE All	229	r	1.05%	6.32%	-16.65%	22.63%	1.47	0.51
	100	Jr	2.53%	6.45%	-16.65%	20.68%	0.56	0.19
	61	Pjr	6.39%	4.66%	0.37%	20.68%	0.81	1.07
	34	Njr	-4.13%	3.39%	-16.65%	-0.54%	4.66	-1.94

Notes: There were some months in which positive jumps were incurred, but the average monthly returns are negative, and some months in which negative jumps incurred but the average monthly returns are positive. All those jumps are excluded in descriptive stats. The descriptive in Table 4.4 shows only positive returns due to the positive jumps and negative returns due to the negative jumps.

per month during normal periods. In Asian emerging markets, returns during jump periods behave differently as compared with Asian developed markets. In Asian emerging markets, a market with average volatility and average returns during normal periods earn the highest return during positive jump periods. Its returns are the least vulnerable during negative jump periods, i.e., the Nifty 50 index. However, highly volatile markets tend to earn high returns during positive jump periods, i.e., the Shanghai Composite index and KSE-100 index. However, highly volatile markets with high returns during normal periods are less vulnerable during periods of negative jumps, i.e., the KSE-100 index. In contrast, highly volatile markets with the lowest returns during normal periods are highly vulnerable during periods of negative jumps, i.e., the Shanghai composite.

The results of Table 4.3 and Table 4.4 provide important insights to the investors in Asian developed and Asian emerging markets to earn the highest returns during jump periods. Investors can earn the highest returns during jump periods by investing in more volatile markets in Asian developed markets whereas investors in Asian emerging markets can earn the highest returns during jump periods by investing in averagely volatile markets.

4.2.3 Role of Jumps in Equity Returns of Asian Developed Markets: A Dummy Variable Regression Model

Tables 4.5 to 4.8 reports the estimated results of the dummy variable regression model for each of the Asian developed equity markets. Each table report estimated results for two dummy variable regression models.

In the first model, monthly index returns are regressed on a dummy variable representing returns during jump periods (JP). If there is a jump in the index prices for the month, the dummy variable is assigned a value of one, and if there is not a jump, the dummy variable is assigned a value of zero.

In the second model, months with positive and negative jumps are separated from months that do not have jumps, and two dummy variables are created. The first dummy variable is index returns during positive jumps periods (PJP), it takes the value of one if the month has a positive jump, and otherwise, it takes the value of zero. The second dummy variable is index reruns during negative jumps periods; it takes the value of one if the month has a negative jump; otherwise, it takes the value of zero. In the second model, the index return is regressed over two dummy variables that are PJP and NJP, to examine the role of the presence of positive and negative jumps on index returns in each Asian developed equity market separately.

TABLE 4.5: Dummy Variable Regression Model for S&P ASX 200

Dependent Variable: S&P ASX 200 Index Return		
	(Model 1)	**(Model 2)**
JP	0.446	
	(0.55)	
PJP		3.816***
		(0.608)
NJP		-3.388***
		(0.642)
C	0.226	0.226
	(0.286)	(0.247)
R2	0.003	0.26
Adj R2	0.001	0.254
RSE	3.697 (df = 227)	3.192 (df = 226)
Fstat	0.659 (df = 1; 227)	39.767*** (df = 2; 226)

Note: *p<0.1; **p<0.05; ***p<0.01

*Values in brackets are standard errors

The regression results of two models for the S&P ASX 200 index are shown in Table 4.5. The S&P ASX 200 index returns are regressed on the dummy variable for returns during jump periods (JP) in model one. Both positive and negative jump periods are included in the jump period (JP). The results of model one show that at a 5% significance level, the slope value of JP is statistically insignificant, implying that the S&P ASX 200 index returns during jump periods are the same as returns during non-jump periods. The reason for this could be that the jump period includes both positive and negative jumps that offset the effect of one another, making the slope of JP statistically insignificant.

When two dummy variables are created by separating positive and negative jump periods in model two, the slope of the index returns during positive jump periods (PJP) and the slope of the index returns during negative jump periods (NJP) are statistically significant. The value of the intercept term in model two is 0.226, which is positive and insignificant, implying that the S&P ASX 200 index's average monthly return is 0.226 per cent without accounting for jump periods. The slope of positive jump periods' returns (PJP) is 3.816, which is positive and significant at the 1% level of significance, indicating that positive jump periods' returns are 3.816 percent higher than non-jump periods' returns. Monthly total returns during positive jump periods are (0.226 + 3.816 = 4.042). The slope of returns during negative jump periods (NJP) is -3.388, which is negative and significant at the 1% level of significance, implying that returns during negative jump periods are 3.816 per cent lower than non-jump periods. Total returns during negative jump periods is (0.226 - 3.388 = -3.162) percent per month. It is concluded from table 5.1 that positive and negative jumps play an important role in predicting returns of the S&P ASX 200 index. Total monthly returns during negative jump periods are (0.226 - 3.388 = -3.162) percent. Table 4.5 shows that positive and negative jumps play an important role in predicting S&P ASX 200 index returns.

Table 4.6 shows the regression results of two models for the Hang Seng index. In model one, the index returns of Hang Sang are regressed on a dummy variable for returns during jump periods (JP). The jump period (JP) includes both positive jump periods and negative jump periods. The results of model one indicate that the slope value of JP is statistically insignificant at a 5% significance level which implies that the returns of the Hang Seng index during jumps periods are the same as returns during non-jump periods. The possible reason here may be that

TABLE 4.6: Dummy Variable Regression Model for Hang Seng Index

Dependent Variable: Hang Seng Index Return		
	(Model 1)	**(Model 2)**
JP	1.154	
	(0.815)	
PJP		5.429***
		(0.840)
NJP		-5.411***
		(1.00)
C	0.008	0.008
	(0.454)	(0.388)
R2	0.009	0.276
Adj R2	0.004	0.27
RSE	5.701 (df = 227)	4.882 (df = 226)
Fstat	2.007 (df = 1; 227)	43.172*** (df = 2; 226)

Note: *p<0.1; **p<0.05; ***p<0.01

*Values in brackets are standard errors

the jump period includes both positive jumps and negative jumps that offset the effect of one another; therefore, the slope of JP is statistically insignificant.

In model two, the slope of the index returns during positive jump periods (PJP) and the slope of the index returns during negative jump periods (NJP) is statistically significant when two dummy variables are created by separating positive and negative jump periods. In model two, the value of the intercept term is 0.008, which is positive and insignificant, implying that the average return of the Hang Seng index is 0.008 per cent per month without accounting for the presence of jump periods. The slope of the returns during positive jump periods (PJP) is 5.429, which is positive and significant at the 1% level of significance, indicating that the returns during positive jump periods are 5.429 per cent higher than the returns during non-jump periods. Total returns during positive jump periods is

(0.008 + 5.429 = 5.437) percent per month. Whereas the slope of the returns during negative jump periods (NJP) is -5.411, which is negative and significant at the 1% level of significance, indicating that the returns during negative jump periods are -5.411 per cent lower than the returns during non-jump periods. Total returns during negative jump periods is (0.008- 5.411 = -5.403) percent per month. It is concluded from table 4.6 that positive and negative jumps play an important role in predicting returns of the Hang Seng index.

TABLE 4.7: Dummy Variable Regression Model for Nikkei 225 Index

Dependent Variable: Nikkei 225 Index Returns		
	(Model 1)	**(Model 2)**
JP	0.88	
	(0.81)	
PJP		4.806***
		(0.91)
NJP		-4.753***
		(1.06)
C	0.148	0.148
	(0.40)	(0.36)
R2	0.005	0.199
Adj R2	0.001	0.192
RSE	5.296 (df = 227)	4.764 (df = 226)
Fstat	1.169 (df = 1; 227)	28.004*** (df = 2; 226)

Note: *p<0.1; **p<0.05; ***p<0.01

*Values in brackets are standard errors

Table 4.7 displays the regression results of two models for the Nikkei 225 index. In the first model, Nikkei 225 index returns are regressed on a dummy variable for returns during jump periods (JP). The results show that the slope value of JP is statistically insignificant at a 5% significance level, implying that Nikkei 225 index returns during jumps are the same as returns during non jump periods. Because the jump period includes both positive and negative jumps that cancel each other, the slope of JP is statistically insignificant.

In the second model, the slope of the index returns during positive jump periods (PJP) and the slope of the index returns during negative jump periods (NJP) is statistically significant when two dummy variables are created by separating positive and negative jump periods. In the second model, the value of the intercept term is 0.148, which is positive and insignificant, implying that the average return of the Nikkei 225 index is 0.148 per cent per month without accounting for the presence of jump periods. The slope of the returns during positive jump periods (PJP) is 4.806, which is positive and significant at the 1% level of significance, indicating that the returns during positive jump periods are 4.806 per cent higher than the returns during non-jump periods. Total returns during positive jump periods are (0.148+ 4.806= 4.954) per cent per month. Whereas the slope of the returns during negative jump periods (NJP) is -4.753, which is negative and significant at the 1% level of significance, indicating that the returns during negative jump periods are -4.753 per cent lower than the returns during non-jump periods. Total returns during negative jump periods is 0.148 - 4.753 = -4.605) percent per month. It is concluded from table 4.7 that positive and negative jumps play an important role in predicting returns of the Nikkei 225 index.

Table 4.8 shows the regression results of two models for the NZX 50 index. In model one, index returns of NZX 50 are regressed on the dummy variable for returns during jump periods (JP). The jump period (JP) includes both positive jump periods and negative jump periods. The results of model one indicate that the slope value of JP is statistically insignificant at a 5% significance level, which implies that the returns of NZX 50 index during jumps periods is the same as returns during non-jump periods. The possible reason here may be that the jump period includes both positive jumps and negative jumps that offset the effect of one another; therefore, the slope of JP is statistically insignificant.

Table 4.8: Dummy Variable Regression Model for NZX 50 Index

Dependent Variable: NZX 50 Index Returns		
	(Model 1)	**(Model 2)**
JP	-0.412	
	(0.51)	
PJP		2.644***
		(0.56)
NJP		-4.173***
		(0.61)
C	0.851***	0.851***
	(0.26)	(0.22)
R2	0.003	0.263
Adj R2	-0.002	0.256
RSE	3.355 (df = 227)	2.891 (df = 226)
Fstat	0.652 (df = 1; 227)	40.323*** (df = 2; 226)

Note: *p<0.1; **p<0.05; ***p<0.01

*Values in brackets are standard errors

In model two, the slope of the index returns during positive jump periods (PJP) and the slope of the index returns during negative jump periods (NJP) is statistically significant when two dummy variables are created by separating positive and negative jump periods. In model two, the value of the intercept term is 0.851, which is positive and insignificant, implying that the average return of the Hang Sang index is 0.851 per cent per month without accounting for the presence of jump periods. The slope of the returns during positive jump periods (PJP) is 2.644, which is positive and significant at the 1% level of significance, indicating that the returns during positive jump periods are 2.644percent higher than the returns during non-jump periods. Total returns during positive jump periods is (0.851 + 2.644= 3.495) percent per month. Whereas the slope of the returns during negative jump periods (NJP) is -4.173, which is negative and significant at the

1% level of significance, indicating that the returns during negative jump periods are -4.173 per cent lower than the returns during non-jump periods. Total returns during negative jump periods are (0.851 -4.173 = -3.322) percent per month. It is concluded from table 4.8 that positive and negative jumps play an important role in predicting returns of the NZX 50 index.

From Table 4.5 to Table 4.8, it is concluded that among Asian developed markets Hang Seng index earns the highest per month returns during positive jumps periods, whereas NZX 50 index earns the lowest returns per month during positive jump periods as compared to other developed markets. Whereas the Hang Sang index has maximum price decline during negative jumps periods and S&P ASX 200 index has minimum price decline during negative jumps periods. These findings are also consistent with the earlier discussion in Table 4.3 and Table 4.4.

4.2.4 Role of Jumps in Equity Returns of Asian Emerging Markets: A Dummy Variable Regression Model

Table 4.9 to 4.14 reports the estimated results of the dummy variable regression model for each of the Asian emerging equity markets. Each table report estimated results for two dummy variable regression models.

In the first model, monthly index returns are regressed on a dummy variable that represents index returns during jump periods (JP). If there is a jump in the index prices for the month, the dummy variable is assigned a value of one, and if there is no jump, the dummy variable is assigned a value of zero.

For the second model, months that have positive jumps and negative jumps are separated from months that do not have jumps, and two dummy variables are created. First is index returns during positive jumps periods (PJP); it takes the value of one if the month has a positive jump; otherwise, it takes the value of zero. The second dummy variable is index reruns during negative jumps periods, and it takes the value of one if the month has a negative jump; otherwise, it takes the value of zero. In the second model, the index return is regressed over two dummy variables that are PJP and NJP, to examine the role of the presence of positive and negative jumps on index returns in each Asian emerging equity market separately.

TABLE 4.9: Dummy Variable Regression Model for Shanghai Composite Index

Dependent Variable: Shanghai Composite Index Returns		
	(Model 1)	**(Model 2)**
JP	-1.191	
	(1.026)	
PJP		5.689***
		(1.169)
NJP		-6.615***
		(1.070)
C	0.804	0.804
	(0.654)	(0.563)
R2	0.006	0.267
Adj R2	0.002	0.261
RSE	7.625 (df = 227)	6.560 (df = 226)
Fstat	1.347 (df = 1; 227)	41.231*** (df = 2; 226)

Note: *p<0.1; **p<0.05; ***p<0.01

*Values in brackets are standard errors

Table 4.9 shows the regression results of two models for the Shanghai Composite index. In model one, index returns of the Shanghai Composite are regressed on the dummy variable for returns during jump periods (JP). The jump period (JP) includes both positive jump periods and negative jump periods. The results of model one indicate that the slope value of JP is statistically insignificant at a 5% significance level which implies that the returns of Shanghai Composite during jumps periods are the same as returns during non-jump periods. The possible reason here may be that the jump period includes both positive jumps and negative jumps that offset the effect of one another; therefore, the slope of JP is statistically insignificant.

In model two, the slope of the index returns during positive jump periods (PJP) and the slope of the index returns during negative jump periods (NJP) is statistically significant when two dummy variables are created by separating positive and negative jump periods. In model two, the value of the intercept term is 0.804, which is positive and insignificant, implying that the average return of the Shanghai Composite index. is 0.804 per cent per month without accounting for the presence of jump periods. The slope of the returns during positive jump periods (PJP) is 5.689, which is positive and significant at the 1% level of significance, indicating that the returns during positive jump periods are 5.689 per cent higher than the returns during non-jump periods. Total returns during positive jump periods is (0.804 + 5.689 = 6.493) percent per month. Whereas the slope of the returns during negative jump periods (NJP) is -6.615, which is negative and significant at the 1% level of significance, indicating that the returns during negative jump periods are -6.615 per cent lower than the returns during non-jump periods. Total returns during negative jump periods is (0.804 -6.615 = -5.811) percent per month. It is concluded from table 4.9 that positive and negative jumps play an important role in predicting returns of the Shanghai Composite.

Table 4.10 shows the regression results of two models for the Nifty 50 index. In model one, index returns of Nifty 50 are regressed on the dummy variable for returns during jump periods (JP). The jump period (JP) includes both positive jump periods and negative jump periods. The results of model one indicate that the slope of JP is positive and is statistically significant at a 5% significance level which implies that the returns of the Nifty 50 index during jumps periods are higher than returns during non-jump periods. The returns during jump periods for Nifty 50 index is (0.094 + 2.753= 2.847%) per month. The possible reason for the significant slop of JP is that there are 63 months that have jumps for the Nifty 50 index, in which 40 months have positive and 23 months have negative jumps. The positive months exceed the negative months by 17 months and the returns during these 17 months are larger than non jump periods therefore positive jumps and negative jumps could not offset the effect of one another and making the slop of JP significant.

TABLE 4.10: Dummy Variable Regression Model for Nifty 50 Index

Dependent Variable: Nifty 50 Index Returns		
	(Model 1)	**(Model 2)**
JP	2.753***	
	(0.934)	
PJP		7.060***
		(0.981)
NJP		-4.736***
		(1.239)
C	0.094	0.094
	(0.490)	(0.432)
R2	0.037	0.253
Adj R2	0.033	0.247
RSE	6.312 (df = 227)	5.570 (df = 226)
Fstat	8.690*** (df = 1; 227)	38.321*** (df = 2; 226)

Note: *p<0.1; **p<0.05; ***p<0.01

*Values in brackets are standard errors

In model two, the slope of the index returns during positive jump periods (PJP) and the slope of the index returns during negative jump periods (NJP) is statistically significant when two dummy variables are created by separating positive and negative jump periods. In model two, the value of the intercept term is 0.094, which is positive and insignificant, implying that the average return of the Nifty 50 index is 0.094 per cent per month without accounting for the presence of jump periods. The slope of the returns during positive jump periods (PJP) is 7.060, which is positive and significant at the 1% level of significance, indicating that the returns during positive jump periods are 7.060 per cent higher than the returns during non-jump periods. Total returns during positive jump periods is (0.094 + 7.060 = 7.154) percent per month. Whereas the slope of the returns during negative jump periods (NJP) is -4.736, which is negative and significant at the

1% level of significance, indicating that the returns during negative jump periods are -4.736 per cent lower than the returns during non-jump periods. Total returns during negative jump periods is (0.094 - 4.736 = -4.642) percent per month. It is concluded from table 4.10 that positive and negative jumps play an important role in predicting returns of the Nifty 50 index.

Table 4.11: Dummy Variable Regression Model for JKSE Index

Dependent Variable: JKSE Index Returns		
	(Model 1)	**(Model 2)**
JP	0.984	
	(0.827)	
PJP		5.381***
		(0.847)
NJP		-5.949***
		(1.024)
C	0.866*	0.866**
	(0.447)	(0.381)
R2	0.006	0.282
Adj R2	0.002	0.276
RSE	5.691 (df = 227)	4.847 (df = 226)
Fstat	1.417 (df = 1; 227)	44.436*** (df = 2; 226)

Note: *p<0.1; **p<0.05; ***p<0.01

*Values in brackets are standard errors

Table 4.11 shows the regression results of two models for the JKSE index. In model one, index returns of JKSE are regressed on the dummy variable for returns during jump periods (JP). The jump period (JP) includes both positive jump periods and negative jump periods. The results of model one indicate that the slope value of JP is statistically insignificant at a 5% significance level which implies that the returns of the JKSE index during jumps periods are the same as returns during non-jump periods. The possible reason here may be that the jump period includes both positive jumps and negative jumps that offset the effect of one another; therefore, the slope of JP is statistically insignificant.

In model two, the slope of the index returns during positive jump periods (PJP) and the slope of the index returns during negative jump periods (NJP) is statistically significant when two dummy variables are created by separating positive and negative jump periods. In model two, the value of the intercept term is 0.866, which is positive and insignificant, implying that the average return of the JKSE index is 0.866 per cent per month without accounting for the presence of jump periods. The slope of the returns during positive jump periods (PJP) is 5.381, which is positive and significant at the 1% level of significance, indicating that the returns during positive jump periods are 5.381 per cent higher than the returns during non-jump periods. Total returns during positive jump periods are (0.866+ 5.381= 6.247) per cent per month. Whereas the slope of the returns during negative jump periods (NJP) is -5.949, which is negative and significant at the 1% level of significance, indicating that the returns during negative jump periods are -5.949 per cent lower than the returns during non-jump periods. Total returns during negative jump periods is (0.866 -5.949 = -5.083) percent per month. It is concluded from Table 4.11 that positive and negative jumps play an important role in predicting returns of the JKSE index.

Table 4.12 shows the regression results of two models for the KSE-100 index. In model one, index returns of KSE-100 are regressed on the dummy variable for returns during jump periods (JP). The jump period (JP) includes both positive jump periods and negative jump periods. The results of model one indicate that the slope of JP is positive and is statistically significant at a 5% significance level which implies that the returns of the KSE-100 index during jumps periods are higher than returns during non-jump periods. The returns during jump periods for KSE-100 index is (0.274 + 3.752 = 4.026 %) per month. The possible reason for the significant slop of JP is that there are 73 months that have jumps for the KSE-100 index, in which 56 months have positive and 17 months have negative jumps. The positive months exceed the negative months by 39 months and the

TABLE 4.12: Dummy Variable Regression Model for KSE-100 Index

Dependent Variable: KSE-100 Index Returns		
	(Model 1)	**(Model 2)**
JP	3.752***	
	(0.965)	
PJP		6.430***
		(0.971)
NJP		-5.072***
		(1.592)
C	0.274	0.274
	(0.545)	(0.499)
R2	0.062	0.216
Adj R2	0.058	0.209
RSE	6.803 (df = 227)	6.233 (df = 226)
Fstat	15.122*** (df = 1; 227	31.207*** (df = 2; 226)

Note: *p<0.1; **p<0.05; ***p<0.01

*Values in brackets are standard errors

returns during these 39 months are larger than returns during non jump periods therefore positive jumps and negative jumps could not offset the effect of one another and making the slop of JP significant.

In model two, the slope of the index returns during positive jump periods (PJP) and the slope of the index returns during negative jump periods (NJP) is statistically significant when two dummy variables are created by separating positive and negative jump periods. In model two, the value of the intercept term is 0.274, which is positive and insignificant, implying that the average return of the KSE-100 index is 0.274 per cent per month without accounting for the presence of jump periods. The slope of the returns during positive jump periods (PJP) is 6.430, which is positive and significant at the 1% level of significance, indicating that the returns during positive jump periods are 6.430 per cent higher than the returns during non-jump periods. Total returns during positive jump periods is (0.274 + 6.430 = 6.704) percent per month. Whereas the slope of the returns during negative jump periods (NJP) is -5.072, which is negative and significant at the 1% level of significance, indicating that the returns during negative jump periods are -5.072 per cent lower than the returns during non-jump periods. Total returns during negative jump periods is (0.274 -5.072 = -4.798) percent per month. It is concluded from Table 4.12 that positive and negative jumps play an important role in predicting returns of the KSE-100 index.

Table 4.13: Dummy Variable Regression Model for SET Index

Dependent Variable: SET Index Returns		
	(Model 1)	**(Model 2)**
JP	1.415*	
	(0.819)	
PJP		5.442***
		(0.817)
NJP		-5.632***
		(1.023)
C	0.152	0.152
	(0.475)	(0.403)
R2	0.013	0.29
Adj R2	0.009	0.284
RSE	5.853 (df = 227)	4.974 (df = 226)
Fstat	2.986* (df = 1; 227)	46.224*** (df = 2; 226)

Note: *p<0.1; **p<0.05; ***p<0.01

*Values in brackets are standard errors

Table 4.13 shows the regression results of two models for the SET index. In model one, index returns of is regressed on the dummy variable for returns during jump periods (JP). The jump period (JP) includes both positive jump periods and negative jump periods. The results of model one indicate that the slope value of JP is statistically insignificant at a 5% significance level which implies that the returns of the SET index during jumps periods are the same as returns during non-jump periods. The possible reason here may be that the jump period includes both positive jumps and negative jumps that offset the effect of one another; therefore, the slope of JP is statistically insignificant.

In model two, the slope of the index returns during positive jump periods (PJP) and the slope of the index returns during negative jump periods (NJP) is statistically significant when two dummy variables are created by separating positive and negative jump periods. In model two, the value of the intercept term is 0.152, which is positive and insignificant, implying that the average return of the SET index is 0.152 per cent per month without accounting for the presence of jump periods. The slope of the returns during positive jump periods (PJP) is 5.442, which is positive and significant at the 1% level of significance, indicating that the returns during positive jump periods are 5.442 per cent higher than the returns during non-jump periods. Total returns during positive jump periods is (0.152 + 5.442 = 5.594) percent per month. Whereas the slope of the returns during negative jump periods (NJP) is -5.632, which is negative and significant at the 1% level of significance, indicating that the returns during negative jump periods are -5.632 per cent lower than the returns during non-jump periods. Total returns during negative jump periods is (0.152 -5.632 = -5.48) percent per month. It is concluded from Table 4.13 that positive and negative jumps play an important role in predicting returns of the SET index.

Table 4.14 shows the regression results of two models for the CSE All index. In model one, index returns of CSE All are regressed on the dummy variable for returns during jump periods (JP). The jump period (JP) includes both positive jump periods and negative jump periods. The results of model one indicate that the slope of JP is positive and is statistically significant at a 5% significance level which implies that the returns of the CSE All index during jumps periods are higher than returns during non-jump periods. The returns during jump periods for CSE All index is (0.041 + 2.583= 2.624%) per month. The possible reason for

Table 4.14: Dummy Variable Regression Model for CSE All Index

Dependent Variable: CSE All Index Returns		
	(Model 1)	**(Model 2)**
JP	2.583***	
	(0.827)	
PJP		6.248***
		(0.822)
NJP		-3.656***
		(1.00)
C	0.041	0.041
	(0.546)	(0.471)
R2	0.041	0.292
Adj R2	0.037	0.286
RSE	6.206 (df = 227)	5.345 (df = 226)
Fstat	9.760*** (df = 1; 227)	46.592*** (df = 2; 226)

Note: *p<0.1; **p<0.05; ***p<0.01

*Values in brackets are standard errors

the significant slop of JP is that there are 100 months that have jumps for CSE All index, in which 63 months have positive and 37 months have negative jumps. The positive months exceed the negative months by 26 months and the returns during these 26 months are larger than returns during non jump periods therefore positive jumps and negative jumps could not offset the effect of one another and making the slop of JP significant.

In model two, the slope of the index returns during positive jump periods (PJP) and the slope of the index returns during negative jump periods (NJP) is statistically significant when two dummy variables are created by separating positive and negative jump periods. In model two, the value of the intercept term is 0.041, which is positive and insignificant, implying that the average return of the CSE All index is 0.041 per cent per month without accounting for the presence of jump periods. The slope of the returns during positive jump periods (PJP) is 6.248, which is positive and significant at the 1% level of significance, indicating that the returns during positive jump periods are 6.248 per cent higher than the returns during non-jump periods. Total returns during positive jump periods is (0.041 + 6.248 = 6.289) percent per month. Whereas the slope of the returns during negative jump periods (NJP) is -3.656, which is negative and significant at the 1% level of significance, indicating that the returns during negative jump periods are -3.656 per cent lower than the returns during non-jump periods. Total returns during negative jump periods is (0.041 -3.656 = -3.615) percent per month. It is concluded from Table 4.14 that positive and negative jumps play an important role in predicting returns of the CSE All index.

It is concluded from Tables 4.9 to 4.14 that in Asian emerging markets the Nifty 50 index earns the highest monthly returns during positive jump periods, while the SET index earns the lowest monthly returns during positive jump periods. Whereas the Shanghai Composite Index has the greatest price decline during negative jumps periods, and the CSE All Index has the least price decline during periods of negative jumps. These findings are also in line with the descriptive statistics given in Table 4.3 and Table 4.4.

From the overall analysis presented in Tables 4.5 to 4.14, it is concluded that the range of returns during positive jump periods in Asian developed markets is 3.49 per cent to 5.37 per cent monthly, while the range of returns during positive jump periods in Asian emerging markets is 5.59 per cent to 7.15 per cent monthly. During negative jump periods, price declines in Asian developed markets range from 3.16 per cent to 5.40 per cent, while price declines in Asian emerging markets range from 3.65 per cent to 5.81 per cent. Asian emerging markets earn higher returns during positive jump periods than Asian developed markets, and price declines are also higher in Asian emerging markets than in Asian developed markets.

The higher returns of Asian emerging markets during periods of positive jumps and higher decline in index prices during periods of negative jumps as compare to Asian developed markets are due to the riskier and more volatile nature of Asian emerging markets. The Asian emerging markets have political instability whereas Asian developed markets are rather stable, the corporate governance in Asian emerging markets are comparatively poor than Asian developed markets. Furthermore, Asian emerging markets have a thin structure, having low liquidity and inflation rates are high than Asian developed markets. Moreover, the currency of Asian emerging markets devalues most of the time and having high interest rate risk, and cross-border cash flows are high as compared to Asian developed markets. These factors hurt the Asian emerging economies and make the Asian emerging stock markets highly volatile, which increases the possibility of higher returns during positive jumps periods and higher price decline during negative jump periods.

4.3 Association of Fama and French Five Factors and Jump Returns

The fourth objective of the study is to explore the link between Fama and French five factors and jump returns. To achieve this objective, Table 4.15 and Table 4.16 reports the empirical results of the association between Fama and French five factors and jump returns. Table 4.15 reports empirical results of the association between Fama and French five factor and jump returns for Asian developed markets whereas Table 4.16 reports the empirical results of the association between Fama and French five factor and jump returns for Asian emerging markets.

4.3.1 Association of Fama and French Five Factors and Jump Returns for Asian Developed Markets

Table 4.15 reports the results of three models in the context of Asian developed markets. The first model reports empirical results of the association between Fama and French five factor and jump returns (include both positive and negative jump returns). The second model reports empirical results of the association between Fama and French five factor and positive jump returns. Whereas the third model reports empirical results of the association between Fama and French five factor and negative jump returns. The purpose of these three regression models is to know which risk factors of the Fama and French five-factor model explain jump returns, positive jump returns, and negative jump returns in the context of Asian developed markets.

Table 4.15: Fama and French's Five Factors Risk Premia and Jump Returns for Asian Developed Markets

	Model 1	**Model 2**	**Model 3**
		Dependent Variable	
	Jumps return	Positive jumps return	Negative jumps return
Constant	0.122	3.015***	-2.966***
	(0.253)	(0.278)	(0.36)
MKT	0.728***	0.368***	0.426***
	(0.047)	(0.054)	(0.069)
SMB	-0.182*	-0.115	-0.006
	(0.097)	(0.075)	(0.119)
HML	0.206*	0.139	0.09
	(0.116)	(0.098)	(0.135)
RMW	0.04	-0.184	-0.102
	(0.125)	(0.113)	(0.133)
CMA	-0.374**	-0.623***	-0.256
	(0.147)	(0.127)	(0.176)
R2	0.753	0.676	0.571
Adj R2	0.743	0.655	0.524
RSE	2.647 (df = 131)	1.656 (df = 78)	1.905 (df = 46)
Fstat	79.826*** (df = 5; 131)	32.553*** (df = 5; 78)	12.223*** (df = 5; 46)

Note: *p<0.1; **p<0.05; ***p<0.01

*Values in brackets are standard errors

In the first model, Fama and French's five factors risk premium are regressed against jump returns (including both positive jump returns and negative jump returns) for Asian developed markets. In model one, the coefficient value of the market premium is significant at 1% significance level and investment premium is significant at 5% level of significance whereas size and value premium is significant at 10% level of significance. However, profitability premium is insignificant and also found a redundant risk factor for explaining jump returns as excluding profitability premium improves adjusted r-square of the model. So, it is concluded from model one that in the context of Asian developed markets, the market premium and investment premium significantly explain the jump returns Whereas, size premium and value premium are also important factors and contribute to the model for explaining jump returns because excluding size or value premium reduces the explanatory power of the model. In model one, the Fama and French five risk factors explain 75.3% of the variations in jumps returns.

In the second model, Fama and French's five factors risk premium are regressed against positive jump returns for Asian developed markets. In the second model, the coefficient value of market premium and investment premium significantly explain variations in positive jump returns at a 1% level of significance. However, size premium, value premium, and profitability premium also contribute to the model as excluding each of these three factors decreases the adjusted r-square of the model. From the estimated results of the second model, it is concluded that market premium and investment premium significantly explain positive jump returns. But size premium, value premium, and profitability premium also play an important role in explaining positive jump returns. In the second model, the Fama and French five risk factors explain 67.6% of the variations in positive jumps returns.

In the third model, Fama and French's five factors risk premium are regressed against negative jump returns for Asian developed markets. In model three, the only risk factor that is significant is the market risk premium which is significant at a 1% level of significance. However, profitability premium and investment premium also play an important role in explaining negative jump returns because excluding profitability or investment premium reduces the explanatory power of the model. Whereas size premium and value premium do not explain the negative jump returns of developed markets. So it is concluded from model three that market premium, profitability premium, and investment explain the negative jumps returns in the context of developed markets. In the thirds model, the Fama and French five risk factors explain 57.1% of the variations in negative jumps returns.

The conclusion is that in developed markets, all five factors explain positive jump returns. Whereas market premium, profitability premium, and investment premium explain negative jump returns.

4.3.2 Association of Fama and French Five Factors and Jump Returns for Asian Emerging Markets

Table 4.16 reports estimated results of Fama and French five factors and jump return for Asian emerging markets. There are three models; model one shows results of the Fama and French five factors model and jump returns (including both positive and negative jump returns). Model two gives results of Fama and French five factors and positive jump returns only, whereas model three provides results for Fama and French five factors and negative jump returns. The purpose of these three models is to know which risk factor of the Fama and French five factor model explain jump returns, positive jump returns, and negative jump returns in the context of Asian emerging markets.

In the first model, Fama and French's five factors risk premium are regressed against jump returns (including both positive jump returns and negative jump returns) for Asian emerging markets. In the first model, the slope of market premium, size premium, and value premium is significant at a 1% level of significance. Whereas the slope of profitability premium and investment premium is insignificant at a 1% level of significance. Furthermore, profitability premium and investment premium are found to be redundant factors for explaining jump returns as including profitability premium or investment premium decrease the adjusted r-square value. Therefore, it is concluded from one that in Fama and French five factors, only market premium, size premium, and value premium explain the jump returns in the context of Asian developed markets. The explanatory power of model one is 55.1%, which means that model one explains 55.1% variations in jump returns for Asian emerging markets.

Table 4.16: Fama and French's five Factors Risk Premia and Jump Returns for Asian Emerging Markets

	Model 1	Model 2	Model 3
	Dependent Variable		
	Jumps return	Positive jumps return	Negative jumps return
Constant	0.495	5.686***	-4.579***
	(0.366)	(0.437)	(0.468)
MKT	0.813***	0.246***	0.286***
	(0.079)	(0.089)	(0.103)
SMB	0.562***	0.147	0.206
	(0.196)	(0.202)	(0.258)
HML	0.645***	0.246	0.243
	(0.226)	(0.223)	(0.28)
RMW	0.174	-0.104	-0.477
	(0.295)	(0.282)	(0.416)
CMA	-0.129	-0.443	-1.152***
	(0.29)	(0.283)	(0.392)
R2	0.551	0.162	0.305
Adj R2	0.539	0.134	0.274
RSE	4.505 (df = 200)	3.922 (df = 151)	4.411 (df = 110)
Fstat	49.021*** (df = 5; 200)	5.820*** (df = 5; 151)	9.676*** (df = 5; 110)

Note: *p<0.1; **p<0.05; ***p<0.01

*Values in brackets are standard errors

In the second model, Fama and French's five factors risk premium are regressed against positive jump returns for Asian emerging markets. In the second model, the only risk factor that is significant is the market premium which is significant at a 1% level of significance. Whereas investment premium is insignificant but also found an important factor in explaining positive jump returns as excluding investment premium from model decrease adjusted r-square value of the model. However, the slope of size premium, value premium, and profitability premium are insignificant at a 1% level of significance. These three variables are also found to be a redundant factor as including these three factors do not increase the explanatory power of the model. The explanatory power of the second model is 16.2%, which means that model one explains 16.2% variations in positive jump returns for Asian emerging markets.

In the third model, Fama and French's five factors risk premium are regressed against negative jump returns for Asian developed markets. Model three shows results of Fama and French five factors and negative jump returns for Asian emerging markets. In model three, market premium and investment premium are significant at a 1% significance level. Whereas size premium and value premium is insignificant but including these two factors increase the explanatory power of the model. However, the profitability premium is insignificant and is redundant as well. It means that in the context of Asian emerging markets, except profitability premium, the rest of the four factors play an important role in explaining negative jump returns. The explanatory power of the third model is 30.5%, which means that model one explains 30.5% variations in negative jump returns for Asian emerging markets.As the number of jump returns increases by combining the number of positive and negative jump returns, SMB and HML become highly significant from all jump returns. However, when positive and negative jumps are separated, the number of jump returns decreases. As a result, SMB and HML have no effect on positive or negative jumps.

It is concluded from Table 4.15 and 4.16 that in the context of Asian developed markets, all the five factors of the Fama and French five factor model explain positive jump returns, whereas, in the context of Asian emerging markets, two factors of Fama and French five factor model explain positive jump returns, which are market premium and investment premium. Similarly, market premium, profitability premium, and investment premium explain negative jump returns in Asian developed markets, whereas market premium, size premium, value premium, and investment premium explain negative jump returns in Asian emerging markets.

This significant relationship between factor premia and jump returns has implications for asset pricing. It implies that the premium associated with these factors is linked to large amounts of unexpected information captured via jumps. It also implies that investors may be able to build better asset pricing models by incorporating the jumps into the model.

4.4 Integrated Volatility Measures and Integrated Volatility During Jumps Periods

The fifth objective of the study is to provide insight into integrated volatility during periods of positive jumps and periods of negative jumps for Asian developed and Asian emerging markets. To achieve the fifth objective, this study first provides descriptive statistics of three integrated volatility measure which includes total realized volatility (RV), realized bipower variation (BPV), and tripower variation (TPV). Table 4.17 exhibits descriptive statistics of integrated volatility measures for Asian developed markets whereas Table 4.18 exhibits descriptive statistics of integrated volatility measures for Asian emerging markets.

Then the three volatility measures are depicted in graphs to get a clearer pictorial representation of the three volatility measures. Figure 4.2 to Figure 4.5 provides graphs for integrated volatility measures for Asian developed markets where Figure 4.6 to Figure 4.11 shows a pictorial representation for Asian emerging markets.

Then integrated volatility due to jump component and continuous component is separated from total realized volatility using Andersen et al. (2007) method and estimate descriptive statistics of the volatility of jump component during jump periods. Integrated volatility of jump component is further disentangled into integrated volatility during positive jump periods and negative jump periods and estimate descriptive statistics of integrated volatility of the jump component during positive jump periods, and descriptive statistics of integrated volatility of the jump component during negative jump periods for Asian developed markets and Asian emerging markets. Table 4.19 exhibits descriptive statistics of integrated volatility during jump periods, descriptive statistics of integrated volatility during positive jump periods, and descriptive statistics of integrated volatility during negative jump periods for Asian developed markets whereas Table 4.20 exhibits descriptive statistics of integrated volatility during jump periods, descriptive statistics of integrated volatility during positive jump periods, and descriptive statistics of integrated volatility during negative jump periods for Asian emerging markets.

Then the ratio of volatility due to jump component and total realized volatility is calculated for Asian developed as in Table 4.21 and for Asian emerging markets as in Table 4.22.

4.4.1 Descriptive Statistics of Integrated Volatility Measures for Asian Developed Markets

Table 4.17 provides descriptive statistics of three integrated volatility measures; total realized volatility (RV), realized bipower variation (BPV), and tripower variation (TPV) for each Asian developed market for the sample period of period February 2001 - February 2020.

Table 4.17 summarizes integrated volatility, estimated using three volatility measures RV (measures total volatility), BPV (measures continuous component of quadratic variation), and TPV (also measures the continuous component of quadratic variation). The mean, standard deviation, minimum and maximum values are all in terms of 10^{-3}. It is observed from Table 4.17 that in terms of total realized volatility, the Nikkei 225 index and Hang Seng index are more volatile markets whereas S&P ASX 200 and NZX 50 index are less volatile markets among the developed market. Nikkei 225 index has the highest volatility for the three integrated volatility measures whereas NZX 50 index is the least volatile market in terms of three integrated volatility measures.

4.4.2 Descriptive Statistics of Integrated Volatility Measures for Asian Emerging Markets

Table 4.18 provides descriptive statistics of total realized volatility (RV), realized bipower variation (BPV), and tripower variation (TPV) for each Asian emerging

Table 4.17: Descriptive Statistics of Integrated Volatility Measures for Asian Developed Markets

Indices	**Volatility Measures**	**Mean**	**SD**	**Min**	**Max**	**Kur**	**Skew**
S&P ASX 200	RV	1.453	1.080	0.350	5.802	2.657	1.612
	BPV	1.349	1.028	0.297	6.016	3.834	1.782
	TPV	1.155	0.890	0.231	5.305	3.699	1.779
Hang Seng	RV	2.932	2.156	0.786	11.024	3.352	1.850
	BPV	2.507	1.951	0.543	9.172	2.112	1.635
	TPV	2.109	1.616	0.447	8.119	1.694	1.510
Nikkei225	RV	3.425	2.257	0.797	11.914	1.777	1.335
	BPV	2.977	1.946	0.688	10.338	1.243	1.222
	TPV	2.484	1.660	0.550	7.758	0.718	1.146
NZX 50	RV	0.770	0.465	0.297	2.242	1.383	1.443
	BPV	0.730	0.430	0.233	2.103	1.356	1.385
	TPV	0.634	0.380	0.180	1.933	2.306	1.561

Notes: Table 4.17 gives the descriptive statistics of integrated volatility measures for Asian developed markets. Mean, standard deviation, min, and max values are all in terms of 10^{-3}

market for the sample period of period February 2001 - February 2020.

Whereas among Asian emerging markets, the Shanghai Composite index shows maximum price fluctuations because it shows the highest average values of total integrated volatility. The CSE all index is the least volatile as its mean value of total integrated volatility is the lowest among all emerging markets.

TPV is a better estimation technique of continuous components of quadratic variation than BPV as it understates the average integrated volatility and has the minimum standard deviation. This pattern is consistent across all Asian developed and Asian emerging markets. So volatility of the jump component can be better estimated by the difference between RV and TPV as compared with the difference of RV and BPV. Moreover, on average Asian emerging markets show higher integrated volatility than Asian developed markets for all of the three measures of integrated volatility as the mean value of RV, BPV, and TPV is larger for

TABLE 4.18: Descriptive Statistics of Integrated Volatility Measures for Asian Emerging Markets

Indices	**Volatility Measures**	**Mean**	**SD**	**Min**	**Max**	**Kur**	**Skew**
Shanghai Composite	RV	3.995	3.507	0.768	17.212	3.359	1.891
	BPV	3.353	3.139	0.602	14.928	3.292	1.923
	TPV	2.838	2.664	0.509	12.305	2.712	1.810
Nifty 50	RV	2.828	2.328	0.621	13.413	4.599	2.052
	BPV	2.572	2.227	0.564	11.747	3.742	1.968
	TPV	2.173	1.949	0.427	10.046	4.510	2.086
JKSE	RV	2.600	1.949	0.522	9.087	1.854	1.534
	BPV	2.381	1.900	0.465	9.584	2.727	1.711
	TPV	1.989	1.563	0.386	7.988	2.278	1.591
KSE-100	RV	2.598	2.069	0.454	10.750	3.332	1.717
	BPV	2.452	2.236	0.414	12.355	5.584	2.207
	TPV	2.095	2.054	0.354	11.639	6.949	2.435
SET Index	RV	2.360	1.751	0.449	7.765	0.908	1.220
	BPV	2.088	1.660	0.302	8.253	1.873	1.447
	TPV	1.793	1.561	0.237	7.828	2.648	1.656
CSE All	RV	1.401	1.555	0.169	8.203	5.893	2.329
	BPV	1.296	1.485	0.151	8.133	6.838	2.386
	TPV	1.076	1.284	0.111	6.974	6.934	2.433

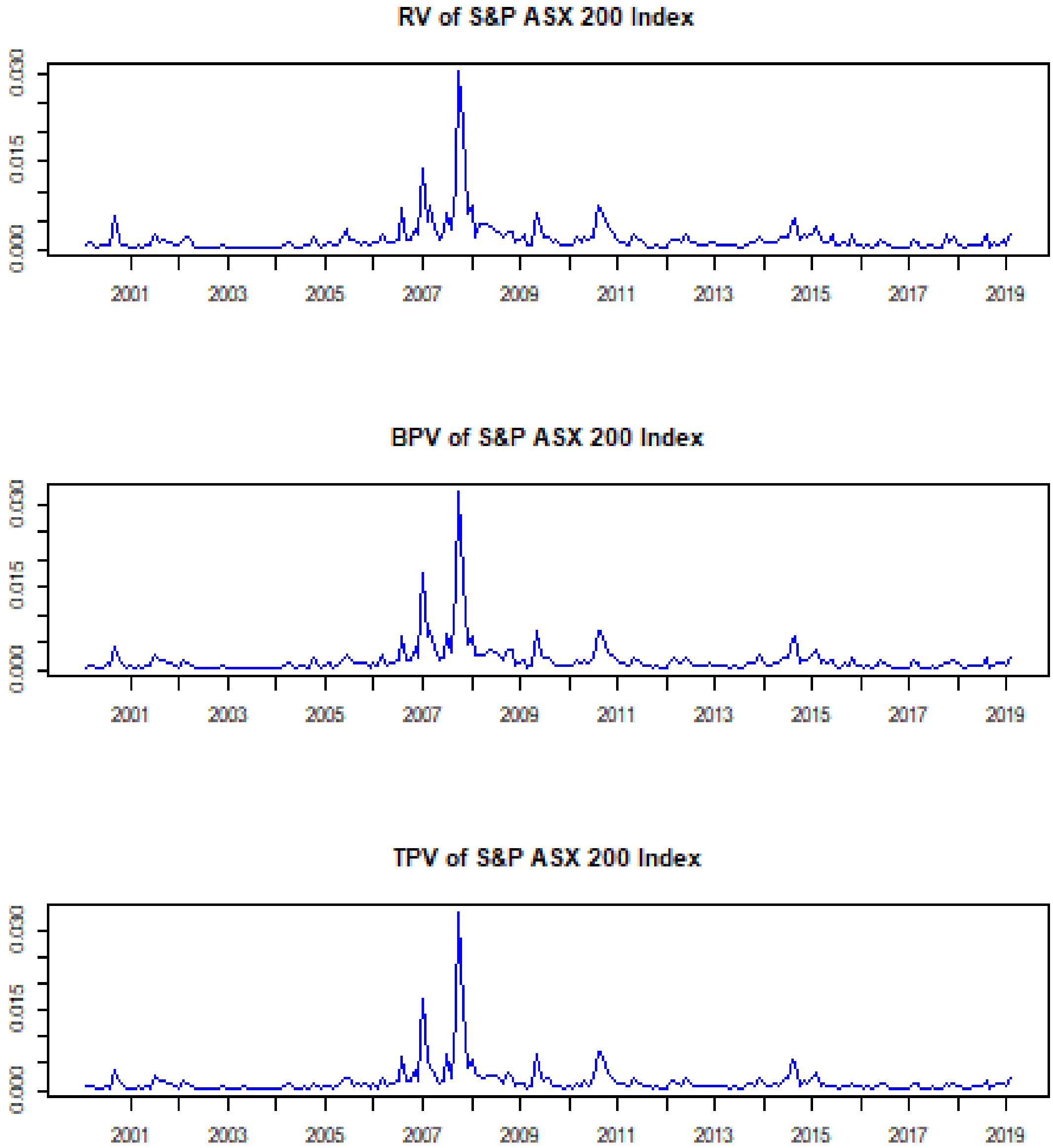
Notes: Table 4.18 gives the descriptive statistics of integrated volatility measures for Asian emerging markets. Mean, standard deviation, min, and max values are all in terms of 10^{-3}.

Asian emerging markets as compared with Asian developed markets.

Figures 4.2–4.5 display integrated volatility of the three integrated volatility measures for Asian developed markets to get a clearer idea of how volatility differs across the Asian developed markets.

Figure 4.2 displays realized volatility (RV), bipower variation (BPV), and tripower variation (TPV) of the S&P ASX 200 index for the sample period of 229 months from February 2001 – February 2020. It is observed from the figure that S&P ASX 200 index has experienced high volatility for all of the three measures of integrated

Figure 4.2: Integrated Volatility Measures—S&P ASX 200 Index

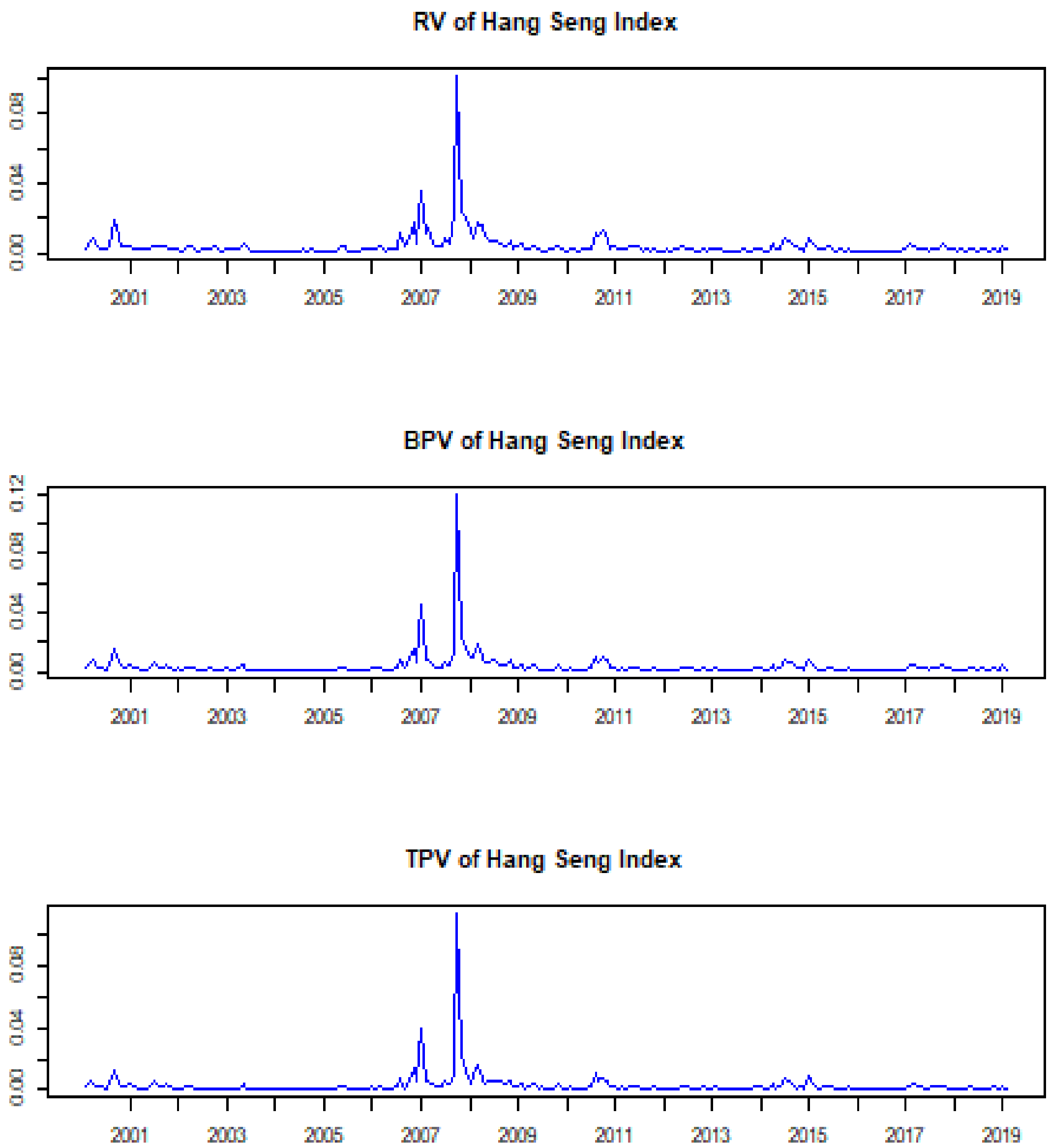


Notes: Figure 4.2 displays realized volatility, bi-power variation, and tri-power variation for S&P ASX 200 index

volatility in the last quarter of 2001, during mid of 2007 till mid of 2009, in the first quarter of 2010, during the mid of 2011 till the end of 2011, during mid of 2015 till the end of 2015. These periods are considered as periods of high volatility than other periods. However, peak volatility is observed during the mid of 2007 till mid of 2009 for the S&P ASX 200 index which is the period of the global financial crisis.

Figure 4.3 displays realized volatility (RV), bipower variation (BPV), and tripower

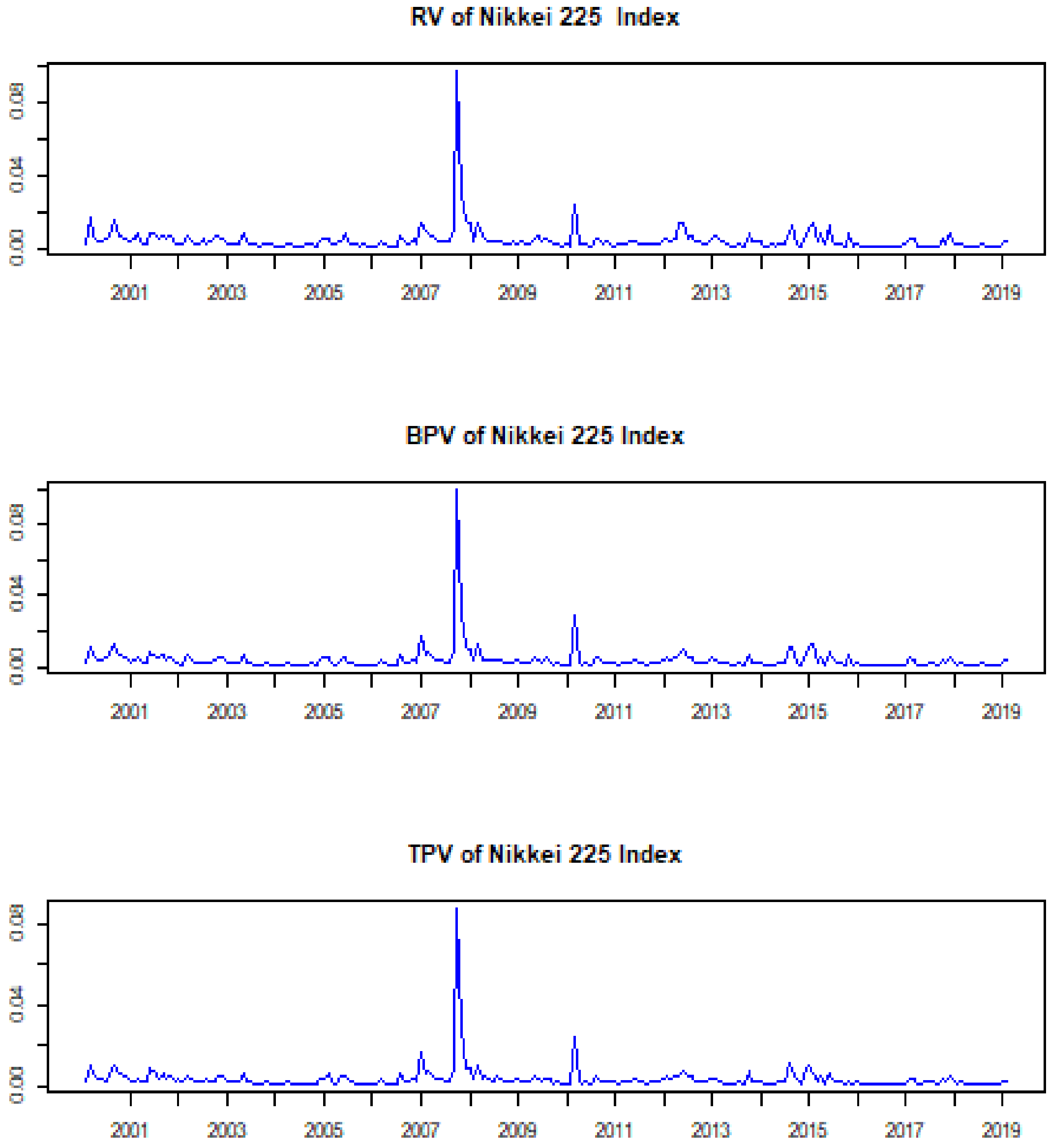
FIGURE 4.3: Integrated Volatility Measures—Hang Seng Index



Notes: Figure 4.3 displays realized volatility, bi-power variation, and tri-power variation for the Hang Seng index

variation (TPV) of the Hang Seng index for the sample period of 229 months from February 2001 – February 2020. It is observed from the figure that the Hang Seng index has experienced high volatility for all of the three measures of integrated volatility in the last quarter of 2001, during the mid of 2007 till mid of 2009, during mid of 2011 till the end of 2011, during mid of 2015 till the end of 2015. These periods are considered as periods of high volatility than other periods. However, peak volatility is observed during the mid of 2007 till mid of 2009 for the Hang

FIGURE 4.4: Integrated Volatility Measures—Nikkei 225 Index

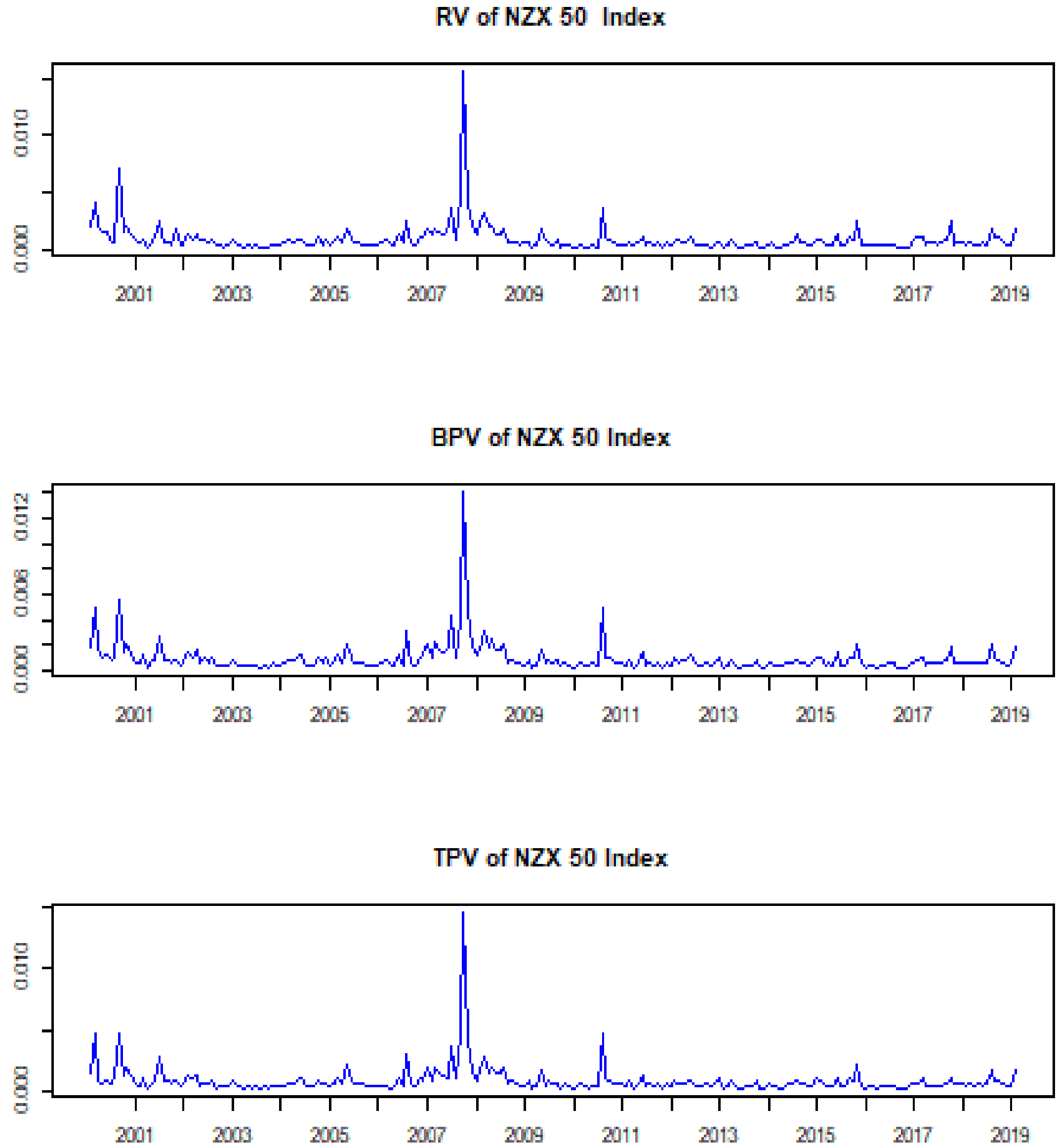


Notes: Figure 4.4 displays realized volatility, bi-power variation, and tri-power variation for Nikkei 225 index

Seng index which is the period of the global financial crisis.

Figure 4.4 displays realized volatility (RV), bipower variation (BPV), and tripower variation (TPV) of the Nikkei 225 index for the sample period of 229 months from February 2001 – February 2020. It is observed from the figure that Nikkei 225 index has experienced high volatility for all of the three measures of integrated volatility during 2001, at the beginning of 2007 till the first quarter of 2008, in the first quarter of 2011, in the last quarter of 2015 and first quarter of 2015. These

FIGURE 4.5: Integrated Volatility Measures—NZX 50 Index



Notes: Figure 4.5 displays realized volatility, bi-power variation, and tri-power variation for NZX 50 index

periods are considered as periods of high volatility than other periods. However, peak volatility is observed during the mid of 2007 till mid of 2009 for the Nikkei 225 index which is the period of the global financial crisis.

Figure 4.5 displays realized volatility (RV), bipower variation (BPV), and tripower variation (TPV) of the NZX 50 index for the sample period of 229 months from February 2001 – February 2020. It is observed from the figure that NZX 50 index has experience high volatility for all of the three measures of integrated volatility during 2001 and the first quarter of 2002, in the first quarter of 2006, during the mid of 2007 till mid 2009, and during mid of 2011. These periods are considered as periods of high volatility than other periods. However, peak volatility is observed during the mid of 2007 till mid of 2009 for the NZX 50 index which is the period of the global financial crisis.

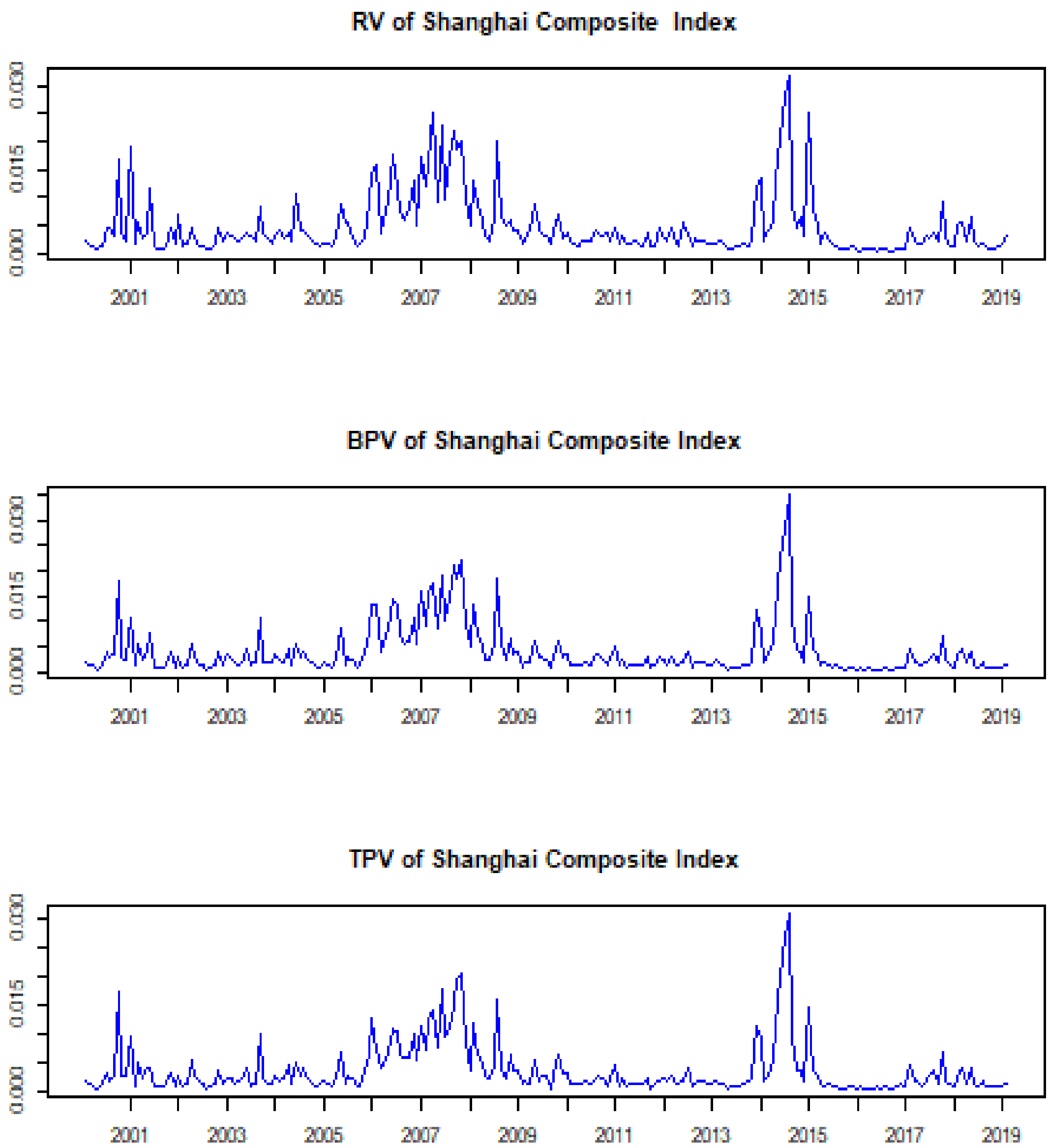
It is concluded from Figures 4.2 to Figure 4.5 that high volatility is observed for S&P ASX 200 index, Hang Seng index, Nikkei 225 index, and NZX 50 index for all of the three measures of integrated volatility in 2001, and during mid 2007 to mid 2009. These periods are considered as periods of high volatility and are common among all Asian developed markets. The year 2001 is a period of sharp downturn or stock market crash across the United States, Canada, Asia, and Europe. Similarly, the time period of 2007 till 2009 are periods of global financial crises. Therefore, all Asian developed markets have reflected high volatility in 2001 and then in 2007 till 2009.

Figures 4.6–4.11 display integrated volatility of the three integrated volatility measures for Asian emerging markets to get a clearer idea of how volatility differs across the Asian emerging markets.

Figure 4.6 displays realized volatility (RV), bipower variation (BPV), and tripower variation (TPV) of the Shanghai Composite index for the sample period of 229 months from February 2001 – February 2020. It is observed from the figure that the Shanghai Composite index has experienced high volatility for all of the three measures of integrated volatility in the last quarter of 2001, at the beginning of 2007 till 2009, and at 2014 till the first quarter of 2016. These periods are considered as periods of high volatility than other periods. However, peak volatility is observed during mid 2007 to mid 2009 for the Shanghai Composite index which is the period of global financial crisis whereas the Shanghai Composite index has also experienced high volatility during 2015 which is also a crises period in china.

Figure 4.7 displays realized volatility (RV), bipower variation (BPV), and tripower variation (TPV) of the Nifty 50 index for the sample period of 229 months from February 2001 – February 2020. It is observed from the figure that the Nifty 50

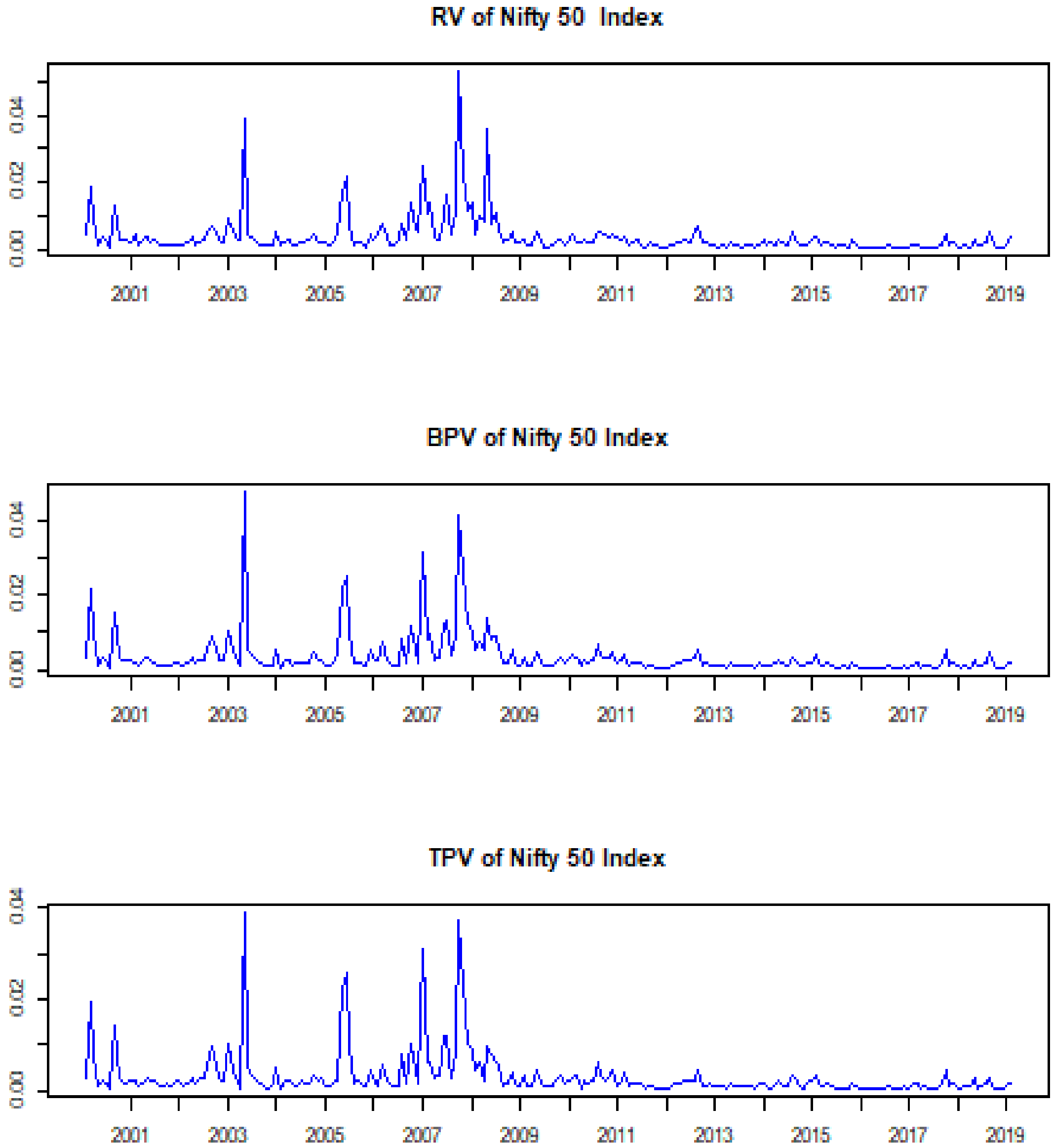
Figure 4.6: Integrated Volatility Measures—Shanghai Composite Index



Notes: Figure 4.6 displays realized volatility, bi-power variation, and tri-power variation for the Shanghai Composite index

index has experience high volatility for all of the three measures of integrated volatility during 2001, in the first quarter of 2004, in the mid of 2006, and during mid 2007 till mid 2009. These periods are considered as periods of high volatility than other periods. However, peak volatility is observed during mid 2007 till mid 2009 for the Nifty 50 index which is the period of global financial crises but the nifty 50 index also have high volatility in 2004 and 2006 which are also crisis periods in India.

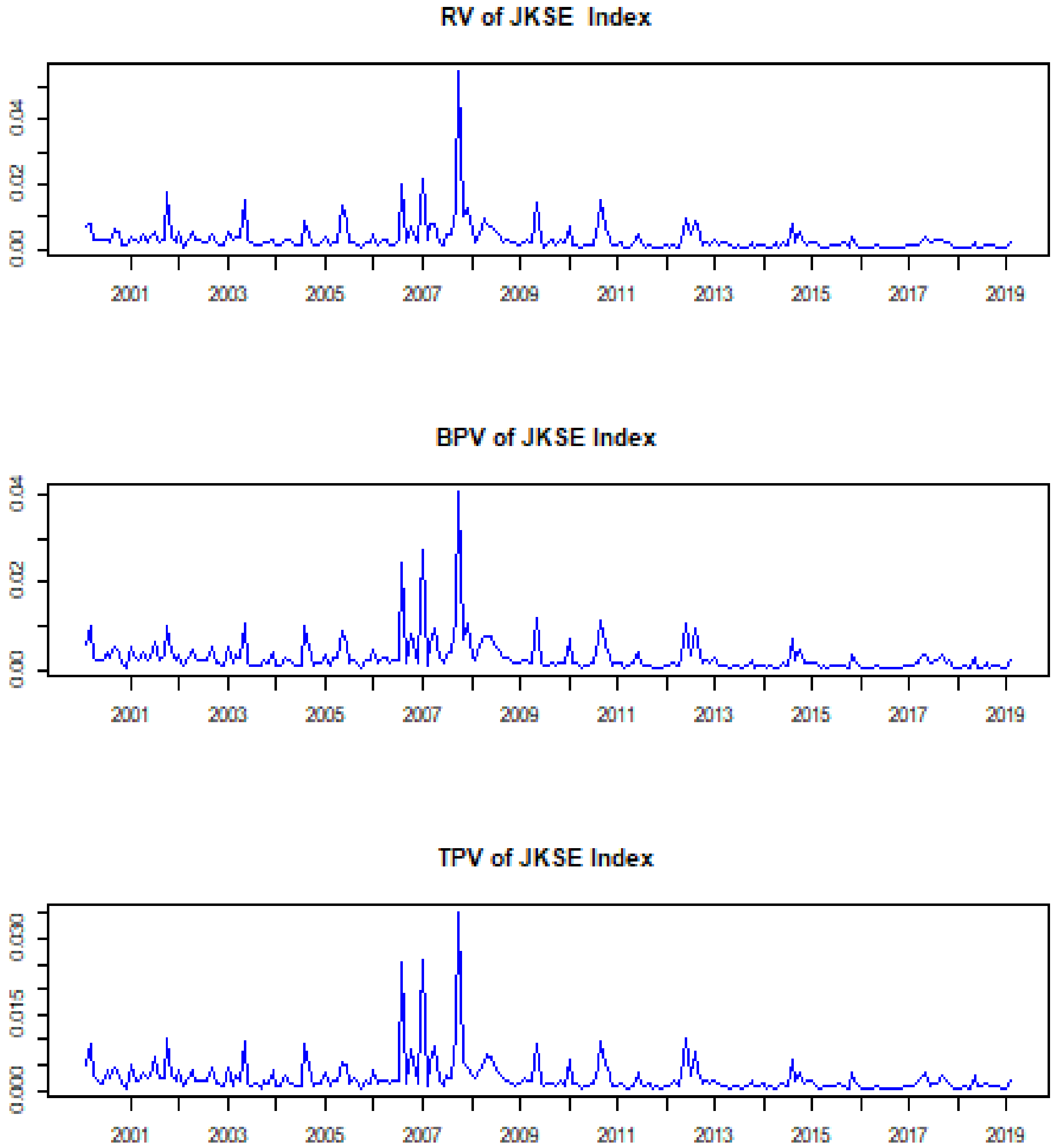
FIGURE 4.7: Integrated Volatility Measures—Nifty50 Index



Notes: Figure 4.7 displays realized volatility, bi-power variation, and tri-power variation for the Nifty 50 index

Figure 4.8 displays realized volatility (RV), bipower variation (BPV), and tripower variation (TPV) of the JKSE index for the sample period of 229 months from February 2001 – February 2020. It is observed from the figure that the JKSE index has experienced high volatility for all of the three measures of integrated volatility from mid 2007 till mid of 2009. This time period is considered as period of high volatility than other periods for the JKSE index, it is also a period of global financial crises.

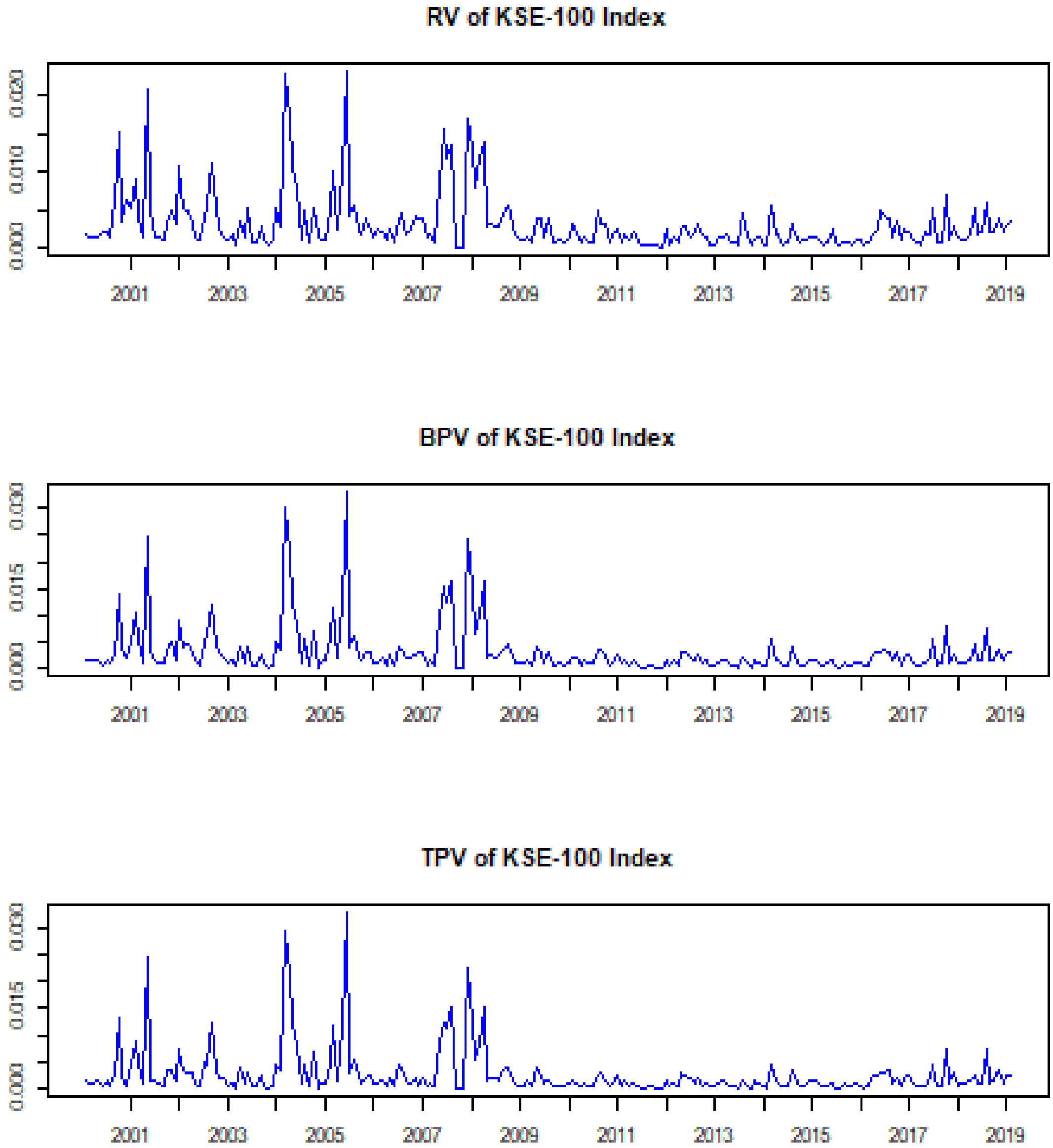
FIGURE 4.8: Integrated Volatility Measures—JKSE Index



Notes: Figure 4.8 displays realized volatility, bi-power variation, and tri-power variation for the JKSE index

Figure 4.9 shows realized volatility (RV), bipower variation (BPV), and tripower variation (TPV) of the KSE-100 index for the sample period of 229 months from February 2001 – February 2020. It is observed from the figure that the KSE-100 index has experienced high volatility for all of the three measures of integrated volatility in the last quarter of 2001 till the first quarter of 2002, during the first half of 2005 and 2006, and at the beginning of 2007 till mid of 2009. These periods are considered as periods of high volatility than other periods. However,

Figure 4.9: Integrated Volatility Measures—KSE-100 Index

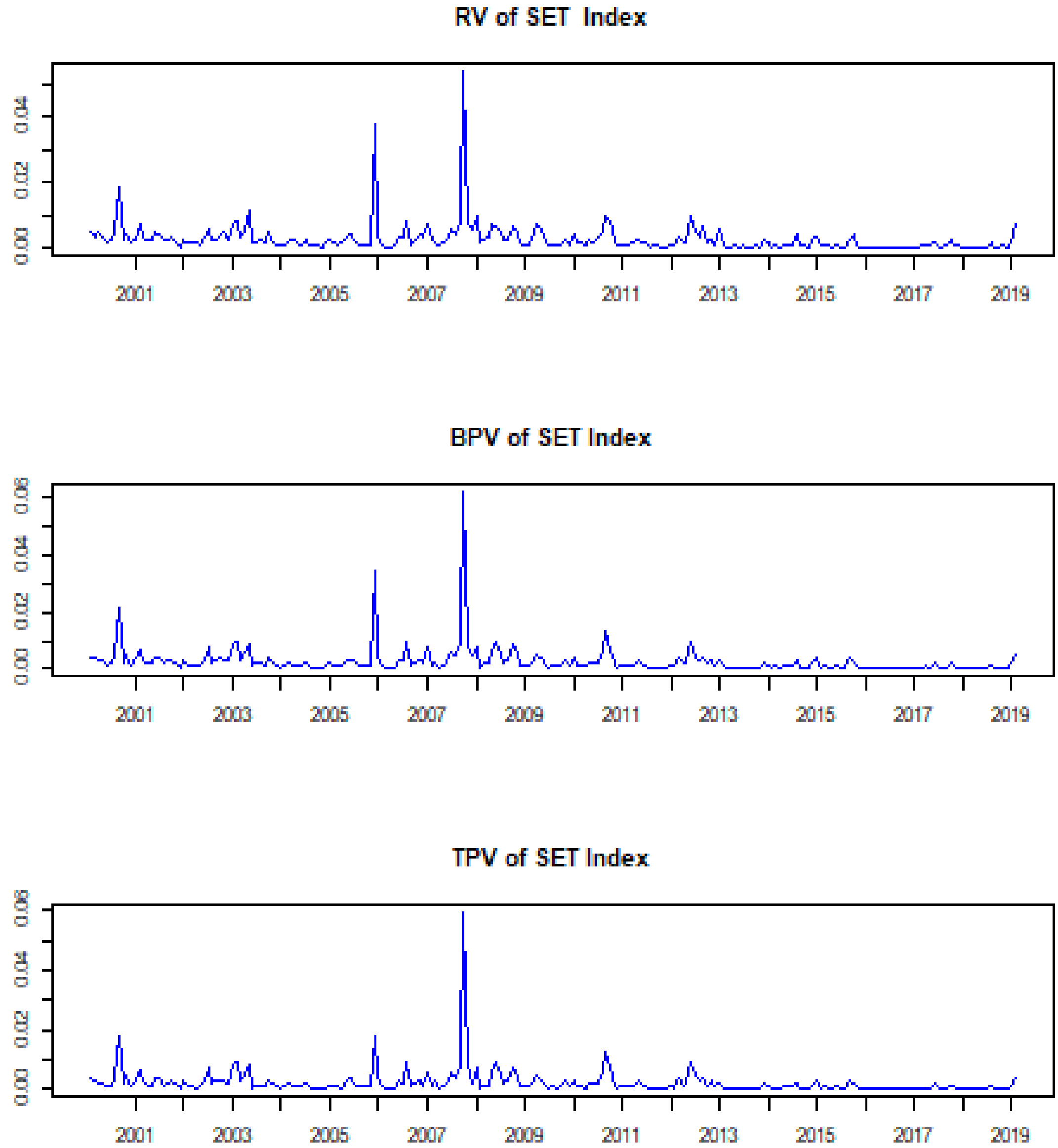


Notes: Figure 4.9 displays realized volatility, bi-power variation, and tri-power variation for the KSE-100 index

peak volatility is observed during mid 2007 till mid 2009 for the KSE-100 index which is the period of global financial crises but the KSE-100 index also have high volatility during the first half of 2005 and 2006 which is also a crises period in Pakistan.

Figure 4.10 demonstrate realized volatility (RV), bipower variation (BPV), and tripower variation (TPV) of the SET index for the sample period of 229 months from February 2001 – February 2020. It is observed from the figure that the SET

FIGURE 4.10: Integrated Volatility Measures—SET Index

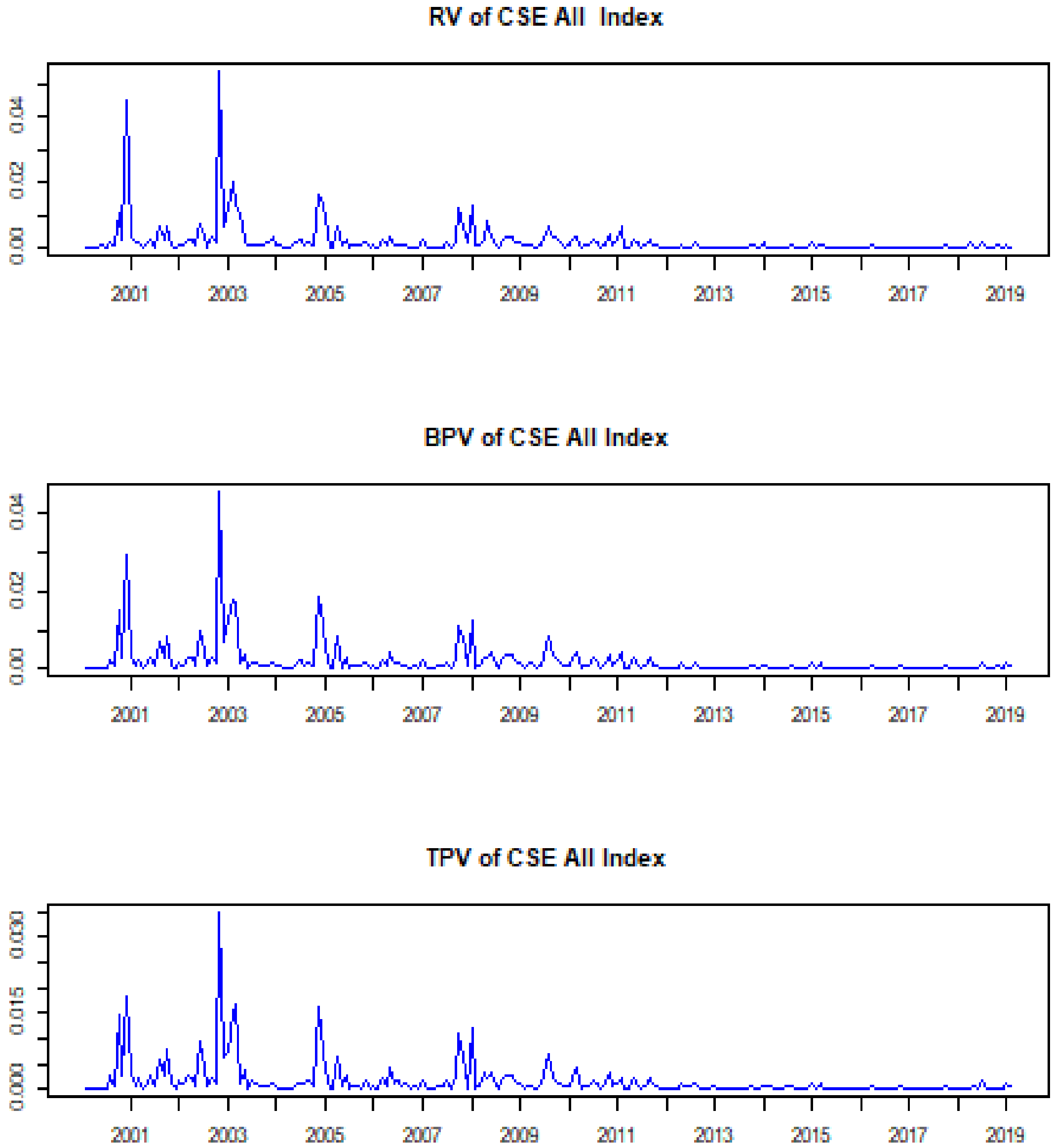


Notes: Figure 4.10 displays realized volatility, bi-power variation, and tri-power variation for SET Index

index has experienced high volatility for all of the three measures of integrated volatility in the last quarter of 2001, at the end of 2006, and during the last half of 2008. These periods are considered as periods of high volatility than other periods. However, peak volatility is observed during the last half of 2008 for the SET index which is the period of global financial crises.

Figure 4.11 displays realized volatility (RV), bipower variation (BPV), and tripower

FIGURE 4.11: Integrated Volatility Measures—CSE All Index



Notes: Figure 4.11 displays realized volatility, bi-power variation, and tri-power variation for CSE All index

variation (TPV) of CSE All index for the sample period of 229 months from February 2001 – February 2020. It is observed from the figure that CSE All index has experienced high volatility for all of the three measures of integrated volatility in the last quarter of 2001, in the first quarter of 2003, at the end of 2005, during the last half of 2008. These periods are considered as periods of high volatility than other periods however, peak volatility is observed during 2003 which was a crisis period in Sri Lanka. The global financial crisis 2007-2009 has not greatly influenced the volatility of the CSE All index.

It is concluded from Figures 4.6 to Figure 4.11 that high volatility is observed for Shanghai Composite index, Nifty 50 index, JKSE index, KSE-100 index, SET index, and CSE All index for all of the three measures of integrated volatility in 2001, and during mid 2007 till mid of 2009. The year 2001 is a period of sharp downturn or stock market crash across the United States, Canada, Asia, and Europe. Similarly, the time period of 2007 till 2009 are periods of global financial crises. Therefore, all Asian developed markets have reflected high volatility in 2001 and then in 2007 till 2009. However, the Shanghai Composite index has experience high volatility from the end of 2014 till the first quarter of 2016 which is also a crises period in china. Whereas Nifty 50 index has experienced high volatility in the first quarter of 2004 and in the mid of 2006 which are also crisis periods in India. The KSE-100 index also has high volatility during the first half of 2005 and 2006 which is also a crises period in Pakistan due to the earthquake. Whereas for CSE All index, peak volatility is observed during 2003-2004, and at the end of 2005 which are crisis periods in Sri Lanka. Moreover, the global financial crisis 2007-2009 has not greatly influenced the volatility of the CSE All index.

It is concluded from Figure 4.2 to Figure 4.11 that Asian developed markets and Asian emerging markets have high volatility during 2001 and during the 2007-2009 periods. This is also in line with earlier discussion on jumps identification; in Figure1, it can be observed that most of the jumps have occurred during crisis periods. In the United States, Canada, Asia, and Europe, the year 2001 is a period of sharp downturn or stock market crash. Similarly, global financial crises characterised the years 2007 to 2009. As a result, high volatility hit all Asian developed markets in 2001, and then again from 2007 to 2009. For the S&P ASX 200 index (Figure 2), Hang Seng index (Figure 4.3), Nikkei 225 index (Figure 4.4), NZX 50 index (Figure 4.5), JKSE index (Figure 4.8), and SET Index (Figure 4.10), there seems to be little difference in terms of estimated volatility across the different volatility measures. However, in the Shanghai Composite index (Figure 4.6), the highest volatility was in the 2015 period, a crisis period in China; however, a similar pattern is also observed during the 2008 financial crisis. For the Nifty

50 index (Figure 4.7), the peak was during 2008, but few spikes were recorded in 2004 and 2006 which is considered as a crisis period in India. The KSE-100 index (Figure 4.9) is somewhat different from all others, which had major spikes in 2003, 2005, 2006, 2008, and at the beginning of 2009; all these periods were crisis periods in Pakistan. However, for all volatility measures the CSE All index (Figure 4.11) had major spikes in 2003-2004 and some spikes in 2008. Furthermore, the global financial crisis of 2007-2009 had little impact on the volatility of the CSE All index.

4.4.3 Integrated Volatility During Jump Periods for Asian Developed Markets

Table 4.19 provides integrated volatility during jump periods for Asian developed markets. The total realized volatility as calculated in table 4.17 is decomposed into volatility due to the jump component (JV) and volatility due to the continuous component. Then volatility due to the jump component is further disentangled into volatility due to positive jumps (PJV) and volatility due to negative jumps (NJV). Descriptive statistics are calculated for the volatility of the jump component during jump periods (including both volatility of positive and volatility of negative jumps), for volatility during positive jump periods, and for volatility during negative jump periods.

In Asian developed markets, the jump component shows a considerable amount of volatility in total realized volatility for all markets during jump periods. However, volatility during negative jump periods is higher than volatility during positive jumps periods in developed markets except for with the Hang Seng, where volatility during positive jump periods is higher than volatility during negative jump periods. Nikkei 225 index shows the highest volatility during jump periods whereas NZX 50 index shows the lowest volatility during jump periods.

Table 4.19: Descriptive Statistics of Integrated Volatility During Jump Periods for Asian Developed Markets

Indices	Volatility	Jumps	Mean	SD	Min	Max	Kur	Skew
S&P ASX 200	JV	62	0.522	0.501	0.003	2.191	2.777	1.703
	PJV	32	0.377	0.357	0.003	1.570	3.005	1.678
	NJV	27	0.695	0.591	0.031	2.191	1.123	1.352
Hang Seng	JV	71	1.334	1.839	0.126	11.966	18.544	4.023
	PJV	43	1.385	2.135	0.126	11.966	16.128	3.860
	NJV	28	1.257	1.292	0.129	6.919	13.943	3.327
Nikkei 225	JV	56	1.536	1.813	0.001	8.344	4.358	2.103
	PJV	33	1.384	1.681	0.159	7.219	4.144	2.099
	NJV	23	1.754	2.006	0.001	8.344	4.937	2.148
NZX 50	JV	58	0.342	0.420	0.011	2.404	9.869	2.817
	PJV	32	0.225	0.267	0.011	1.278	8.693	2.875
	NJV	26	0.487	0.524	0.024	2.404	6.401	2.314

Notes: Mean, standard deviation, minimum, and maximum values are all in terms of 10^{-3}.

4.4.4 Integrated Volatility During Jump Periods for Asian Emerging Markets

Table 4.20 shows integrated volatility for Asian developed markets during jump periods. The total realised volatility that is given in Table 4.18 is separated volatility due to the jump component (JV) and volatility due to the continuous component. Volatility due to jumps is further subdivided into volatility due to positive jumps (PJV) and volatility due to negative jumps (NJV). Descriptive statistics are computed for the volatility of the jump component during jump periods, volatility during positive jump periods, and volatility during negative jump periods.

The jump component also shows a significant amount of volatility for Asian developed markets during jump periods. Furthermore, volatility during negative jump periods is higher than volatility during positive jump periods in Asian emerging markets, with the exception of the Nifty 50 index and CSE All index, which have higher volatility during positive jumps than negative jumps. Furthermore, the

Table 4.20: Descriptive Statistics of Integrated Volatility During Jump Periods for Asian Emerging Markets

Indices	**Volatility**	**Jumps**	**Mean**	**SD**	**Min**	**Max**	**Kur**	**Skew**
Shanghai	JV	93	1.944	2.168	0.120	10.997	6.276	2.362
Composite	PJV	41	1.876	2.194	0.120	10.974	7.572	2.568
	NJV	52	1.998	2.168	0.158	10.997	6.072	2.275
	JV	63	1.430	3.379	0.051	25.960	48.081	6.638
Nifty 50	PJV	38	1.550	4.226	0.051	25.960	32.192	5.523
	NJV	23	1.233	1.023	0.121	4.025	1.921	1.555
	JV	67	1.559	2.810	0.076	19.578	26.215	4.632
JKSE	PJV	41	1.087	1.486	0.076	8.244	13.270	3.259
	NJV	26	2.305	4.046	0.239	19.578	13.839	3.519
	JV	73	0.996	1.071	0.000	5.690	5.242	2.101
KSE-100	PJV	51	0.740	0.768	0.000	3.394	4.377	2.044
	NJV	17	1.765	1.458	0.241	5.690	1.972	1.391
	JV	77	1.086	2.381	0.045	20.365	59.029	7.303
SET Index	PJV	49	0.789	0.798	0.058	4.148	5.994	2.160
	NJV	27	1.626	3.835	0.045	20.365	24.258	4.826
	JV	100	0.952	3.022	0.016	27.090	61.312	7.383
CSE All	PJV	59	1.021	3.613	0.028	27.090	48.806	6.786
	NJV	36	0.841	1.695	0.016	9.608	21.326	4.317

Notes: Mean, standard deviation, minimum, and maximum values are all in terms of 10^{-3}.

Shanghai Composite index has the highest volatility, whereas the CSE All index has the lowest volatility as compared with other Asian emerging markets.

It is concluded from Table 4.19 and Table 4.20 that both Asian developed and Asian emerging markets show a significant amount of volatility of the jump component during jump periods. The pattern of the high volatility of the jump component during negative periods as compared with volatility of jump component during positive jump periods is consistent across Asian developed and Asian emerging markets.

4.4.5 Ratio of Variations Due to Jump Component to Total Variations for Asian Developed Markets

Table 4.21: Average Ratio of Jump Variation to Total Variations for Asian Developed Markets

Indices	The average ratio of jumps variations to total variations	The average ratio of positive jumps variations to total variations	The average ratio of negative jumps variations to total variations
S&P ASX 200	32.56%	33.17%	36.04%
Hang Seng	41.34%	44.12%	37.08%
Nikkei 225	39.86%	42.47%	36.13%
NZX 50	33.94%	34.12%	33.72%

It is observed from Table 4.21 that the ratio of jump variations to total realized variance is maximum for Hang Seng index followed by Nikkei 225 index whereas minimum for S&P ASX 200 index followed by NZX 50 index. On average the ratio of variation due to positive jumps to total realized variance is higher than the variation due to negative jumps in Asian developed markets

4.4.6 Ratio of Variations Due to Jump Component to Total Variations for Asian Emerging Markets

It is observed from Table 4.22 that the ratio of jump variations to total realized variance is maximum for Shanghai Composite index followed by nifty 50 index whereas minimum for JSE index followed by KSE-100 index. In Asian emerging markets, the ratio of variation due to negative jumps to total realized variance is higher than the variation due to positive jumps.

From Table 4.21 and Table 4.22 it is concluded that in both Asian developed and Asian emerging markets the ratio of variation due to jump component to total realized variance shows a significant amount of variations however when compare Asian developed and Asian emerging markets, on average, the ratio of jump variations to total variations is higher in Asian emerging markets. However,

Table 4.22: Average Ratio of Jump Variation to Total Variations for Asian Emerging Markets

Indices	**The average ratio of jumps variations to total variations**	**The average ratio of positive jumps variations to total variations**	**The average ratio of negative jumps variations to total variations**
Shanghai Composite	41.82%	43.20%	40.73%
Nifty 50	39.55%	38.23%	45.53%
JKSE	36.60%	33.85%	40.94%
KSE-100	37.03%	38.93%	44.11%
SET Index	39.34%	41.81%	36.71%
CSE All	38.99%	39.97%	44.11%

in Asian developed markets, on average the ratio of variation due to positive jumps to total realized variance is higher than the ratio of variation due to negative jumps to total realized variance. In the contrast, in Asian emerging markets the ratio of variation due to negative jumps to total realized variance is higher.

The finding of this study are in line with those of (Tversky and Kahneman, 1992; Andersen et al., 2003a; Amaya and Vasquez, 2011; Apergis and Apergis, 2020; Baker et al., 2020; Barndorff-Nielsen and Shephard, 2004; Corsi et al., 2010; Dutta et al., 2021; Eraker et al., 2003; Jiang et al., 2011; Jiang and Yao, 2013; Mizrach et al., 2018; Odusami, 2021; Sharif et al., 2020; Yan, 2011; Zhang et al., 2020)

Zhang et al. (2020) conducted a study on the Chinese stock market which is an Asian emerging market whereas emerging markets are mostly speculative due to the availability of a limited number of shares for trading in stock markets and the increasing role of institutional investors who act as noise traders. Therefore, more jumps are expected to occur in emerging markets.

The findings of the current study also provide similar results of more jumps in Asian emerging markets than in Asian developed markets. Moreover, this study further added to the literature that average positive jumps arises more frequently than negative jumps however the tendency of a larger number of positive jumps to occurs relative to negative jumps is the same in both Asian developed and Asian emerging markets.

Eraker et al. (2003) found evidence for the jump in returns and jumps in the volatility of option prices for the S&P 500 index and Nasdaq 100 index. Similarly, Aït-Sahalia (2004) also documented that jumps play a vital role in asset returns. Furthermore, Amaya and Vasquez (2011) show that jumps significantly predict the equity returns whereas returns of large negative jumps are larger as compare with large positive jumps. The study suggests that positive jumps raise the prices of securities; therefore, a risk-averse investor prefers positive jumps over negative jumps therefore negative jumps earn jumps premium. Odusami (2021) observed asymmetry in the distribution of jumps, with a higher magnitude of negative jumps than positive jumps. Whereas, Yan (2011) shows that a stock with negative jumps must be compensated with higher returns than a stock with positive jumps. Jiang et al. (2011) examined jumps in the prices of U.S. treasury bonds that how the announcement of macroeconomic news and variation in market liquidity explains the jumps in U.S. treasury bonds. It is found that during the scheduled announcement of macroeconomic news, a large number of jumps has occurred. Jiang and Yao (2013) finds that size, value, and liquidity effects are determined by jumps. The empirical evidence of this study suggests that size, illiquidity, and significant part of value premium is a challenge to risk base explanation of cross-sectional stock returns predictability. Mizrach et al. (2018) disentangle the jumps into upside (positive) and downside (negative) jumps to study the significance of jumps in predicting future returns. It is revealed from findings that pricing "upside" and "downside" jumps improve predictions of cross-sectional return.

The findings of current study are consistent with prospect theory of Tversky and Kahneman (1992), which states that investors are loss averse, and they value the losses and gains differently. Because losses have a more substantial emotional effect than gains, the utility received from a profit is the inverse of the disutility received from the same amount of loss, i.e., if an investor is provided with two choices, both of which are equal. Still, one is presented in potential gains and the other in potential losses; the investor will choose the earlier option. However, the results of this study show that in both markets, the size of large negative jumps is greater than that of large positive jumps. In contrast to Asian developed markets, this pattern is significantly more pronounced in Asian emerging markets. In the context of Asian developed markets, there is no distinction between the magnitude of negative and positive jumps in small-size jumps. However, small negative jumps in Asian emerging markets tend to be larger on average compared to small positive jumps. It indicates that investors gave more weight to negative than positive information. However, the depth of feeling is higher in emerging markets. It may be due to investors' lack of confidence in the information that may cause an overreaction to negative news.

Furthermore, the findings also provide an important piece of information to investors in Asian developed and Asian emerging markets to earn maximum returns during jump periods. During jump periods, investors can earn the highest returns by investing in highly volatile markets in Asian developed markets. Whereas investors in Asian emerging markets can earn higher returns during jump periods by investing in averagely volatile markets. Moreover, Asian emerging markets earn higher returns during positive jump periods than Asian developed markets however there is also a larger price decline during negative jump periods in Asian emerging markets as compared with Asian developed markets. Additionally, when Fama and French five factors are regressed on positive jump returns and negative jumps returns, the study finds that in the context of Asian developed markets, all the five factors of Fama and French five factor model explain positive jump returns, whereas in the context of Asian emerging markets, only market premium and investment premium explain positive jump returns. Similarly, market premium, profitability premium, and investment premium explain negative jump returns in Asian developed markets, whereas market premium, size premium, value premium, and investment premium explain negative jump returns in Asian emerging markets.

Barndorff-Nielsen and Shephard (2004) introduce a better technique to estimate integrated volatility called Tripower Variation (TPV) which is considered a more efficient technique than Bipower Variation (BPV) technique. BPV is an unbiased estimator of integrated volatility in the presence of jumps, but it is subject to an upward bias in a finite sample.

The findings of the current study are also in line with that of (Barndorff-Nielsen and Shephard, 2004). This study also finds that TPV is a better estimation technique of continuous components of quadratic variation than BPV as it understates the average integrated volatility and has the minimum standard deviation. This pattern is consistent across all Asian developed and Asian emerging markets.

Andersen et al. (2003a) use the jump component as an independent variable and found the coefficient of the jump component highly significant in forecasting asset returns volatility. It is suggested that separating the continuous and jump components can improve the derivative pricing, risk management, and allocation of financial assets. Corsi et al. (2010) found that jumps significantly improve the accuracy of volatility forecasts. Similarly, Dutta et al. (2020) also suggested that a more reliable model for volatility and for asset pricing can be developed by including the jump component in the model. Baker et al. (2020) investigated the potential causes of the unusual reaction of the US stock market to the COVID-19 pandemic. The study shows that the COVID-19 pandemic has a significant impact on the US stock market than others. Sharif et al. (2020) investigated the relationship between COVID-19, the stock market, geopolitical risk, and economic policy uncertainty. Analysis has shown that COVID-19 and oil price shocks have been found to have an impact on geopolitical risk levels, economic policy uncertainty, and stock market volatility. Apergis and Apergis (2020) analyzed the impact of the COVID-19 pandemic on the returns and volatility of the Chinese stock market. The analysis shows that COVID-19 has had a significant negative impact on stock returns and a significant positive effect on volatility.

The findings of the present study also provide similar results. It is found from the analysis that both Asian developed and Asian emerging markets show a significant amount of volatility of the jump component during jump periods. However high volatility is observed during negative jump periods whereas the pattern of high volatility during negative periods as compared with volatility during positive jump periods is consistent across Asian developed and Asian emerging markets. Furthermore, the ratio of variation due to jump component to total realized variance shows a significant amount of variations however when compare Asian developed and Asian emerging markets, on average, the ratio of jump variations to total variations is higher in Asian emerging markets. Additionally, the findings also add to the literature that in Asian developed markets, on average the ratio of variation due to positive jumps to total realized variance is higher than the ratio of variation due to negative jumps to total realized variance. In the contrast, in Asian emerging markets the ratio of variation due to negative jumps to total realized variance is higher.

The findings also report high volatility during periods of crisis. It reports that all Asian developed markets and Asian emerging markets have high volatility during 2001 and during the 2007-2009 periods. In the United States, Canada, Asia, and Europe, the year 2001 is a period of sharp downturn or stock market crash. Similarly, global financial crises characterised the years 2007 to 2009. As a result, high volatility hit all Asian developed markets in 2001, and then again from 2007 to 2009. However, in the Shanghai Composite index, the highest volatility was in the 2015 period, a crisis period in China. Similarly, the Nifty 50 index also have higher volatility in 2004 and 2006 - a crisis period in India. The KSE-100 index (Figure 9) is somewhat different from all others, which had major spikes in 2003, 2005, 2006, 2008, and at the beginning of 2009; all these periods were crisis periods in Pakistan.

Chapter 5

Conclusion, Limitations, and Future Directions

The purpose of this study is to identify the presence of jumps in Asian developed and Asian emerging markets and to examines the role of jumps specifically positive and negative jumps in predicting equity returns of Asian developed and Asian emerging markets. Furthermore, it explores the connection between factor premia and jumps returns for Asian developed and Asian emerging markets and finally, it provides insight into integrated volatility during periods of positive and negative jumps for Asian developed and Asian emerging markets. To accomplish the goal, this study first determines the jumps in market returns for both Asian developed and Asian emerging equity markets, including the S&P ASX 200, Hang Seng, Nikkei225, NZX 50, Shanghai Composite, Nifty50, JKSE, KSE-100, SET Index, and CSE All index. The identified jumps are then disentangled into positive and negative jumps to compare the returns during positive jump periods and returns during negative jump periods with returns during non-jump periods for both markets and compared their results. Then Fama and French five factors are regressed on jump returns for Asian developed and Asian emerging market separately to identify that which factors of Fama and French five factor model is associated with jump returns. Finally, integrated volatility during jump periods is calculated for Asian developed markets and Asian emerging markets and compared the results.

This study is based on the theory of efficient capital market of Fama (1970) which states that security prices fully reflect all relevant information and bring stock markets towards efficiency and leave no room for investors to earn excess returns. However, sometimes there exist abnormal movements or large discontinuous changes in stock prices that are infrequent but large. These extreme movements are known as jumps or information shocks that are associated with the arrival of unexpected new information (Ferriani and Zoi, 2020; Jiang and Zhu, 2017; Sun and Gao, 2020). Jumps capture all types of information, regardless of whether it is public or private information, including insider trading. Since risk-averse investors prefer positive jumps over negative jumps as positive jumps raise stock prices, stocks with negative jumps should receive a higher premium than those with positive jumps (Amaya and Vasquez, 2011).

This study has used the swap variance (SwV) approach developed by Jiang and Oomen (2008) to identify monthly jumps in the equity prices from both Asian developed and Asian emerging markets from February 2001 to February 2020. Further, the method developed by Andersen et al. (2007) was used to separate the volatility of the jump component from the total realized volatility.

The empirical results of this study show that jumps play an important role in equity returns and integrated volatility of Asian developed and Asian emerging markets. The findings of this study are that jumps arise in all equity markets; however, Asian developed markets have fewer jumps relative to Asian emerging markets. Furthermore, in all markets, positive jumps occur more frequently than negative jumps. Moreover, the magnitude of negative jumps is larger than that of positive jumps in both big and small jumps categories in both Asian developed and Asian emerging markets. However, this pattern is much higher in Asian emerging markets as compared with Asian developed markets.

When average monthly returns during non jump periods are compared with average monthly returns during jump periods, this study finds that average monthly returns during jump periods are higher than returns during non jump periods. This study provides important insights to the investors in Asian developed and

Asian emerging markets to earn the highest returns during jump periods. Investors can earn the highest returns during jump periods by investing in more volatile markets in Asian developed markets whereas investors in Asian emerging markets can earn the highest returns during jump periods by investing in averagely volatile markets. Moreover, before investing in foreign indices or stocks, investors must consider transaction costs, liquidity, and the volatility of exchange rates. Investors can reduce exchange rate risk by using hedging techniques such as options, futures, and forward contracts. Foreign stock investors can monitor the bid-ask spread and trading volume. Stocks with a low bid-ask spread and a high trading volume are more liquid in general.

Furthermore, this study reveals that in the context of Asian developed markets, all the five factors of the Fama and French five factor model explain positive jump returns, whereas in the context of Asian emerging markets, only market premium and investment premium explain positive jump returns. Similarly, market premium, profitability premium, and investment premium explain negative jump returns in Asian developed markets, whereas market premium, size premium, value premium, and investment premium explain negative jump returns in Asian emerging markets. It implies that the premium associated with these factors is related to large amounts of unexpected information captured through jumps. It also implies that by incorporating the jumps into the model, investors may be able to build better asset pricing models.

This study also compares the two measures of continuous component of integrated volatility, the study finds that TPV is a better estimation technique of continuous components of quadratic variation. The BPV overstate the average integrated volatility whereas TPV has a minimum mean value and minimum standard deviation and this pattern is consistent across all Asian developed and Asian emerging markets. Moreover, both Asian developed markets and Asian emerging markets have high volatility during 2001 and during the 2007-2009 global financial crises periods. Additionally, both Asian developed and Asian emerging markets show a significant amount of volatility of the jump component during jump periods.

Furthermore, Integrated volatility is high during periods of negative jumps compared with periods during positive jumps and the pattern of high volatility during negative periods as compared with volatility during positive jump periods is consistent across Asian developed and Asian emerging markets. The ratio of variation due to jump component to total realized variance shows a considerable amount of variations in both Asian developed and Asian emerging markets; however, when comparing Asian developed and Asian emerging markets, on average, the ratio of jump variations to total variations is higher in Asian emerging markets.

The findings of this study infer that Asian emerging markets are not as efficient as Asian developed markets, and thus, jumps occur more frequently in Asian emerging markets. Investors in all markets prefer to get positive jumps to negative jumps so that stocks with more negative jumps should have a jump risk premium. The findings also infer that investors should avoid markets with lower returns and higher volatility due to adverse effects during negative jump periods. Investors in Asian emerging markets perceive the negative information more serious than in Asian developed markets because integrated volatility is high during negative jumps periods compared with periods during positive jumps.

The implication of this study is for all types of investors for both Asian developed and Asian emerging markets. This study also provides insights to academics, practitioners, and policymakers on the asymmetric effect of jumps in equity market returns and integrated volatility in the context of Asian developed and Asian emerging markets.

As large discontinuous changes in the market price of financial assets, called jumps, are considered a proxy for information shocks. The presence of more jumps, higher risk and returns, and higher integrated volatility in Asian emerging markets as compared with Asian developed markets implies the presence of large information asymmetry among buyers and sellers of Asian emerging markets. The small and individual investors are affected due to information asymmetry because most of the big investors, or family and group investors, drive the market movements that are not according to market fundamentals. Sometimes it led to market failure, as evident in the 2007-2008 crisis (subprime mortgage), which was caused by asymmetric information. This study provides policy recommendations for regulators to enforce a separate circuit breaker on positive and negative jumps to protect the interest of small and individual investors. The enforcement of separate circuit breakers will restrict the big investors, family, and group-based investors from driving the market movements up to certain limits, protect small individual investors, and help bring market efficiency.

The findings in this study suggest individual investors and portfolio managers of Asian developed and Asian emerging markets avoid investment in assets and markets that are too volatile and have lower returns because these assets and markets are affected adversely during negative jump periods. However, this study encourages investors and portfolio managers to invest in highly volatile assets with positive jumps because it will enable investors to earn higher returns. Furthermore, for investors in developing markets, investment in the averagely volatile assets and markets is the most efficient investment during the positive jumps period. The implication is also very important for asset pricing theory as investors prefer positive jumps to negative jumps. Therefore, stocks with negative jumps should earn a premium compared to stocks with positive jumps. This is also an important factor in consideration of investment.

One of the limitations of this study is that the data does not cover the COVID-19 period, and the study is limited to Asian developed and emerging equity markets because the focus of this study is on Asian developed and emerging markets. Thus, future researchers could extend this study to cover the COVID-19 period and include all markets from MSCI countries, or all markets from the developed region, or all markets from the emerging region, according to MSCI classification.

Moreover, the analysis in this study has been carried out using daily data. If intraday data is available, a future study could be conducted by replicating this study using intraday data. The analysis in this study is limited to daily data because intraday data is not available in Pakistan; the only major data source with only four universities in Pakistan is data-stream, and even data-stream has intraday data for only three months.

Further to that, this study employs the SwV approach for jump identification, which has been widely used by Jiang and Oomen (2008); Jiang and Yao (2013); Jiang and Zhu (2017) in conducting analysis using daily data. Future studies can use high-frequency data and other techniques to estimate jumps, such as the jump identification methods developed by Aït-Sahalia and Jacod (2009a); Barndorff-Nielsen and Shephard (2006); Lee and Mykland (2008) as well as the jump identification method of Jiang and Oomen (2008), for comparison and robustness of the models. Most importantly, because there is a link between factor premia and jump returns (one of the study's findings), future studies could include jumps as a factor in asset pricing models.

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