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Assessing the Carbon Footprints of Income Growth, Green Finance, Institutional Quality and Renewable Energy Consumption in Emerging Asian Economies

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Abstract: Research Question: What is the applicability of the Environmental Kuznets Curve (EKC) hypothesis in emerging East and South Asian countries? Do institutional quality, trade openness, renewable energy consumption, green finance, financial development, and their interaction influence carbon emissions? **Motivation:** A new assessment of green finance, institutional quality, financial development, and other relevant variables in shaping the EKC hypothesis is required. **Idea:** In the context of emerging Asian countries, it requires consideration of cross-sectional dependence (CSD) due to the high economic integration among East and South Asian countries. They shared residual interdependency and cross-sectional exposure to common shocks, such as oil shocks, global financial shocks, and supply chain disruptions; hence, a more nuanced and multidisciplinary approach is needed. **Data:** A panel dataset that ranges from 2000 to 2019 is employed for ten developing East and South Asian economies, including China, India, Pakistan, Bangladesh, Sri Lanka, Indonesia, Malaysia, Thailand, Vietnam, and the Philippines. **Method/Tools:** A series of panel analyses, including the CSD test, slope heterogeneity test, the 2nd generation panel unit root and cointegration tests, and CS-ARDL modelling, have been employed to address heterogeneity and cross-sectional dependence issues. Robustness tests using the Augmented Mean Group (AMG) and Common Correlated Effects Mean Group (CCEMG) estimators corroborate the findings, reinforcing the study's credibility and policy implications. **Findings:** Both the short- and long-run results consistently confirm the income-environmental degradation link, but the U-type EKC effect is absent. While green finance, trade openness, and financial development have insignificant impacts on carbon emissions, institutional quality and renewable energy consumption exhibit negative effects, highlighting their importance in curbing environmental degradation. More policy efforts are needed to promote investment in environmental financing, upgrade clean production technology, and enhance the decarbonization process. This study also identifies heterogeneity and cross-sectional dependence on environmental policies among these nations. **Contributions:** Green finance and R&D investments in green technologies are inadequate. Efforts to promote carbon neutrality by redirecting financing towards the sustainable and renewable energy sectors are needed. These findings underscore the need for greater collaborative efforts among emerging

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Asian nations, particularly China, to safeguard the environment and achieve sustainable development.

Keywords: EKC, environmental degradation, income growth, green finance, institutional quality, renewable energy consumption.
JEL Classification: Q50, Q58, C33, G18

1. Introduction

The impacts of globalization and international trade on the environment in emerging East and South Asia have been significant, complex, and multifaceted. The growth of these economies has been based on an export-oriented manufacturing model, which has led to increased industrialization and intensification of resource extraction and use (Scheidel *et al.*, 2018). This has resulted in greenhouse gas emissions, land-use changes, and pollution, causing significant environmental and social consequences (Scheidel *et al.*, 2018). The emergence of global value chains has also led to the relocation of production processes to emerging Asian countries with weaker environmental regulations, resulting in a race to the bottom in environmental standards (Baldwin, 2016; Gerrefi and Fernandez-stark, 2016).

Environmental losses are evident following the expansion of industrial supply chains, particularly in manufacturing and construction, which are both energy- and resource-intensive (Chen and Ngniatedema, 2018). For example, China has become the world's largest producer of steel, cement, and chemicals, and its manufacturing sector accounts for over 60% of the country's energy consumption and more than 70% of its carbon emissions (Guan *et al.*, 2018). Similarly, the Indian manufacturing sector is growing rapidly, with the government aiming to increase its contribution to the economy from the current level of 16% to 25% by 2025 (Rijesh, 2019). However, this growth has come at a cost to the environment, with air and water pollution becoming major issues in India and other South Asian nations. Being the major players in manufacturing and global supply chains, ASEAN countries also exposes to severe air and water pollution, waste generation, and greenhouse gas emissions (Sovacool *et al.*, 2020a). Moreover, Malaysia and Indonesia – the world's largest producers of palm oil, rubber, and other commodities – are facing widespread deforestation, land degradation, and biodiversity loss in the region (ADB, 2019). The emerging Asian nations, while facing the challenge of harmonizing economic growth and environmental degradation, have made commitments of carbon reduction under the Kyoto Protocol and the Paris Agreement (2016). Table 1 depicts the overview of environmental commitments among the Asian, in the mitigation of climate change impacts and to achieve sustainable development:

Following the seminal works by Grossman and Krueger (1991) and Shafik (1994), the so-called Environmental Kuznets Curve (EKC) hypothesis has become the dominant approach for modelling ambient pollution concentrations and aggregate emissions. The EKC underlines the pollution trajectory between the periods and income. In line with the growing literature, there has been increasing interest in the potential role of financial advances in addressing environmental challenges associated with economic development. Nevertheless, the limited empirical evidence on emerging economies is mixed. Pande and Debnath (2020) and Alam *et al.* (2018) did not support the EKC hypothesis such that financial development in ASEAN has not able to reduce environmental degradation. Mainly, there is a lack of institutional capacity to enforce environmental regulations (Pande and Debnath, 2020) while investment in renewable energy is still low (World Bank, 2020), especially for ASEAN and South Asian like Bangladesh and Pakistan. Others have claimed that the positive effects of financial development on the environment may be offset by other factors, such as political will, regulatory oversight, and structural changes in the economy (see Yadav *et al.*, 2020; Srivastava and Chakraborty, 2020; for the case of India). Additionally, there may be a trade-off between short-term growth and long-term environmental sustainability, which can be exacerbated by financial development. For instance, China's focus on short-term economic growth coupled with a lack of regulatory oversight and enforcement has contributed to environmental problems (Deng *et al.*, 2021).

Table 1: Environmental commitments among the emerging Asian

Country	Kyoto Protocol[1]	Paris Agreement (2016)
China	Classified as developing country, not bound by mandatory emission reduction targets. Actively participated in the CDM projects.	world's largest emitter of greenhouse gases, pledged to peak its carbon dioxide emissions before 2030 and achieve carbon neutrality by 2060.
Indonesia	Classified as developing country, not bound by mandatory emission reduction targets. Actively participated in the CDM projects.	Indonesia's NDC aims to reduce greenhouse gas emissions by 29% by 2030 compared to business-as-usual levels, with the potential to increase the reduction to 41% with international support.
Malaysia	Classified as developing country, not bound by mandatory emission reduction targets. Actively participated in the CDM projects.	Malaysia's NDC targets a 35% reduction in greenhouse gas emissions by 2030 compared to business-as-usual levels, contingent on financial and technical support.
Philippines	Classified as developing country, not bound by mandatory emission reduction targets. Actively participated in the CDM projects.	The Philippines' NDC aims for a 70% reduction in greenhouse gas emissions by 2030 compared to business-as-usual levels.
Thailand	Classified as developing country, not bound by mandatory emission reduction targets. Actively participated in the CDM projects.	Thailand's NDC aims to reduce greenhouse gas emissions by 20-25% by 2030 compared to business-as-usual levels.
Vietnam	Classified as developing country, not bound by mandatory emission reduction targets. Actively participated in the CDM projects.	Vietnam's NDC aims to reduce greenhouse gas emissions by 8% by 2030 compared to business-as-usual levels, and up to 25% with international support.
India	Classified as developing country, not bound by mandatory emission reduction targets. Actively participated in the CDM projects.	India's NDC aims to reduce the carbon intensity of its GDP by 33-35% by 2030 compared to 2005 levels and increasing non-fossil fuel capacity to 40% of total power capacity by 2030. India also aims for carbon neutrality by 2070.
Pakistan	Classified as developing country, not bound by mandatory emission reduction targets. Actively participated in the CDM projects.	Pakistan's NDC aims to reduce greenhouse gas emissions by 20% by 2030 compared to business-as-usual levels.
Bangladesh	Classified as developing country, not bound by mandatory emission reduction targets. Actively participated in the CDM projects.	Bangladesh's NDC aims to reduce greenhouse gas emissions by 5% by 2030 compared to business-as-usual levels, with the potential to increase the reduction to 15% with international support.
Sri Lanka	Classified as developing country, not bound by mandatory emission reduction targets. Actively participated in the CDM projects.	Sri Lanka's NDC outlines actions to achieve a low-carbon and climate-resilient development pathway, including efforts to increase renewable energy capacity and enhance energy efficiency.

Notes: CDM - Clean Development Mechanism, NDC - Nationally Determined Contribution.

[1]Kyoto Protocol was adopted on 11 December 1997 and enforced on 16 February 2005. Under the Kyoto Protocol, developing countries like China, ASEAN nations, and South Asian countries were not subject to binding emission reduction targets. Instead, they had the opportunity to participate in the CDM by hosting projects that generated emission reduction credits. These credits could be sold to developed countries looking to meet their targets. This mechanism aimed to facilitate technology transfer, investment, and sustainable development in these countries while contributing to global emission reduction efforts.

Overall, although there have been significant advances in our understanding of the relationship between economic development, globalization, and environmental degradation, there are still important gaps and inconsistencies in the literature. Among these, the financial development-decarbonization nexus has been increasingly examined but inconsistently reported. Green finance has started to grow in China and emerging Asia, providing new business opportunities as well as policy options for market correction of environmental degradation. However, the problem statement has been well-documented. First, EKC curve may not hold for emerging countries because of differences in institutional quality, technological capabilities, and environmental regulations (Kanbur *et al.*, 2021). The effectiveness of green finance may be hindered by institutional barriers such as weak regulatory frameworks and a lack of financial infrastructure (Li *et al.*, 2020). Second, the drivers of environmental degradation differ between the developed and emerging economies. In developed economies, the main drivers of environmental degradation often associated with consumption patterns such as energy use and transportation (Galeotti *et al.*, 2020). However, in emerging economies, the main drivers of environmental degradation often associated with production processes such as industrialization and urbanization (Li *et al.*, 2020). Third, policy responses in developed economies often focus on market-based mechanisms such as carbon pricing and emissions trading systems (Stern, 2017). But in emerging economies, policy responses often focus on command-and-control measures such as pollution regulations and environmental taxes (Kanbur *et al.*, 2021).

Based on the preceding discussions, our study contributes significantly to three key areas. First, it emphasizes the role of green finance in achieving a harmonious balance between economic growth and environmental quality, as supported by relevant studies (Razzaq *et al.*, 2021; Mngumi *et al.*, 2022). Green finance facilitates the efficient allocation of funds from surplus economic sectors to eco-friendly and sustainable projects, as evidenced by Ibrahim *et al.* (2022). Additionally, instruments such as green bonds, carbon market tools, and fintech contribute to the realization of sustainable development goals (Sachs *et al.*, 2019). Crucially, green finances play a vital role in the transition to green energy sources and are essential for promoting environmental sustainability (Iqbal *et al.* 2021). Notably, amidst recent global shocks, such as the Covid-19 pandemic, green finances have made significant contributions to green projects (Rasoulinezhad and Taghizadeh-Hesary, 2022). These findings underscore the importance of green finance in shaping the environmental outcomes of emerging economies in South and East Asia, thereby enriching the empirical literature on this subject.

Second, our study underscores the increasing relevance of financial development in the context of environmental considerations, particularly within the green finance framework (Ibrahim *et al.*, 2022). Recent research highlights the crucial role of robust financial systems in facilitating green financial investments, thereby contributing to environmental goals (Li *et al.*, 2021). Consequently, a resilient financial system is imperative for the effective allocation of funds to environmentally friendly projects, thereby enhancing their overall efficiency. Recognizing the pivotal role of the financial system in the success of green finance, we incorporated financial development into our estimation model to explore the combined impact of green finance and financial development on carbon emissions in emerging Asian economies.

Third, the effective utilization of green finance to achieve sustainable environmental goals requires a sound institutional environment. Green finance integrates environmental considerations into financial decisions, demanding a robust institutional framework to realize its objectives (UN Environment Program, 2018). Fu *et al.* (2023) underscore the role of a robust regulatory framework in the success of green finance, while Çitil *et al.* (2023) find that both green finance and institutional quality significantly influence air quality in G-

20 countries. Consequently, green finance requires a robust institutional environment and a regulatory framework to achieve its objectives. Therefore, we include institutional quality alongside green finance, financial development, energy consumption, and economic growth in our examination of their impact on carbon emissions in emerging Asian economies.

A new assessment of green finance, institutional quality, financial development, and other relevant variables in shaping the EKC hypothesis is required for new academic and policy insights. In the context of emerging Asian, it requires consideration of cross-sectional dependence (CSD) due to high economic integration among East and South Asian countries. CSD arises from residual interdependency and cross-sections exposure to common shocks, such as the oil shocks, global financial shocks, the Covid-19 pandemic, and supply-chain disruptions, etc (Tao *et al.*, 2021; Zhao *et al.*, 2022). The presence of CSD biases the analysis of the relationship between EC, GDP, and CO2, and should not be disregarded (Munir *et al.*, 2019; Salim *et al.*, 2017). Addressing these gaps will require a more nuanced and multidisciplinary approach that considers the complex interactions between economic, social, and environmental systems, and the need for more effective governance and regulation of global trade and finance. This study has employed a series of panel analysis that consider slope heterogeneity and CSD in the analysis. These include the Pesaran's (2015) CSD test, the Pesaran and Yamagata (2008)'s slope heterogeneity test, 2nd generation panel unit root tests (Pesaran, 2007; Pesaran *et al.*, 2009), Panel cointegration tests (Westerlund and Edgerton, 2008; Pedroni, 2004), as well as the CS-ARDL modelling of long- and short-run dynamics of EKC framework. The CS-ARDL was conceptualized by Pesaran and Smith (1995) and further enriched by Chudik and Pesaran (2015).

However, based on latest dataset, our findings reveal that green finance, financial development, and trade openness among the emerging Asian have limited roles in environmental improvement and capital efficiency enhancement, which yet to improve the energy structure of the economy significantly. On the other hand, institutional quality and renewable energy consumption exhibited negative impacts on carbon emissions. More policy efforts needed to help companies invest in environmental financing, upgrade clean production technology, and enhance the decarbonization process. In the ASEAN and South Asian region, environmental performance has deteriorated owing to massive energy imports and consumption, and foreign direct investment in energy based industry. Therefore, the government must provide financial support for energy-efficient and environmentally beneficial initiatives (Anwar *et al.*, 2021; Fu and Irfan 2022). Policies for industrial structure customization in countries with high regional heterogeneity, such as China, are crucial for achieving effective green financing (Guo *et al.*, 2022; Lee *et al.*, 2023). This study recognizes the differences in the drivers of environmental degradation and policy responses between developed and emerging economies to devise effective policies to mitigate environmental issues and achieve sustainable development.

The remainder of this paper is organized as follows. The next section reviews the recent literature, focusing on the dynamic roles of green finance and financial development in shaping the EKC hypothesis. The third section presents the data and the methodology used. A detailed description of the heterogenous panel tests and the CS-ARDL method is provided. The penultimate section discusses the empirical results, while the final section summarizes the key findings with the support of policy implications.

2. Literature Review

Kuznets (1955) first hypothesized an inverse U-shaped relationship between economic development and income inequality that income inequality first rises and then falls as economic development proceeds. Grossman and Krueger (1991) and Shafik (1994) have advocated the Environmental Kuznets Curve (EKC) hypothesis for modelling ambient pollution concentrations and aggregate emissions. The EKC underlines the pollution trajectory between the periods and income growth. The EKC is generally divided into three phases: the early stage of economic development, the turning point, and the later stage (Stern, 2018). In the first phase, there is vast use of resources and a prompt increase in environmental degradation. The second phase, namely, the turning point, is achieved when a certain level of income has been reached, which causes a shift in the pollution trajectory. This further led to the third phase, which was characterized by mitigating environmental. However, when the phase reaches the turning point, the income level begins to be inseparable from emissions and environmental degradation, which eventually leads to the next phase of economic growth, where the deployment of clean technology and innovation begins to emerge (Leal and Marques, 2022). Numerous studies have tested the form of the EKC and produced various verification results. In addition to inverted U-shaped curves, studies have shown the presence of linear shapes: U-positive, N-inverted, and positive N-shaped (e.g., Chen and Ngniatedema, 2018; Kallis and Bliss, 2019; Nepal and Nirash, 2019; Shahbaz *et al.*, 2021; Kanbur *et al.*, 2021). These results have gradually emerged as research continues to improve. However, sustainable development is necessary to reach this turning point when economic growth is achieved without destroying the economic capital base, leading to low carbon emissions, the efficient use of natural resources, and social inclusion.

The relationship between economic development and environmental degradation is complex, with the costs of environmental degradation often borne by low-income and marginalized communities. While some studies have suggested that the EKC hypothesis provides a useful framework for understanding the relationship between economic growth and environmental degradation (Chen and Ngniatedema, 2018), others have argued that this framework is overly simplistic and overlooks important factors, such as the distribution of environmental costs and the role of institutions and governance in shaping environmental outcomes (Kallis and Bliss, 2019).

Indeed, the heterogeneity of the EKC relationship across different countries and regions is an important gap in the literature that needs to be addressed. In developed economies, the EKC curve often takes an inverted-U shape, where environmental degradation initially increases with economic growth, but then decreases after a certain income threshold (Stern, 2017). However, in emerging economies, the EKC curve may take a different shape, owing to differences in institutional quality, technological capabilities, and environmental regulations (Kanbur *et al.*, 2021). Recent studies on the EKC relationship in China and Southeast Asia have revealed that economic growth is accompanied by a decline in some types of environmental pollution (Chen and Ngniatedema, 2018; Kallis and Bliss, 2019). However, Ding *et al.* (2020) found evidence of an N-shaped EKC curve in China, in which environmental degradation initially increased with economic growth, then decreased, and finally increased again at higher income levels. In contrast, Shahbaz *et al.* (2021) found evidence of an inverted U-shaped EKC curve in India. Other studies have found little or no evidence of an EKC relationship in sub-Saharan Africa or South Asia, where economic growth is associated with increased environmental degradation (Nepal and Nirash, 2019).

This heterogeneity suggests that the relationship between economic development and environmental degradation is shaped by a wide range of contextual factors such as differences in natural resource endowments, governance structures, and cultural attitudes towards the environment. For example, countries that are rich in natural resources, such as oil or minerals, may be more likely to experience a resource curse where economic growth is accompanied by environmental degradation and social conflict (Yin and Zhao, 2019). Similarly, countries with weak governance structures or inadequate environmental regulations are more likely to experience environmental degradation due to economic growth (Kallis and Bliss, 2019). These contextual factors are likely to be particularly important for emerging economies in Asia, such as China, India, and ASEAN countries, which have experienced rapid economic growth but environmental losses in recent decades. While some of these countries have made progress in addressing environmental challenges, such as air pollution in China or water pollution in some parts of ASEAN, they also face significant environmental risks and challenges, such as climate change, deforestation, and biodiversity loss (ADB, 2020). Addressing these challenges will require a better understanding of the complex interactions among economic development, globalization, and the environment, as well as more effective governance and regulation of trade and finance.

Financial development has been explored in justifying the EKC hypothesis, in addition to globalization, trade openness, technology advances, institutional capacity, and so on. However, the support for the EKC-financial development nexus is at best mixed and varies across countries and sectors due to differences in institutional quality, technological capabilities, environmental regulations, political will, and structural changes (Kanbur *et al.*, 2021; Li *et al.*, 2020; Yadav *et al.*, 2020). More of recent, new studies suggest that green finance and its interaction effect with financial development facilitates environmental sustainability through technical innovation, capital support, financial assistance, and resource allocation. It stimulates economic activity while maintaining environmental quality by supporting the financing of renewable energy projects, energy infrastructure, and green energy for decarbonization (Sachs *et al.*, 2019). Through technological innovation, firms engaged in green technological innovation typically receive external credit, thereby supporting their research and development (R&D) activities, contributing to the improvement of energy efficiency utilization, facilitating the rapid growth of the green industry, and mitigating environmental pollution and ecological damage. Li *et al.* (2018) argue that government subsidies in green loans and green production innovation can reduce the financial burden on businesses and encourage the introduction and adoption of technological innovations. However, Lin (2022) revealed that strong urbanization and R&D investment must support the role of green finance. Developing a special mechanism to increase R&D investment is crucial to promote green finance through technological innovation. Such criteria remain a significant challenge for emerging nations in South and East Asia.

In the capital support channel, green finance supports firms with low energy intensity and carbon and pollution emissions, thereby discouraging them from engaging in high-emission and high-pollution business activities. For instance, van Veelen (2021) posited that the inclusion of green credit terms in China significantly affects corporate financing costs. Companies with high pollution and emissions face higher funding costs, whereas environmentally friendly businesses have lower funding costs. Supporting green upgrading of corporations improves ecological integrity both economically and environmentally, demonstrating how green credit policies can affect a company's lending performance (Zhang *et al.*, 2021). In addition, loan issuance for the accomplishment of green projects can reduce pollution, which leads to a better atmosphere, natural resources, and health, thereby reducing the risk of covid-19 (Biduri and Proyogi, 2021).

From the perspective of resource allocation channels, green finance may help enhance capital utilization efficiency through direct capital flows from industries with high emissions and poor efficiency to those with low emissions and high efficiency. Briefly, based on the explanation above, the three channels share certain similarities; by means, both are associated with the external financial support provided to environmentally friendly businesses. In this regard, developed financial systems make substantial contributions through the mobilization and allocation of idle resources to reduce financing costs and the financial burden borne by firms engaging in environmentally friendly and green behaviors (Kim *et al.*, 2020). A rampant study proved that green finance has a significant impact on decarbonization (Mamun *et al.*, 2022; Lan *et al.*, 2023; Fu and Irfan, 2022; Lee *et al.*, 2023a; Guo *et al.*, 2022; Alharbi *et al.*, 2023), improving the performance of sustainable development (Geng *et al.*, 2023; Jinru *et al.*, 2022; Lee *et al.*, 2023), and improving the quality of health during the Covid-19 outbreak (Chien *et al.*, 2021a; Chien *et al.*, 2021b; Biduri and Proyogi, 2021).

Nevertheless, the effectiveness of green finance varies across countries, with developed countries with high levels of credit markets, innovation, and climate change exposure benefiting the most. Investments in the green finance sphere are known to have low risk and high rates of return for investors (Schopohl *et al.*, 2021; Lee *et al.*, 2023). Yet, the weak financial foundation of the government, high costs and risks, and reluctance of the banking industry to fund green investments limit the private sector's interest in green technologies. Although the direction of government policy and national development in various countries play a crucial role in attracting investors, green investments are still considered highly risky by the banking industry (Saydaliev and Chin, 2022). Khan *et al.* (2021) and Hunjra *et al.* (2023) emphasize the importance of financial institution quality and financial development in decarbonization. Poor quality of financial institutions in several countries results in a decrease in environmental quality, whereas strong financial institutions tend to improve environmental quality. Their study inferred that green finance could drive decarbonization through positive signals of economic growth and financial development.

In recent years, numerous studies have focused on the intersection between green finance and the environment. However, most of these investigations have concentrated on individual countries, notably China (e.g., Zhou *et al.*, 2020; Chen and Chen, 2021). Conversely, some studies embrace a multi-country approach, primarily focusing on developed nations (De Haas and Popov, 2019; Meo and Karim, 2022). The literature reveals conflicting evidence concerning the impact of green finance on carbon emissions, with some studies suggesting a positive influence (e.g., Meo and Karim, 2022), while others indicate a negative impact (e.g., Wang and Ma, 2022). Notably, when investigating the impact of green finance on carbon emissions, Khan *et al.* (2021) and Hunjra *et al.* (2023) underscored the critical role of institutional quality and financial development.

Diverse studies have explored the relationship between financial development and carbon emissions, yielding mixed findings. Some studies indicate a negative relationship between financial development and carbon emissions (Sadorsky, 2010) and emission intensity (Tao *et al.*, 2023), whereas others report a positive impact (Ren *et al.*, 2023; Yang *et al.*, 2023). Recent research emphasizes the inclusion of financial development along with green finance, highlighting its pivotal role in the effective allocation of funds, particularly climate funds, to eco-friendly and green projects (Li *et al.*, 2021; Çitil *et al.*, 2023). Beyond financial development, the effective utilization of green finance for decarbonization necessitates a robust institutional environment. Green finance, which integrates environmental considerations into financial decisions, demands supportive institutional frameworks to achieve its objectives (UN Environment Program 2018). Fu *et al.* (2023) underscored the crucial role of a robust regulatory framework in the success of green finance, while Çitil *et al.* (2023) demonstrated the significant influence of both green finance and institutional quality on air quality. Consequently, achieving efficiency in green finance requires concurrent development in both the financial and institutional realms.

In summary, support for the Environmental Kuznets Curve and green finance is characterized by mixed and varied findings across countries and sectors, contingent on disparities in institutional quality, technological capabilities, environmental regulations, political will, and structural changes (Kanbur *et al.*, 2021; Li *et al.*, 2020; Yadav *et al.*, 2020). The substantial differences in the institutional environment, encompassing legal, financial, and regulatory aspects, between developed and emerging countries underscore the need for in-depth investigation. Surprisingly, there is a scarcity of studies exploring the combined impact of green finance, financial development, and institutional development in emerging Asian economies. In light of these gaps, our study aims to fill them by examining the impact of green finance, financial development, institutional quality, energy consumption, and economic growth on carbon emissions in N-10 emerging Asian economies.

3. Methodology

Using the EKC framework, this study examines the impact of green finance (GFin), financial development (FD), trade openness (TO), institutional quality (IQ), and renewable energy consumption (REN) on pollution emissions in ten developing East and South Asian economies. These countries include China, India, Pakistan, Bangladesh, Sri Lanka, Indonesia, Malaysia, Thailand, Vietnam, and the Philippines. A panel dataset that ranges from 2000 to 2019 is employed for analysis of two specified models. We limit our analysis until 2019 because consistent green finance data for all our sample countries were not yet available when we started our study in early 2022. Model 1 assesses the EKC hypothesis via economic growth, GFin, IQ, and FD, renewable energy consumption (REN), and trade openness (TO). In the Model 2, an interaction term between green finance and financial development (GFD) is included. The dependent variable was carbon emissions (CO2), measured in millions of metric tons of CO2 equivalent and sourced from the United Nation.

Among the independent variables, the green finance (GFin) can be defined as financial expenditures with environmental goals and benefits. GFin aims to tackle environmental and sustainability issues by providing funds for enabling technologies to reduce pollutant emissions, save energy, and efficiently use natural resources (Zhang *et al.*, 2022). Following previous studies (Wang *et al.*, 2022; Bakry *et al.*, 2023), we capture GFin using the natural logarithm of international financial support for R&D in clean energy and renewable energy production, including hybrid systems (constant at 2016, US$ millions). The GFin data is sourced from Our World in Data database. Next, the IMF financial development index that incorporates both financial institutions' development and financial market development is taken as proxy for financial development.

To capture institutional quality (IQ), we used 12-point index of "international Country Risk Guide (ICRG)". The index includes "bureaucratic quality, government stability, law and order, corruption, socio-economic conditions, investment profile, demographic accountability, ethnic tensions, religious tensions, internal conflict, external conflict, and military in politics" (PRS Group, 2020). Similar to past studies like Calderón *et al.* (2016), Asif and Majid (2018), and Hussain and Dogan (2021), we used a single ICRG's index for IQ by taking the average of all indices. For the EKC hypothesis, we include real gross domestic product per capita (constant at 2015, US$ millions) and square of it. Both data are extracted from the world development indicators from World Bank. Table 2 presents detailed measurements of the variables and data sources.

Before the empirical estimation, all data are log-transformed to avoid outliers (Stabilizing Variance) and reduce skewness, as well as for elasticities discussion of the coefficients. Because the linear and quadratic series are part of the same equation, mean centering of the series is performed to reduce the high values of the variance inflation factor and tackle the issue of multicollinearity.

Table 2: Variables description

Variable	Description	Source
Carbon emissions per capita (COP)	Annual carbon emissions in Million metric tons of CO_2 equivalent per capita	United Nations Framework Convention on Climate Change (UNFCCC) -(https://di.unfccc.int/detailed_data_by_party)
GDP	Gross Domestic Product per capita (constant 2015 US$)	WDI-World Bank-(https://data.worldbank.org/indicator/NY.GDP.PCAP.KD)
Green finance (GFin)	International financial flows to developing countries in support of clean energy R&D and renewable energy production, including the hybrid systems (US$ millions at constant value)	Our World in Data-(https://ourworldindata.org/grapher/international-finance-clean-energy)
Financial development (FD)	Financial Development Index	IMF-(data.imf.org/?sk=F8032E80-B36C-43B1-AC26-493C5B1CD33B&ref=mondato-insight)
Institutional quality (IQ)	Institutional Quality Composite Index	International Country Risk Guide- The PRS Group Incorporation
Renewable energy consumption (REN)	Renewable energy consumption (% of total final energy consumption)	WDI-World Bank (https://data.worldbank.org/indicator/EG.FEC.RNEW.ZS)
Trade openness (TO)	Trade (percentage of GDP)	WDI-World Bank (https://data.worldbank.org/indicator/NE.TRD.GNFS.ZS)

3.1 Model Specification

The Environmental Kuznets Curve (EKC) postulates a nonlinear relationship between income and pollution. As discussed earlier, a positive association exists between income and environmental degradation during the early growth stages. However, constant economic expansion augments technological development and increases the proportion of total output devoted to the service sector compared to the production sector. In response to these adjustments, the overall ecosystem improves and the relationship between pollution and income becomes negative (Dinda, 2004). For this study, we introduce two new model specifications based on the baseline model that employed by previous studies (e.g., Zhao *et al.*, 2022; Han and Jun, 2023). For Model 1 that specified by Eq. (1), lnCOP denotes carbon emissions per capita, lnGDP and lnGDP^2 are the real GDP per capita and its square, respectively. The rest are green finance ($\text{lnGFin}_{\text{it}}$), financial development (FD), institutional quality (IQ), trade openness (TO), and renewable energy consumptions (REN).

$$\begin{aligned} lnCOP_{it} = \alpha_0 + \alpha_1 lnGDP_{it} + \alpha_2 lnGDP_{it}^2 + \alpha_3 lnGFin_{it} + \alpha_4 lnFD_{it} + \alpha_5 lnIQ_{it} \\ + \alpha_6 lnREN_{it} + \alpha_7 lnTO_{it} + \mu_{it} \end{aligned} \tag{1}$$

In equation (1), the subscripts represent the cross-sectional (i) and time (t) elements of the variables. $\alpha_1 - \alpha_3$ are coefficient estimates, α_0 constant term, and μ_{it} is the white-noise term. The relationship between GDP and COP can take various forms, where if, α_1=α_2= 0, (no relationship), α_1> 0, α_2= 0 (positive monotonic relationship), α_1< 0, α_2= 0 (negative monotonic relationship), α_1> 0, α_2< 0, (inverted U-shape relationship), and α_1< 0, α_2> 0 (U-shape relationship). More Specifically, the positive and significant α_1; and negative and significant α_2, justifies the validity of EKC hypothesis. Next, the negative and significant coefficients attached to α_3 , α_4 , α_5 , and α_6 implies that GFin, FD, IQ, and REN, respectively, can help reduce COP. Finally, the positive significant coefficient associated to α_7 suggests that trade openness can potentially increase COP.

For Model 2 that specified by Eq. (2), an interacting effect of financial development and green finance (FD*GFIN) is introduced. We expect negative and significant coefficient α_5 , which implies that financial markets and institutions development captured by financial development index can facilitate green finance to play a more prominent role in reducing carbon emissions among the East and South Asian economies. The new specification of Model 2 is as follows:

$$\begin{aligned} lnCOP_{it} = {} & \alpha_0 + \alpha_1 lnGDP_{it} + \alpha_2 lnGDP_{it}^2 + \alpha_3 lnGFin_{it} + \alpha_4 lnFD_{it} \\ & + \alpha_5 ln(FD * GFIN)_{it} + \alpha_6 lnIQ_{it} + \alpha_7 lnREN_{it} + \alpha_8 lnTO_{it} + \mu_{it} \end{aligned} \quad (2)$$

We analyse two models due to two main reasons. First, in the empirical literature, some studies used green finance and financial development as separate variables and others investigated the interacting effect of green finance and financial development on carbon emissions (Lv *et al.*, 2022; Ping and Shah, 2023). Second, when we included both green finance and financial development as separate predictors in Model 1, we noticed their insignificant impacts on carbon emissions. Therefore, in the second model, we included their interaction terms, but still we found insignificant impact of green finance and financial development on carbon emissions.

3.2 Econometric Methods

3.2.1 Cross-sectional Dependency

It is believed that due to globalization, financial market integration, and economic interdependence among countries and regions, various macroeconomic and financial variables' impact on one country may extend to others (Tao *et al.*, 2021; Zhao *et al.*, 2022). This interdependence in the data across cross-sectional units is called cross-sectional dependency (CSD). The presence of CSD leads to omitted variables bias (Salim *et al.*, 2017) and inefficient estimation (Zhao *et al.*, 2022). When data suffers from CSD, it requires the application of cross-sectionally augmented panel data estimators. CSD arises from residual interdependency and cross-sections exposure to common shocks. Commodity prices in international markets, global market uncertainty, the Covid-19 pandemic, and supply-chain disruptions are some examples of common shocks, which simultaneously affect various countries. In this way, higher connectivity and exposure to common shocks among the East and South Asian countries may lead to cross-sectional interdependence in the data. Therefore, we use Pesaran's (2015) to determine CSD among the units. Given Eq. (3) denotes Pesaran's CSD test:

$$CSD = \sqrt{\frac{2T}{N(N-1)}\left(\sum_{j=i+1}^{N} \gamma_{ji}\right)} \quad (3)$$

where cross-sectional units (*N*), time (*T*), *i* and *j* represent error correlation among the sample countries.

3.2.2 Slope Heterogeneity

In the presence of CSD, Pesaran and Yamagata (2008) established a random regression model to observe heterogeneity in slope parameters in panel data analysis. The inability to accommodate slope heterogeneity can lead to unreliable coefficients (see, Li *et al.*, 2022). Therefore, we observe slope heterogeneity through Pesaran and Yamagata (2008), where the null hypothesis assumes slope homogeneity.

3.2.3 Stationarity Testing

An important procedure before the cointegration and error correction modelling is to examine the variables' stationarity properties. When panel data suffers from issues like CSD and heterogeneity, we can only apply second-generation panel unit root tests to tackle these panel data issues. Therefore, to observe unit root we use second-generation panel unit root tests CIPS and Pesaran's CADF (PSCASDF) of Pesaran *et al.* (2009) and Pesaran (2007), respectively. These tests perform well in the presence of structural breaks, CSD, and slope heterogeneity (Moon and Perron, 2012).

3.2.4 Panel Cointegration

The next step is to establish a cointegrating relationship between the studied variables across all sample countries. For this matter, we are using Westerlund and Edgerton's (2008) test for panel cointegration. This test efficiently adjusts to cross-sectional structural breaks, CSD, slope parameters heterogeneity, and autocorrelated standard errors (Tao *et al.*, 2021). Next, due to the long panel (*T*>*N*) in the current study, we also use Pedroni's (2004) panel cointegration test which better performs in long panels (see, Neal, 2014).

3.2.5 Cross-sectionally Augmented Autoregressive Distributed Lag (CS-ARDL)

Once we established cointegration and determined slope heterogeneity and CSD in the data, CS-ARDL is the most suitable model to study both short- and long-term dynamic relationships. This model was originally conceptualized by Pesaran and Smith (1995) and further enriched by Chudik and Pesaran (2015). Previous studies have advocated (see, Yao *et al.*, 2019; Ahmed, 2020) that CS-ARDL addresses slope heterogeneity, cross-country error dependency, and helps estimate dynamic common correlation effects. Further, this method is credited to dealing with endogeneity problems (Chudik and Pesaran, 2015). Although one of the study limitations is small sample size (*T*-20; *N*=10). However, with a similar sample sizes CS-ARDL method has been applied in the literature (see, Tao *et al.*, 2021; Zhao *et al.*, 2022). Besides, CS-ARDL has been argued to infer accurate results even with small sample size (Hao *et al.*, 2021; Zhao *et al.*, 2022). Specifically, the CS-ARDL model becomes more relevant when *T*>*N* (Erülgen *et al.*, 2020), such is the case in this work. Due to these strong assumptions and the data properties, we apply the CS-ARDL method, which specifications are given in equation (4) as:

$$Z_{i,t} = \sum_{i=0}^{Pu} \theta_{i,t} W_{i,t-1} + \sum_{i=0}^{Pv} \rho_{i,t} X_{i,t-1} + \varepsilon_{i,t} \tag{4}$$

Next, we extend Eq. (4) into Eq. (5) by including the cross-section averages of the dependent and independent variables.

$$Z_{i,t} = \sum_{i=0}^{Pu} \theta_{i,t} Z_{i,t-1} + \sum_{i=0}^{Pv} \rho_{i,t} X_{i,t-1} + \sum_{i=0}^{Pw} \alpha_i \bar{X}_{t-1} + \varepsilon_{i,t} \tag{5}$$

where the symbol Z is the dependent variable depicting carbon emissions of country i at time t. The parameter $W_{i,t-1}$ denotes all the regressors LGDP, LGDP^2, LGFin, FD, IQ, TO, REN and LGFD. Moreover, $\bar{X}_{t-1}$ shows cross-sectional averages of all variables to alleviate the CSD problem due to the common spillover effect. Lastly, the titles Pu, Pv, and Pw illustrate the lagged effects of each of the variables. Now we present the mean group estimator and the long-run effects with the help of Eq. (6) and Eq. (7), respectively.

$$\hat{\lambda}CD - ARDL_i = \frac{\sum_{i=0}^{pv} \widehat{\gamma_{li}}}{1 = \sum_{i=0}} \hat{\Omega}_{l,t} \tag{6}$$

$$\bar{\hat{\lambda}}_{MG} = \frac{1}{N} \sum_{i=1}^{N} \hat{\lambda}_i \tag{7}$$

In the current study, the short-term coefficients are estimated as follows:

$$\Delta Z_{it} = \theta_i\left[Z_{i,t-1} - \delta_i X_{i,t-1}\right] - \sum_{i=0}^{Pu-1} \theta_{i,t}\Delta_i Z_{i,t-1} + \sum_{i=0}^{Pv} \rho_{i,t}\Delta_i X_{i,t-1} + \sum_{i=0}^{Pw} \alpha_i \bar{X}_t + \varepsilon_{i,t} \tag{8}$$

where in the above equation:

$$\Delta_i = \mathrm{t} - (\mathrm{t} - 1)$$

$$\hat{\lambda} = -\left(1 - \sum_{i=0}^{Pu-1} \hat{\Omega}_{i,t}\right) \tag{9}$$

$$\hat{\lambda}_i = \frac{\sum_{i=0}^{pv} \hat{\gamma}_{i,t}}{\hat{\tau}_i} \tag{10}$$

$$\bar{\hat{\lambda}}_{MG} = \frac{1}{N}\sum_{i=1}^{N} \hat{\lambda}_i \tag{11}$$

3.2.6 Robustness Checks (AMG and CCEMG)

For robustness checks of the CS-ARDL results, we applied the Augmented Mean Group (AMG) and Common Correlated Effects Mean Group (CCEMG) estimators of Eberhardt and Teal (2010) and Pesaran (2006). These methods are consistent, reliable, and offer efficient estimates that allow for group-specific regressions and cross-group average coefficients. Specifically, these estimators deal well with slope heterogeneity, CSD, and structural breaks (Li *et al.*, 2021). In addition, AMG is credited with performing well in the presence of endogeneity problems and non-stationarity (Eberhardt, 2012). CCEMG is also a common dynamic process that induces CSD, time-variant factors, and slope heterogeneity effect with identification issues (Eberhardt and Teal, 2010).

4. Findings and Discussion

4.1 Empirical Results and Discussion

This section begins with the data properties evaluation. The descriptive statistics are presented in Table 3, followed by correlation analysis in Table 4, Variance Inflation Factor (VIF) analysis in Table 5, CSD test of cross-sectional dependence in Table 6, slope heterogeneity test in Table 7, and the second-generation panel unit root tests in Table 8. The reported descriptive statistics include mean, standard deviation, minimum and maximum to ensure data consistency and reliability. In addition, the skewness and kurtosis statistics, and Adj. $\chi2$ are estimated to gauge the normal distribution of our sample data. However, like many time series studies, the data are generally non-normally distributed.

Table 3: Descriptive statistics

Variable	N	Mean	Std. dev.	Min	Max	Pr(Skew)	Pr(Kurt.)	Adj. χ^2
LCOP	200	0.448	0.943	-1.583	2.109	0.319	0.000	15.780***
LGDP	200	7.832	0.727	6.471	9.316	0.319	0.000	18.160***
LGDP^2	200	4.316	0.954	0.000	5.298	0.000	0.000	54.130***
LGFin	193	4.194	0.940	0.000	5.187	0.000	0.000	48.900***
FD	200	0.391	0.150	0.135	0.735	0.002	0.006	14.710***
IQ	200	4.960	0.652	3.458	6.375	0.871	0.015	5.850**
LGFD	193	1.622	0.738	0.000	3.618	0.000	0.329	14.710***
TO	200	76.970	48.080	24.700	220.410	0.000	0.794	21.380***
REN	200	33.307	16.333	1.960	64.160	0.286	0.002	9.260**

Notes: *** and ** indicate significance at the 1% and 5% level, respectively. Pr (Skew) and Pr (Kurt.) are p-values for skewness and kurtosis, whereas Adj. χ^2 is the adjusted chi-square. Together, these three tests check for the data distribution and normality. Data transformation into natural logarithm includes the variables of Carbon emissions (LCOP), GDP (LGDP), GDP^2 (LGDP^2), Green Finance (LGFin) and the interaction variable (LGFD). As for the percentage, scale and ratio data, natural logarithm is not taken, such as the Financial development (FD), Institutional Quality (IQ), Trade openness (TO), and Renewable energy consumption (REN).

From the correlation analysis in Table 4, we found different degree of correlations among variables, ranging from -0.049 to 0.856. In what follows, we rely on the VIF and 1/VIF statistics that reported in Table 5, as diagnostic tools to identify multicollinearity. For Model 1, VIF ranges from 1.15 to 3.18, while for Model 2, VIF statistics are well below 3. At the same time, 0 < 1/VIF < 1 for both Model 1 and 2. Both VIF and 1/VIF statistics indicate moderate multicollinearity. In other words, there is some correlation between the variables and other independent variables, but it is not severe enough to cause significant issues in the analysis, that unstable and unreliable regression coefficient estimates are unlikely.

Table 4: Correlation analysis

Variables	LCOP	LGDP	LGDP^2	LGF	FD	IQ	LGFD	TO	REN
LCOP	1.000								
LGDP	0.856*	1.000							
LGDP^2	0.228*	0.316*	1.000						
LGFin	-0.049	-0.033	0.056	1.000					
FD	0.881*	0.748*	0.183*	-0.030	1.000				
IQ	0.622*	0.562*	0.245*	-0.067	0.570*	1.000			
LGFD	0.716*	0.604*	0.163*	0.486*	0.838*	0.421*	1.000		
TO	0.555*	0.554*	0.228*	-0.064	0.575*	0.657*	0.439*	1.000	
REN	-0.861*	-0.739*	-0.188*	0.049	-0.787*	-0.629*	-0.627*	-0.536*	1.000

Notes: * indicates significance at the 5% level. Definition of variables refers to Table 3.

Table 5: Variance Inflation Factor (VIF)

DV: LCOP	Model 1		Model 2	
	VIF	1/VIF	VIF	1/VIF
LGDP	2.740	0.364	2.490	0.402
LGDP^2	1.150	0.872	1.190	0.844
LGFin	1.990	0.501	1.010	0.988
FD	3.230	0.310	2.900	0.345
IQ	2.070	0.482	2.040	0.491
TO	1.900	0.528	1.720	0.582
REN	3.180	0.315	2.780	0.360
LGFD	-	-	1.990	0.503
Mean VIF	2.180		2.140	

Notes: Definition of variables refers to Table 4.1. VIF = 1: No multicollinearity; VIF > 1 and < 5: Moderate multicollinearity; VIF >= 5: High multicollinearity. 1/VIF = 1: No multicollinearity; 0 < 1/VIF < 1: Moderate multicollinearity; 1/VIF = 0: High multicollinearity.

Next, we checked cross-sectional dependence using Pesaran (2015)'s CSD test reported in Table 6. Despite the Institutional quality (IQ) that fail to reject the null hypothesis of no cross-sectional dependence, all other variables are reported significant at 10%, 5% and 1% level. This result implies that a shock in any of the East and South Asian is highly spill over to other economies in the region. It can be due to supply-chain integration, commodity price linkage, interconnectivity in the financial system, and various environmental protocols like the Kyoto Protocol and Paris Agreement. In brief, LCOP, LGDP, $LGDP^2$, LGFin, FD, IQ, TO, REN and LGFD are dependent among the emerging East and South Asian countries.

Table 6: Output of Pesaran's (2015) CSD test

Variable	CSD-test	p-value
LCOP	25.140***	0.000
LGDP	29.620***	0.000
$LGDP^2$	-1.660*	0.097
LGFin	1.910*	0.056
FD	8.750***	0.000
IQ	0.590	0.554
TO	4.460***	0.000
REN	8.950***	0.000
LGFD	2.460**	0.014

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. CSD = cross-sectional dependence. H0: Cross-sectional Independence.

In the next step, we check whether the slope parameters are heterogenous or homogenous through the test advocated by Pesaran and Yamagata (2008). Using this method, we estimated the delta (Δ) and adjusted delta (Adjusted Δ) to evaluate the alternate hypothesis of slope heterogeneity against the null hypothesis of slope homogeneity. At 5% significance level, slope homogenous have been rejected for Model 1 and 2. Table 7 confirms the supports for slope heterogeneity, which suggests that slope parameters vary across the cross-sectional units represented by developing East and South Asian economies.

Table 7: Slope heterogeneity (Pesaran and Yamagata, 2008)

DV: LCOP	Model 1	Model 2
Δ tilde	5.420**	4.389**
Δ tilde Adjusted	7.419**	6.322**

Notes: ** denotes significance at 5% level. H_0: slope coefficients are homogeneous.

Given the issues of CSD and slope heterogeneity in the data, we must proceed with the second-generation panel unit root tests that accommodate the panel data issues. For this matter, we applied CIPS and Pesaran's CADF (PSCADF) tests of Pesaran *et al.* (2009) and Pesaran (2007) panel unit root tests, respectively. From the results in Table 8, both the CIPS and PSCADF tests imply a $I(1)$ process among variables after the first-differencing. It implies that the mean and variance of the variables used in the models varies over time.

Now we aim to establish the cointegrating relationship between the studied variables. For this matter, we apply Westerlund and Edgerton's (2008) and Pedroni's (2004) cointegration tests. In Table 9, the results overwhelmingly accept the alternate hypothesis of a stable and long-term cointegrating relationship among the studied variables presented in both Model 1 and 2.

Table 8: Results of panel unit root tests

Variables	Level				
	CIPS		CIPS-M		
	Constant	Constant and trend	Constant	Constant and trend	
LCOP	-1.908	-1.959	-1.908	-1.959	
LGDP	-1.665	-1.249	-2.027	-1.197	
$LGDP^2$	-1.604	-1.762	-1.604	-1.762	
LGFin	-2.616	-2.617	-2.197	-2.195	
FD	-2.207	-2.756	-2.280	-2.822	
IQ	-2.224	-2.601	-2.321	-2.695	
TO	-1.001	-1.045	-1.098	-1.045	
REN	-1.273	-1.36	-1.426	-1.481	
LGFD	-1.918	-1.992	-2.002	-1.826	
Variables	First Difference				Order
	CIPS		CIPS-M		
	Constant	Constant and trend	Constant	Constant and trend	
LCOP	-3.726***	-4.114***	-3.726***	-4.142***	$I(1)$
LGDP	-2.473***	-2.939**	-2.473**	-2.939**	$I(1)$
$LGDP^2$	-3.686***	-3.814***	-3.686***	-3.814***	$I(1)$
LGFin	-5.956***	-6.062***	-5.551***	-5.638***	$I(1)$
FD	-4.286***	-4.192***	-4.265***	-4.246***	$I(1)$
IQ	-4.392***	-4.401***	-4.392***	-4.401***	$I(1)$
TO	-3.424***	-3.838***	-3.085***	-3.362***	$I(1)$
REN	-3.085***	-3.362***	-3.424***	-3.989***	$I(1)$
LGFD	-5.676***	-5.656***	-5.139***	-5.252***	$I(1)$

Notes: *** and ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 9: Models panel cointegration tests

Cointegration tests	Model 1 (t-statistic)	Model 2 (t-statistic)
<u>Westerlund and Edgerton test</u>		
Variance ratio	-2.129**	-1.615**
<u>Pedroni test</u>		
Modified Phillips–Perron t	3.663***	3.934***
Phillips–Perron t	-5.873***	-4.282***
Augmented Dickey–Fuller t	-5.403***	-4.198***

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

After establishing the cointegration relationship, we proceed with the CS-ARDL estimation reported at Table 10, to assess the dynamic long- and short-run impacts of the examined variables on carbon emissions. The significant long-run economic coefficient, represented by GDP per capita (LGDP), was reported as 0.425 (Model 1) and 0.465 (Model 2). The positive relationship between LCOP and LGDP indicates that economic development in emerging Asian countries comes at the cost of increased carbon emissions, leading to environmental degradation in the long run. Many Asian countries have focused on energy-intensive production and industrial sectors over the past three decades, resulting in higher carbon emissions. Among others, Indonesia and Malaysia have faced deforestation due to palm oil plantations and rubber estates. Interestingly, the quadratic term of GDP ($LGDP^2$) showed negative but insignificant impacts on carbon emissions with respective coefficients of -0.033 (Model 1) and -0.043 (Model 2). These results do not support the inverted-U shaped Environmental Kuznets Curve (EKC) hypothesis, which suggests that beyond a certain level of economic development, environmental degradation starts to decline, and environmental quality improves. This finding serves as an early warning signal regarding the environmental consequences of ongoing economic growth.

Table 10: Long-run estimates and short-run dynamics (CS-ARDL)

	Model 1		Model 2	
DV: LCOP	Coefficient	Std. Err.	Coefficient	Std. Err.
Long-run estimates				
LGDP	0.425***	0.179	0.465**	0.221
$LGDP^2$	-0.033	0.041	-0.043	0.065
LGFin	-0.001	0.003	0.117	0.120
FD	-0.090	0.546	1.070	2.029
IQ	-0.061**	0.028	-0.072***	0.026
TO	-0.001	0.002	-0.001	0.002
REN	-0.033***	0.009	-0.035***	0.010
LGFD (interaction)	-	-	-0.294	0.360
CSD-Statistic	-0.570	-	-0.640	-
Short-run dynamics				
$\Delta LCOP_{t-1}$	0.007**	0.149	0.033	0.129
ΔLGDP	0.427***	0.174	0.446**	0.198
$\Delta LGDP^2$	-0.021	0.031	-0.032	0.050
ΔLGFin	0.001	0.003	0.043	0.061
ΔFD	-0.340	0.355	-0.195	1.065
ΔIQ	-0.059**	0.029	-0.062**	0.025
ΔTO	-0.001	0.001	0.000	0.001
ΔREN	-0.029***	0.008	-0.029***	0.008
ΔLGFD (interaction)	-	-	-0.061	0.186
ECT_{t-1}	-0.993***	0.148	-0.9669***	0.128

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Definition of variables refers to Table 3. Δ indicates the changes of variables, CSD denotes Cross-sectional dependence, and ECT denotes Error Correction Term.

When assessing institutional quality (IQ) and renewable energy consumption (REN), both coefficients are significant and have the expected signs in both Model 1 and Model 2. In Table 10, the long-run estimates for IQ are reported as -0.061 and -0.072, and for REN as -0.033 and -0.035, with and without considering the interaction effect of green finance. The negative signs indicate that both IQ and REN contribute to environmental quality improvements by reducing carbon emissions. An enhancement of IQ by 1% reduce the CO_2 by 0.061%-0.072%, whereas an increasing of REN reduce the CO_2 by 0.033%-0.035%. This finding aligns with previous studies such as Ibrahim and Law (2016) and Lau *et al.* (2018), which highlight institutional quality as a significant yet often overlooked factor influencing environmental sustainability. Likewise, the significant outcome of REN on CO_2 corresponds with the findings of Spiegel-Feld *et al.* (2016) and Khan *et al.* (2020), who established that renewable energy consumption improves environmental quality.

However, the other macro variable, trade openness (TO), did not show a significant impact on carbon emissions. In addition, green finance, financial development, and the interaction between these variables were all found to be insignificant in supporting the Environmental Kuznets Curve (EKC) hypothesis. These results contradict the findings of Bhatti (2020) and Othman (2020) but are consistent with the research by Nasreen (2015), who observed that financial development reduces environmental degradation in high-income countries but increases it in middle- and low-income countries. The ineffectiveness of green finance in our study may be attributed to institutional barriers, such as weak regulatory frameworks and a lack of financial infrastructure among the emerging Asian countries, as noted by Li *et al.* (2020).

Table 10 also presents the short-run findings, which are consistent with the long-run effects at different magnitudes. First, ΔLGDP shows a positive and significant effect on carbon emissions in Model 1 and 2, indicating an increase in non-sustainable economic development among the emerging Asian countries. Second, ΔIQ and ΔREN exhibit significant and negative impacts on per capita carbon emissions in East and South Asian economies. Both institutional quality and renewable energy consumption mimic the pattern of carbon mitigation effect, and when used together, they produce the same effect in both short and long-run periods. Moreover, the lag effect attached to carbon emissions changes ($\Delta LCOP_{t-1}$) is highly significant and positive, suggesting a lag effect of carbon emissions. In other words, emissions in the previous period significantly and positively affect emissions in the current period.

Third, the error correction terms (ECT_{t-1}) are negative and significant in both Model 1 and 2, which illustrates significant adjustments towards the long-term equilibrium. These ECT coefficients show fast convergence towards steady-state equilibrium with a 99.3% (Model 1) and 96.7% (Model 2) annual adjustment rate, respectively. In other words, the error corrections in response to external shocks require 1-1.1 years of adjustment for Model 1 and Model 2.

Table 11: Robustness results from AMG and CCEMG

Variables DV=LCOP	Augmented Mean Group (AMG)			
	Model 1		Model 2	
	Coefficient	Std.Err.	Coefficient	Std.Err.
LGDP	0.757***	0.204	2.408**	1.269
$LGDP^2$	-0.017	0.019	-0.071	0.049
LGFin	-0.001	0.002	-0.034	0.080
FD	-0.137	0.357	-0.990	0.913
IQ	-0.037**	0.023	-0.216**	0.117
TO	0.000	0.001	0.000	0.003
REN	-0.030***	0.009	-0.094**	0.041
LGfd	-	-	-0.093	0.159
Wald test	49.720***		70.980***	
CSD	-1.980**		-1.113	
Variables DV=LCOP	**Common Correlated Affects Mean Group (CCEMG)**			
	Model 1		Model 2	
	Coef.	Std. Err.	Coefficient	Std.Err.
LGDP	1.183***	0.511	0.868**	0.432
$LGDP^2$	-0.094	0.078	-0.127	0.131
LGFin	-0.006	0.010	-0.054	0.068
FD	0.578	0.805	-0.132	0.221
IQ	-0.136**	0.057	-0.331**	0.132
TO	0.000	0.003	0.255	0.265
REN	-0.021***	0.001	-0.522***	0.232
LGfd	-	-	-0.176	0.205
Wald test	81.840***		55.200***	
CSD	-0.213		-1.799*	

Notes: ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively. Definition of variables refers to Table 3. Δ indicates the changes of variables, CSD denotes Cross-sectional dependence.

Next, we conducted robustness checks using the Augmented Mean Group (AMG) and Common Correlated Effects Mean Group (CCEMG) estimators. The findings are consistent with those reported in Table 10 previously. For instance, Table 11 shows that LGDP has a positive and significant coefficient, while $LGDP^2$ has a negative but insignificant coefficient, thus not supporting the U-shaped EKC hypothesis in both AMG and CCEMG estimators. Additionally, the results from both estimators suggest the important role of institutional quality (IQ) and renewable energy consumption (REN) in reducing carbon emissions in developing South and East Asian economies. However, LGfin, FD, TQ, and the interaction term (LGfd) are again insignificant in curbing carbon emissions among the ten emerging Asian economies. In short, the results from the AMG and CCEMG estimators are consistent with those of the CS-ARDL results. The regression adequacy results presented in Table 11 are acceptable. The Wald tests are all highly significant for all our models. The CSD tests are rather mixed for Model 1 and 2.

4.2 Market Mechanism and Policy Implications

The positive relationship observed between income growth and CO_2 emissions in the East and South Asian countries in our sample is primarily driven by rapid globalization and industrialization, which have come at the cost of the environment in these economies. For instance, the ASEAN region is a major producer of palm oil, rubber, and other commodities, leading to widespread deforestation, land degradation, and biodiversity loss (ADB, 2019). Moreover, countries like China, India, and ASEAN have become key centres for manufacturing and global supply chains, resulting in significant air and water pollution, waste generation, and greenhouse gas emissions (Sovacool *et al.*, 2020b). Based on World bank data base, the ten emerging Asian being studied accounted for half of the world manufacturing output and CO_2 emissions in 2021. The combination of rapid industrial growth and transportation, coupled with inadequate environmental regulations and enforcement, has led to high levels of carbon emissions in these emerging East and South Asian economies.

From Table 9, we observe that the impact coefficients of green finance (LGFin), trade openness (TO), and financial development (FD) on carbon emissions (COP) are negative but statistically insignificant, both with and without the green finance interactions. This finding contradicts the results of studies such as Al-Mulali *et al.* (2015), which found that financial development reduces environmental degradation in 129 sample countries, both in the short-term and long-term. Similarly, it is inconsistent with the findings of Zhao *et al.* (2021), which revealed a significant negative relationship between financial development and carbon emissions in China.

We interpret this result as an indication that the domestic financial markets and financial institutions' development, while stimulating manufacturing exports and attracting foreign direct and portfolio inflows, have not adequately promoted R&D investment that lead to potentially higher technological capabilities and energy-related efficiencies. Most of the financing and investment have been directed toward assembly and production activities that have not effectively reduced carbon emissions. Similarly, the development of commercial banking and credit markets has not sufficiently supported the renewable energy sector. This inefficiency in policy implementation requires urgent attention from policymakers, and further efforts are needed to achieve the goal of carbon neutrality. Literature has already highlighted that the financial sector plays a key role in reducing CO_2 emissions by improving the technological capability of the energy sector (Abbasi and Riaz, 2016). The renewable energy sector's higher dependency on debt and equity financing leads to faster growth in countries with robust financial markets (Kim and Park, 2016). In addition, green finance can also encourage companies to upgrade clean production technology, which will ultimately reduce industrial pollution emissions (Alharbi *et al.*, 2023; Lan *et al.*, 2023).

Recent studies have also revealed the inconsistent support for the EKC hypothesis and financial development, mainly due to factors such as institutional quality, technological capabilities, environmental regulations, political will, and structural changes (Kanbur *et al.*, 2021; Li *et al.*, 2020; Yadav *et al.*, 2020). However, these studies may have overlooked the role of unequal distribution of benefits. Financial development may not equally benefit all segments of the population, especially in many developing Asian countries where financial markets are dominated by a few large players, and access to finance is limited for smaller businesses and households. As a result, the benefits of financial development may not be distributed evenly across society, and environmental degradation may persist or even worsen.

On the other hand, our analysis uncovers that the renewable energy consumption exerts a negative impact on CO_2 emissions. From the viewpoint of climate change, the utilization of renewable energy sources has been considered to have a significant influence on environmental sustainability by decreasing the level of greenhouse gas pollution in the atmosphere (Bhattacharya *et al.*, 2017). This was supported by OECD (2013) that investment in green energy sources is usually considered less carbon-intensive than conventional energy. At present, China is the world's largest producer and consumer of renewable energy, with significant investments in renewable energy infrastructure and capacity. Hydroelectric power is the dominant renewable energy source in China, followed by wind and solar power. South Asian countries, including India, Pakistan, Bangladesh, Sri Lanka, and others, have also been increasing their focus on renewable energy projects such hydroelectric power and wind energy. India, in particular, has made significant strides in renewable energy development, with a strong emphasis on solar power. As for ASEAN, Thailand and the Philippines have been actively promoting renewable energy, including solar and wind power. Indonesia has significant geothermal resources, making geothermal energy a potential source of renewable power. Malaysia and Vietnam are also making progress in incorporating renewable energy into their energy mix, but the development is relatively slow. While the renew energy sectors are increasing receiving positive attention in the region, a few concerns are on the rise. First, the renewable energy landscape in these countries is constantly evolving due to changing policies, technological advancements, and investments in the renewable energy sector. Second, renewable energy market is more labour-intensive than the non-renewable energy sector (Blazejczak *et al.*, 2014) and the economic added values are relatively lower.

In addition, our analysis reveals the crucial role of institutional quality (IQ) in mitigating environmental degradation through effective environmental governance and regulation among emerging Asian economies, even though the Environmental Kuznets Curve (EKC) hypothesis is not supported. This finding aligns with Lau (2018), who emphasizes the importance of institutional quality and good governance in reducing CO_2 emissions, and Wu (2022), who emphasizes the significance of appropriate commercial laws to translate the benefits of foreign direct investment into environmentally sustainable development. Strong institutions play a vital role in promoting sustainable resource management practices, including policies that encourage responsible extraction of natural resources, reforestation, conservation of biodiversity, and protection of ecosystems, thus reducing environmental degradation. Additionally, as countries undergo development, citizens become more aware of environmental issues and demand better environmental protection. Strong institutions are better equipped to respond to these demands, leading to improvements in environmental policies and regulations. Transparent governance empowers citizens and stakeholders to participate in decision-making processes, advocate for environmental issues, and hold authorities accountable for their actions or lack of action regarding environmental challenges.

Among the emerging Asian economies, the status of institutional quality has shown improvements, but it still varies, and this has implications for environmental regulations across the region. The Chinese government has acknowledged the importance of addressing environmental challenges and has made efforts to strengthen environmental regulations and enforcement. However, the effectiveness of these regulations can be influenced by bureaucratic inefficiencies and corruption, particularly at the local governance level. In India, there exists a well-defined legal framework and environmental laws aimed at protecting the environment. Nevertheless, concerns persist regarding administrative efficiency and transparency. Other South Asian countries, such as Pakistan, Bangladesh, and Sri Lanka, have made progress in strengthening environmental governance and regulations. However, challenges persist, including corruption, bureaucratic hurdles, and limited resources for monitoring and enforcement. In ASEAN countries, some have made significant strides in addressing environmental challenges and promoting sustainable practices, while others face challenges related to institutional capacity, corruption, and coordination among various agencies involved in environmental governance. Overall, effective institutional quality is essential for achieving environmental sustainability and addressing environmental challenges in emerging Asian economies. Continuous improvements in institutional quality and enhanced regional cooperation on issues such as institutional capacity, transparency, and accountability are crucial for improving environmental regulations and compliance in the region.

5. Concluding Remarks

While the literature has confirmed the interconnections of globalization, manufacturing and decarbonization, the conventional EKC hypothesis has failed to address the pollution trajectory between the periods and income growth among emerging Asian nations. This study reassesses the EKC hypothesis for 10 emerging East and South Asian countries. In addition to institutional quality, renewable energy consumption and trade openness, the paper introduces green finance and its interaction with financial development to curb carbon emission. Possible biases due to slope heterogeneity and cross-sectional dependence (CSD) among the highly integrated East and South Asian countries are being tackled using a series of panel analyses on panel series during 2000-2019, e.g., the CSD test, slope heterogeneity test, the 2nd generation panel unit root tests, panel cointegration tests, and CS-ARDL modelling, as well as robustness tests.

The results are summarized as follows. First, the long- and short run coefficients of income per capita significantly linked to the carbon emissions but the income square ($LGDP^2$) was insignificant. This implies that the rapid economic growth of emerging Asian countries has come at a cost to the environment, with increased greenhouse gas emissions, water and air pollution, and deforestation. However, the U-typed EKC hypothesis was not supported as the insignificant $LGDP^2$ fail to a shift the pollution trajectory that followed by mitigation of environmental degradation. Second, green finance and trade openness are also insignificant in both long- and short-run to uphold the EKC and fail to facilitate financial development to reduce carbon emissions. The analysis suggests that the development of domestic financial markets and institutions in emerging Asian economies has not adequately promoted R&D investment and green technologies, resulting in limited progress in reducing carbon emissions. Policymakers need to address this inefficiency and increase efforts to achieve carbon neutrality by redirecting financing towards sustainable and renewable energy sectors.

Third, institutions quality (IQ) and renewable energy consumption (REN) are both consistently significant with negative impacts on the carbon emissions. This show that the continuous improvement of institutional quality that prioritize transparency and accountability in decision-making are more responsive to public concerns about environmental protection, among the emerging Asian. With higher education and awareness, societies may prioritize environmental quality and be more willing to invest in the renewable energy sectors. Effective institutions can also promote sustainable practices and investments in eco-friendly practices and green technologies, making it economically viable for industries to adopt cleaner production methods.

Finally, our study acknowledges the presence of heterogeneity and cross-sectional dependence issues among China, India, ASEAN, and South Asia concerning environmental policies and efforts. Although the EKC hypothesis is not supported, our analysis demonstrates that institutional quality and renewable energy consumption play crucial roles in mitigating environmental degradation. While progress has been made in reducing environmental degradation through these policies and efforts, achieving sustainable development and environmental protection remains a significant challenge. Among emerging Asian countries, China has shown notable advancements in renewable energy investment and implementing stricter environmental regulations, followed by ASEAN members. However, South Asian countries still grapple with macroeconomic imbalances and inadequate financial development. Balancing short-term growth and long-term environmental sustainability poses a critical dilemma, underscoring the importance of regional collaborations in strengthening environmental regulations and fostering sustainable development in the region.

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Are Malaysian IPO Investors Influenced by Sentiment Factors or Fundamental Factors?

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Abstract: Research Question: This study constructs and employs a composite market sentiment index, and a full range of issue, firm, and market characteristics variables to study Initial Public Offering (IPO) markets in Malaysia. **Motivation:** Radical changes in the Malaysian financial environment, particularly changes in Malaysia's capital market structure in the past few decades, may have increased heterogeneity in the composition of participants and impacted investors' risk-taking behavior. This study provides a more comprehensive understanding of the dynamics that shape IPO behavior in Malaysia. **Idea:** The main objective of this study is to study market sentiment and Malaysian IPOs. To determine whether Malaysian IPOs underpriced, and to identify their key determinants from behavioral and fundamental perspectives. **Data:** This study investigates 571 IPOs firms listed on Bursa Malaysia from January 2000 to December 2020. **Method/Tools:** Multiple and binary regression models are employed to examine the determinants of IPO underpricing. Additionally, interaction analysis and marginal probability analysis are used to explain the short-run IPO share performance. Three different methods are used to construct the Malaysian IPO Market Sentiment Index: (1) Baker and Wurgler's (2007) Principal Component Analysis method; (2) Jiang *et al.*'s (2022) Scaled Principal Component Analysis method; and (3) Huang *et al.*'s (2015) Partial Least Squares method. **Findings:** This study found that overall the Malaysian IPOs underpriced by 28.48% based on the market-adjusted initial return. The findings evidence that sentiment factor plays a significant role in the short-run IPO share performance. The results of this study is consistent with the study by Leite (2005) shown that the presence of sentiment investors in IPOs reduces the winner's curse problem (Rock's hypothesis) in the issue by increasing the relative probability for the least-informed (rational) investor to be allocated underpriced shares. **Contributions:** This study acknowledges the limitations of neoclassical finance theories in explaining the behavior of investors in Malaysian IPO markets. By incorporating behavioral finance theories, this study recognises that fundamental factors might not be the sole driver of investor decisions. This shift in focus toward market sentiment and psychology adds a fresh perspective to understanding IPO underpricing.

Keywords: Malaysian IPOs, market sentiment, behavioral finance, neoclassical finance, multiple regression model, binary regression model.

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1. Introduction

In the past decade, there has been growing attention on the impact of investor sentiment on IPO underpricing and share market performance. Neoclassical finance theories, including the Efficient Market Hypothesis (EMH) and random walk theory, failed to consider investor sentiment as a factor in explaining the diverse behavior of investors. However, behavioral finance theories present an alternative model that recognises market rationality. These theories reveal how investor psychology influences market fluctuations, with Baker and Wurgler (2006) asserting that market sentiment influences investor speculation on share prices, often disregarding fundamental factors.

Empirical studies have explored short-run IPO underpricing on both international and local scales. The majority of these studies have been conducted in developed countries such as the United States (US) and European markets. Researchers such as Ibbotson (1975), Ibbotson and Jaffe (1975), Beatty and Ritter (1986), Tinic (1988), and Ibbotson *et al.* (1994) have documented IPO underpricing in the US market ranging from 10.0% to 15.0%. The phenomenon of short-run IPO underpricing appears to be more pronounced in developing countries. For instance, Dawson (1987) conducted a study on short-run share performance in three Asian markets: Malaysia, Hong Kong, and Singapore. The study revealed that Malaysia reported the highest IPO underpricing at 166.5%. Moreover, Ritter (2003) found that average initial returns for IPOs in 33 countries ranged from 13.6% to 388% in developing countries and 4.2% to 54.4% in developed countries.

Radical changes in Malaysia's financial environment, particularly changes in its capital market structure over the past few decades, may have led to increased heterogeneity among market participants and affected investors' risk-taking behavior. The study of investor sentiment in developing economies with rapidly growing capital markets is still in its early stages, and the impact of investor sentiment on the IPO market has received less exploration compared to previous research, which primarily focused on the influence of investor sentiment on investment returns. Furthermore, according to the Bursa Malaysia Research and Data Centre, between 1991 and 2003, an average of 91.35% of investors consisted of individual traders who were typically uninformed. These investors often based their trades on information from various sources, leading to a significant relationship between IPO underpricing and trading volume behavior (Chong, 2009).

The objective of this study is to enhance our understanding of the short-run performance of Malaysian IPOs and evaluate the impact of changes in Malaysia's capital market structure on IPO performance. While Albada and Yong (2017) focused on fundamental finance theories and factors such as information asymmetry, underwriter reputation, ownership structure, share lock-up period, pricing mechanisms, and institutional investor involvement, the present study extends their research by investigating the impact of investor sentiment and psychology on IPO underpricing. Through the incorporation of behavioral finance theories, this study aims to offer a more comprehensive understanding of the factors shaping IPO behavior in Malaysia. In pursuing a deeper understanding of the short-run performance of Malaysian IPOs and assessing the influence of changes in Malaysia's capital market structure on IPO performance, this study posits that sentiment factors play a significant role in shaping the short-run performance of Malaysian IPOs, while changes in the capital market structure exert a substantial impact on overall IPO performance.

2. Evidences on Changes in Malaysia's Capital Market Structure

Malaysia stock market is known as Malaysian Stock Exchange prior to changing its name to Bursa Malaysia Securities Berhad (Bursa Malaysia) on 14 April 2004. At that time, the

Malaysia stock market contains three listing boards namely Main Board, Second Board and Malaysian Exchange of Securities Dealing and Quotation Berhad (MESDAQ). Main Board is catered for larger sized firms, whereas for small and medium sized firms will seek to be listed on Second Board. For high revenue growth and technology firms that intend to raise funds from the stock market will be recommended to be listed on MESDAQ. In August 2009, Main Board and Second Board were merged and renamed as Main Market, and MESDAQ was renamed as ACE Market stands for "Access, Certainty, Efficiency". ACE Market was established for firms that are technology based with high growth in revenue intend to raise funds via primary market. In December 2017, a new listing board has been introduced by Bursa Malaysia named Leading Entrepreneur Accelerator Platform Market (LEAP) Market. This market is mainly for small and medium firms to raise funds in the capital market which are unable to meet the listing criteria for Main Market and ACE Market (Yaakob and Halim, 2016). Such changes in board listing has affected IPO processes by the relevant authorities.

Figure 1 shows the Malaysia IPOs market trend from 1991 to 2020. Low and Yong (2011) document that in Malaysia stock market the most employed mechanism is the fixed price mechanism. With that, issuing firms and underwriters have minimal information about market demand for the new issuance of IPO shares. Given the uncertainty about the true value of the IPO, differences in opinions among investors are likely to occur as potential investors make different estimates of their expected return from the investment. Since prospective IPO investors have no opportunity to reveal their beliefs in offerings that employ fixed-price mechanism, divergence of opinions among IPO investors is believed to be the greatest in fixed-price IPOs. In Malaysia, given that most of the IPOs are priced using the fixed-price offer system, differences in opinions among investors are likely to be high. For the reason that differences in opinions have important behavioral implications, in this study, we examine factors that could potentially explain the level of IPO underpricing in Malaysia among IPO investors from fundamental and behavioral perspectives.

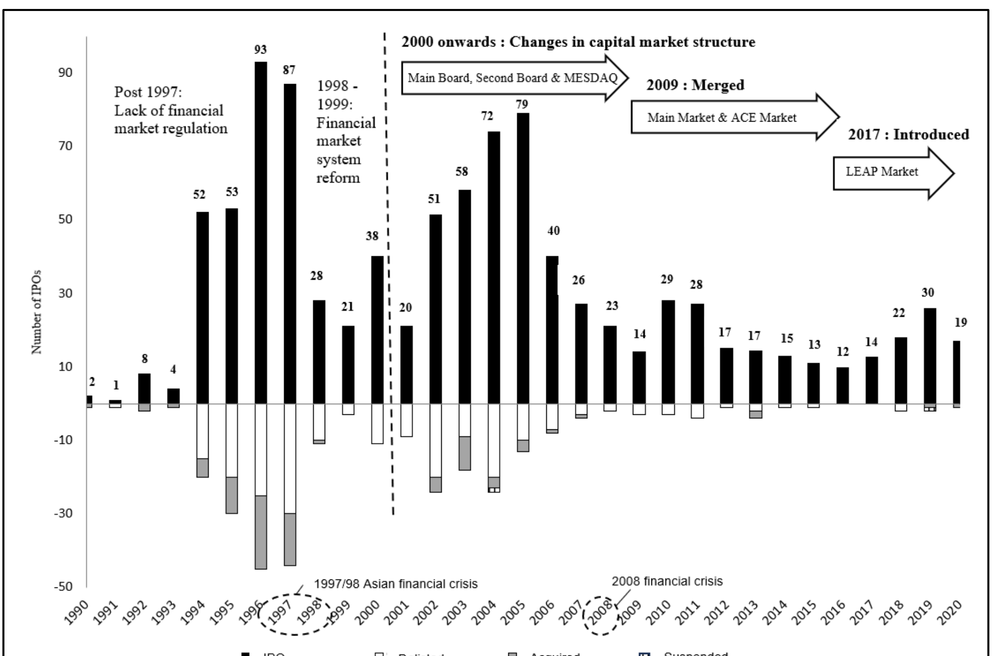

Figure 1: 30-year total number of IPOs, delisted, acquired and suspended cases

3. Literature Review

3.1 Stock Market Reaction Determinants

There are many factors that can affect or disrupt share prices and the market (Atiq *et al.*, 2010). Studies done by Atiq *et al.* (2010), and Al-Tamimia *et al.* (2011) prove that the determinants of stock market share prices include, company ideologies, extraneous factors, and outlook (investor behavior).

Sentiment is defined as the opinions, views and emotions of an individual or group. Meanwhile, market sentiment refers to the expectations and outlook of the entire market (Thorp, 2004). Chang *et al.* (2008) state that the sentiments of investors in the market is quantified by considering the investor's sentiment. Market sentiment, which is often subject to the bias and obstinacy of the individuals in the market is the subject of exploration and discussion in a nascent field of study called behavioral finance. Behavioral finance studies investor conduct and how it affects the prices of shares in the stock market (Haritha and Uchil, 2016). Figure 2 is a visual representation of how the market outlook leads investor's outlook and the behavioral pitfalls that affect sound business and economic judgments.

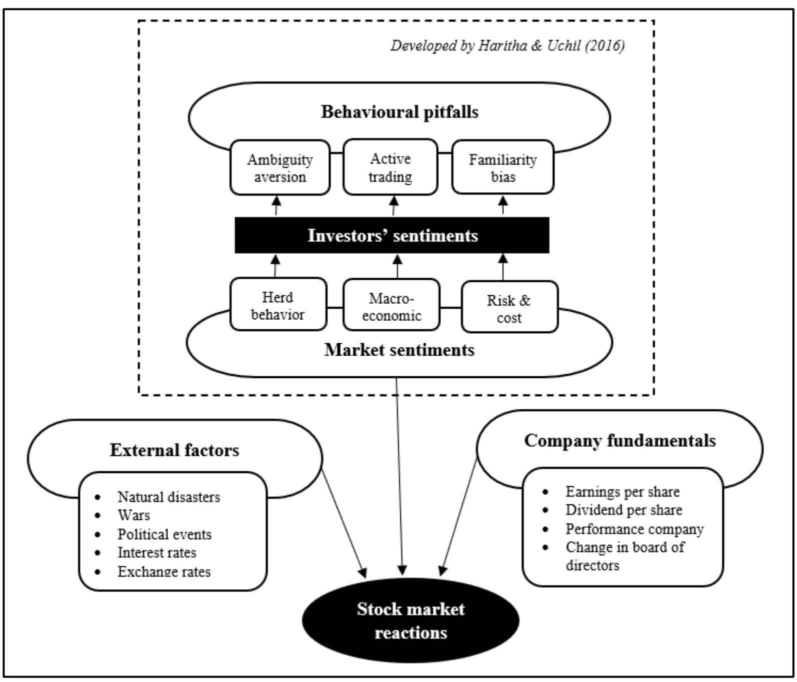

Figure 2: Determinants of stock markets' reaction

3.2 Theoretical Explanations for Short-Run IPO Share Performance

Ljungqvist (1997) classify the theories of IPO underpricing into three broad categories:

(i) information asymmetry based theories;
(ii) institutional based theories; and
(iii) behavioral based theories.

Albada and Yong (2017) find that the average initial return of the Malaysian IPO market is still quite high; perhaps due to the 'still' high level of information asymmetry in the Malaysian IPO market. For institutional based theories of IPO underpricing focus on the marketplace lawsuit and price stabilisation function of the underwriter. There are two main intuitional based theories to explain IPO underpricing. These are legal liability hypothesis (lawsuit hypothesis) and price stabilisation hypothesis. Both of these scenarios are not commonly found in Malaysia stock market; thus, these theories are not apply to Malaysian IPOs. Behavioral theories explained the underpricing phenomena in the presence of 'irrational investors' who opt to purchase IPO's shares beyond their intrinsic value. Yong (2011) examines the bandwagon effect on Malaysian IPOs it shows an 'increased interest' in a particular IPO which resulted in increase in its initial returns were brought in by a group of informed investors in an IPO exercise compared to uninformed investors. Their existence results in high trading activities among investors, as indicated by a higher dispersion of initial returns. This findings evidence the existence of a group of informed investors can create a bandwagon effect when the market overreacts to the underpricing of an IPO.

4. Data and Methodology

4.1 Data and Sample Selection

In this study, all the sample data of IPOs issuing firms selection must be based on the following conditions. First, IPOs includes the IPO's issuing firms listed on Bursa Malaysia from January 2000 to December 2020 (past 20 years). Second, the sample data of IPOs identified for this study were from Main Board and Second Board, which subsequently merged into Main Market after August 2009, and MESDAQ renamed as ACE Market. Third, the eligible offerings considered in this study are limited to those conducted through public issues, offers for sale, or a combination of both, specifically involving the issuance of shares. This is consistent with prior study conducted by Abdul-Rahim and Yong (200) and Yong (2007), certain types of IPOs are excluded from the final sample. These exclusions encompass restricted offer-for-sale, restricted public issue, restricted offer-for-sale to eligible employees, restricted offer-for-sale to Bumiputera investors (referring to Malaysia and other indigenous people in Peninsular and East Malaysia), special and restricted issues to Bumiputera investors, tender offers, and special issues. The rationale behind these exclusions is to avoid including Malaysian companies with a typical types of issuances that may yield less meaningful outcomes in the analysis.

This study has covered the longest sample period (post-2000) as compared to the rest of empirical study done for Malaysian IPOs. The sample period from January 2000 to December 2020 is selected because these periods are characterised by a significant amount of regulatory, policy, capital market changes are inevitably imparted on investor psychology and stock market development which translate to changes in listing boards.

The data collection process are completed following these steps. The first step is to collect all the names of IPO issuing firms that went for listing from January 2000 to December 2020 which are identified from Bursa Malaysia's database available on Bursa Malaysia's website. In the second step, hand collected data were extracted from each of the IPO firm's prospectus such as offer price, IPO period, offer size, total listing costs, total IPO proceeds, listing date, listing board, underwriters, firm age, and book value per share. In the third step, the secondary historical financial and market data such as share price and trading volume are extracted from Bloomberg. Finally, the survey-based data such as business conditions index and consumer sentiment index are obtained from Malaysian Institute of Economic Research's survey reports.

4.2 Methodology

4.2.1 Construction of Malaysian IPO Market Sentiment Index

In order to construct Malaysian IPO Market Sentiment Index (MIMSI) specifically tailored for the Malaysian stock market, this study has employed three different methods: Baker and Wurgler's (2007) analysis using Principal Component Analysis (PCA) method, Jiang *et al.*'s (2022) Scaled Principal Component Analysis (sPCA) method, and Huang *et al.*'s (2015) Partial Least Squares (PLS) method.

PCA is a multivariate method in which several unified quantitative variables describing the observations are reduced to produce single variable via dimensionality reduction. PCA aims to find and extract the most significant information from the data by compressing the size and simplifying the data without losing the important information (Abdi and Williams, 2010). sPCA is a new dimension reduction technique for supervised learning proposed by Huang *et al.* (2022). This method scales each predictor with its predictability for the target variable. Compared with the conventional PCA method, sPCA method improves the predictability for the target variable by capturing the useful information inside the target variable. According to Huang *et al.* (2022), the sPCA method could screen out noisier forecasters and assign shrinking weights to them by letting the target variable be the guide in the dimension reduction. They provide evidence that sPCA method generally improves the predictability of index compared to index generated using conventional PCA method, similarly, forecasting performance of index in the context of Malaysian IPO markets can be improved by using sPCA method. According to Huang *et al.* (2015), and Kelly and Pruitt (2014), compared with the conventional PCA method, the PLS method could separate the common noises which are irrelevant to the target variable from proxies, thus, leading to a more effective predictor.

In this study, Baker and Wurgler (2007) sentiment indicators are adopted as baseline regression because it is extensively accepted in various empirical studies. This study follows the same market-based sentiment measure adopted by Baker and Wurgler (2007) to formulate IPO market sentiment index namely, natural log of Share Turnover (TURN) representing the ratio of the trading volume to the total share capital, Number of IPOs (NIPO) representing the number of IPOs, First-day Returns of IPOs (RIPO) representing the first-day returns of IPOs, Dividend Premium (PDND) in this study, due to the availability of data in Malaysia the dividend premium was calculated using the fraction of net income of an issuing firm pays to its shareholders in the form of dividends, instead of the firm's dividend premium payable into between payers and non-payers at the end of financial year as explained by Baker and Wurgler (2007), and natural log of Equity Shares in New Issues (ESNI) representing total number of total equity and debt issues by all firms. The proxy of Close-End Fund Discount rate (CEFD) has been excluded in this study because there is only one close-end fund company listed on Main Market of Bursa Malaysia. Therefore, it could create biasness to analysis results. According to Naik and Padhi (2016), survey-based sentiment measure are commonly used in combination with market-based sentiment measure. In this study, we have selected two survey-based sentiment measure namely, business conditions index (BCI), and consumer sentiment index (CCI). The data of TURN, NIPO, RIPO, PDND, ESNI, BCI and CCI are compiled based on quarterly basis in accordance with an IPO firm's listing date.

The predictive regression in constructing of MIMSI is as follows:

$$\begin{aligned} SENT_{it} = {} & \beta_1\,TURN_{it} + \beta_2\,NIPO_{it} + \beta_3\,RIPO_{it} + \beta_4\,PDND_{it} + \beta_5\,ESNI_{it} + \beta_6\,BCI_{it} \\ & + \beta_7\,CCI_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

However, the central issue revolves around the selection of sentiment proxy variables. Considering that the indices published by different countries vary and market rules differ, it becomes necessary for each country to adapt the set of proxy variables based on their specific conditions.

4.2.1(a) Principal Component Analysis

In this study, a composite index is created that captures the common component in the seven proxies while also accounting for the fact that certain variables take longer to convey similar attitude. PCA method is used to reduce the dimensionality of huge data sets by reducing a large set of variables into a smaller one that retains most of the information. It is a statistical procedure that, using orthogonal transformation, transform those variables into a set of values, named principal components. The transformation is defined in such a way that the first component explains the most variation and each succeeding component accounts for the highest variance possible. In very beginning standardisation is necessary, since PCA is sensitive to initial variable variances. Therefore, if initial variable ranges differ substantially, larger ranges will prevail, resulting in biased outcomes. To avoid such biasness, it is necessary to standardise the initial variables used as proxy for the composition of index. The equation below is representing the method for the standardisation of each proxy variable:

$$\mathcal{S}_t = \frac{I_{\mathrm{t}} - \bar{X}}{SD} \tag{2}$$

Here, $\mathcal{S}_t$ is representing standardised form of each proxy variable in time t, and I stand for the value of specific observation in time. While $\bar{X}$ and SD are the mean and standard deviations of the variable under standardisation process. The index begins by estimating the first principal component PC_t via seven standardised proxies using lag and level forms in first stage of index generation. As per Baker and Wurgler (2007), the rule is to select the representation of each variable (among lag and level) having maximum correlation with PC_t for optimal representation of each variable for second stage of index generation. Table 1 shows the pairwise correlation of first stage principal component with all lag and level form of proxies.

The results of correlations of first stage principal component with sentiment proxy variables in Table 1 suggested to select lagged for of $TURN, RIPO$ and BCI, and level form of other proxies i.e. $TURN, RIPO$ and BCI for the second stage of index generation. Table 2 represents the results of second stage principal component analysis. Specifically, Panel A represents the proportion of total variance of all the sentiment proxies captured in each principal component. Panel B is represents the part of variance of each sentiment proxy coming into each principal component. By following the study of Baker and Wurgler (2007), this study uses first principal component (C_1) as sentiment index ($\mathrm{SENT}_t^{\mathrm{PCA}}$). The first principal component accounts for 38.04% of the variance observed in the data set, leading researcher to infer that a single factor captures significant portion of the shared variation.

Table 1: Correlation matrix of first principal component

	PC_t	$TURN_t$	$NIPO_t$	$RIPO_t$	P_t^{D-ND}	$ESNI_t$	BCI_t
PC_t	1.0000						
$TURN_t$	0.8692	1.0000					
$NIPO_t$	-0.6792	-0.5259	1.0000				
$RIPO_t$	-0.3419	-0.2296	0.1517	1.0000			
P_t^{D-ND}	0.7345	0.6557	-0.3575	-0.2061	1.0000		
$ESNI_t$	0.0318	0.0175	0.2795	-0.0819	0.1618	1.0000	
BCI_t	0.4238	0.4995	0.0615	-0.1308	0.4651	0.2166	1.0000
CCI_t	-0.5257	-0.2809	0.4441	0.3402	-0.2065	0.0974	0.1506
$TURN_{t-1}$	0.9020	0.8709	-0.5526	-0.1133	0.7338	0.0820	0.4586
$NIPO_{t-1}$	-0.6567	-0.5499	0.7716	0.0773	-0.3142	0.1409	0.0287
$RIPO_{t-1}$	-0.4133	-0.2166	0.1763	0.5440	-0.1513	-0.0672	-0.1560
P_{t-1}^{D-ND}	0.7265	0.6052	-0.3812	-0.2435	0.4634	0.1545	0.2763
$ESNI_{t-1}$	-0.0072	-0.0132	0.0733	-0.1530	0.0531	0.2224	0.1170
BCI_{t-1}	0.4715	0.4065	0.0821	-0.0921	0.5962	0.2966	0.7754
CCI_{t-1}	-0.4944	-0.3051	0.4556	0.3092	-0.1367	0.1789	0.1499

Table 1 *(continued)*

	CCI_t	$TURN_{t-1}$	$NIPO_{t-1}$	$RIPO_{t-1}$	P_{t-1}^{D-ND}	$ESNI_{t-1}$	BCI_{t-1}	CCI_{t-1}
PC_t								
$TURN_t$								
$NIPO_t$								
$RIPO_t$								
P_t^{D-ND}								
$ESNI_t$								
BCI_t								
CCI_t	1.0000							
$TURN_{t-1}$	-0.3410	1.0000						
$NIPO_{t-1}$	0.4310	-0.5269	1.0000					
$RIPO_{t-1}$	0.3649	-0.2272	0.1506	1.0000				
P_{t-1}^{D-ND}	-0.2788	0.6639	-0.3577	-0.2061	1.0000			
$ESNI_{t-1}$	0.1582	-0.0215	0.2972	-0.0760	0.1656	1.0000		
BCI_{t-1}	0.0995	0.4916	0.0660	-0.1280	0.4673	0.1985	1.0000	
CCI_{t-1}	0.7386	-0.2702	0.4427	0.3387	-0.2071	0.1237	0.1622	1.0000

Notes: Table 1 presents the pairwise correlation among first principal component in first stage with their set of sentiment variables. Where, PC_t is first principal component , $TURN_t$ is share turnover, $NIPO_t$ is number of IPOs, $RIPO_t$ is first-day returns of IPOs, P_t^{D-ND} is dividend premium, $ESNI_t$ is equity shares in new issues, BCI_t is business confidence index, CCI_t consumer confidence index. Additionally, t and t-1 represent level and lagged values of each variable.

Table 2: Principal components

	Eigen values	Difference	Proportion explained	Cumulative proportion explained
Panel A: Variance in principal components				
C_1	2.6628	0.9696	0.3804	0.3804
C_2	1.6932	0.6501	0.2419	0.6223
C_3	1.0431	0.3787	0.149	0.7713
C_4	0.6644	0.1941	0.0949	0.8662
C_5	0.4703	0.2098	0.0672	0.9334
C_6	0.2604	0.0549	0.0372	0.9706
C_7	0.2056	-	0.0294	1.0000

Panel B: Variance from variables							
Variable	C_1	C_2	C_3	C_4	C_5	C_6	C_7
$TURN_{t-1}$	0.5558	0.0407	0.1678	0.0900	-0.0853	-0.2558	0.7619
$NIPO_t$	-0.3814	0.4458	-0.2494	-0.2069	0.4980	0.2691	0.4800
$RIPO_{t-1}$	-0.2590	0.1400	0.7375	0.5016	0.3309	-0.0856	-0.0319
P_t^{D-ND}	0.5144	0.2153	0.2218	-0.0243	0.0400	0.7811	-0.1660
$ESNI_t$	0.0578	0.5126	-0.4433	0.6849	-0.2409	-0.0395	-0.0931
BCI_{t-1}	0.3418	0.5238	0.0553	-0.3585	0.3025	-0.4922	-0.3786
CCI_t	-0.3062	0.4434	0.3420	-0.3151	-0.6957	0.0279	0.0931

Notes: Table 2 represents the results of PCA. Where, Panel A represents the eigen values, differences between current eigen value and next eigen value, the proportion of all the proxies explained by each principal component in percentage and cumulative percentage of explanation in components. Additionally, $C_1$to C_7 represent the number of principal components.

Finally, Equation 3 represents detailed portion, direction and representation of each variable used to generate parsimonious sentiment index by PCA method:

$$\begin{aligned} \mathrm{SENT}_t^{\mathrm{PCA}} = {} & 0.5558\, TURN_{t-1} - 0.3814\, NIPO_t - 0.2590\, RIPO_{t-1} \\ & +0.5144\, P_t^{D-ND} + 0.0578\, ESNI_t + 0.3418\, BCI_{t-1} \\ & -0.3062\, CCI_t \end{aligned} \tag{3}$$

Here, $\mathrm{SENT}_t^{\mathrm{PCA}}$ is the sentiment index generated by PCA method, $TURN_{t-1}$ is lag of share turnover, $NIPO_t$ is number of IPOs, $RIPO_{t-1}$ is lag of closing returns of IPOs day, P_t^{D-ND} is dividend premium, $ESNI_t$ is equity shares in new issues, BCI_{t-1} is lag of business confidence index, CCI_t consumer confidence index. Detailed correlation of each sentiment proxy with final sentiment index is represented in Table 3 below.

Table 3: Correlation of $SENT^{PCA}$

	$\mathrm{SENT}_t^{\mathrm{PCA}}$	$TURN_{t-1}$	$NIPO_t$	$RIPO_{t-1}$	P_t^{D-ND}	$ESNI_t$	BCI_{t-1}	CCI_t
$\mathrm{SENT}_t^{\mathrm{PCA}}$	1.0000							
$TURN_{t-1}$	0.9070	1.0000						
$NIPO_t$	-0.6224	-0.5526	1.0000					
$RIPO_{t-1}$	-0.4227	-0.2272	0.1763	1.0000				
P_t^{D-ND}	0.8393	0.7338	-0.3575	-0.1513	1.0000			
$ESNI_t$	0.0943	0.0820	0.2795	-0.0672	0.1618	1.0000		
BCI_{t-1}	0.5578	0.4916	0.0821	-0.1280	0.5962	0.2966	1.0000	
CCI_t	-0.4996	-0.3410	0.4441	0.3649	-0.2065	0.0974	0.0995	1.0000

Notes: Table 3 represents detailed correlation of $\mathrm{SENT}_t^{\mathrm{PCA}}$ sentiment index generated by PCA method with $TURN_{t-1}$ lag of share turnover, $NIPO_t$ number of IPOs, $RIPO_{t-1}$ lag of closing returns of IPOs day, P_t^{D-ND} dividend premium, $ESNI_t$ equity shares in new issues, BCI_{t-1} lag of business confidence index and CCI_t consumer confidence index.

The results of correlation table depict that, $\mathrm{SENT}_t^{\mathrm{PCA}}$ has 90.70% correlation with lag of share turnover, -62.24% with number of IPOs, -42.27% with lag of closing returns of IPOs day, 83.93% with dividend premium, 9.43% with equity shares in new issues, 55.78% with lag of business confidence index and -49.96% with consumer confidence index. The correlation coefficient between the 14-terms first-stage index and $SENT^{PCA}$ index is 96.16%, indicating that there is minimal loss of information after excluding the seven terms with different time subscripts.

4.2.1(b) Scaled Principal Component Analysis

In this study, we extracts the sPCA factors in 2 steps. First, by running a predictive regression of the target on each predictor and scale the predictor with the regression slope. Second, by applying the PCA method to the scaled predictors to obtain principal components as the sPCA factors. In this way, the sPCA tends to down-weight those predictors with weak forecasting power, while overweight those with strong forecasting power. As a result, the sPCA factors are more likely to outperform the PCA factors for forecasting and estimation purposes. The details of each of two steps is as follows:

Step 1: Given N number of orthogonalise sentiment proxies to be $(X_1, X_2, \dots, X_N)$, obtain a panel of scaled predictors $(\widehat{\delta_1}X_1, \widehat{\delta_2}X_2, \dots, \widehat{\delta_N}X_N)$ by running N times time-series regressions. More specifically, the scaled coefficient $\widehat{\delta_\iota}$ is the estimated slope that comes from regressing the target variable (market adjusted initial returns MAIR in this study) on the ι^{th} sentiment proxy as follows:

$$MAIR_{t+h} = \vartheta_i + \delta_i X_{i,t} + \varepsilon_{t+h}; \qquad where\ i = 1,2, \dots, N \tag{4}$$

Consequently, the relationship between the i^{th} sentiment proxy and unobserved $SENT^{sPCA}$ can be represented in Equation 5, and values of estimated slop $\widehat{\delta_\iota}$ for all the sentiment proxies is represented in Table 4 bellow.

$$\delta_i X_{i,t} = \theta_i SENT^{sPCA} + e_{i,t} \tag{5}$$

Table 4: Estimated slopes

	$TURN_t$	$NIPO_t$	$RIPO_t$	$\hat{P}_t^{D-ND}$	$\widehat{ESNI}_t$	BCI_t	CCI_t
$\widehat{\delta_\iota}$	-0.0218	0.0184	0.0640	-0.0282	-0.0231	-0.0181	0.0347
	(-1.64)	(1.37)	(5.55)	(-2.14)	(-1.74)	(-1.35)	(2.67)
$R^2(\%)$	3.17	2.25	27.27	5.28	3.57	2.18	8.02

Notes: Table 4 is representing results of estimated slopes to be used to scale each sentiment proxy X_1 to X_N. The dependent variable in all regression models in columns one day ahead market adjusted initial returns $MAIR$ (as target variable). Values in parenthesis are *t*-statistics and R-squared is represented in percentage.

Step 2: In the second step the author used scaled predictors $(\widehat{\delta_1}X_1, \widehat{\delta_2}X_2, \dots, \widehat{\delta_N}X_N)$ obtained in Step 1 to generate sentiment index by sPCA method. Since, the second step of sPCA is dimensionality reduction, same as conventional PCA (Huang *et al.*, 2022), so this begins by estimating the first principal component sPC_t by seven standardised proxies scaled for target variable using lag and level forms. Followed by the selecting optimal representation for second step based on highest correlation among lag and level forms of each proxy. Consequently, Table 5 is representing correlation of first scaled principal component sPC_t with each sentiment proxy variable.

The results of correlation table (in Table 5) depict that, after scaling for the target variable the direction of correlation with all the sentiment proxies changed to positive. Specifically, compared to correlation matrix of first principal component of basic PCA in Table 1 the direction of lagged and level form of $NIPO_t, RIPO_t$ and CCI_t is changed from negative to positive. However, the size of correlation is same since the data of standardised variables is same. Consequently, the optimal representation of sentiment proxies in second stage sPCA as per Baker and Wurgler (2007) is same. The equation number 6 is representing optimal representation of proxy variables.

$$\begin{aligned}\mathrm{SENT}_t^{\mathrm{sPCA}} = {} & 0.5558\, TURN_{t-1} + 0.3814\, NIPO_t + 0.2590\, RIPO_{t-1} \\ & + 0.5144\, P_t^{DND} + 0.0578\, ESNI_t + 0.3418\, BCI_{t-1} + 0.3062\, CCI_t\end{aligned} \tag{6}$$

Table 6 is representing the results of second stage of sPCA. Specifically, Panel A is representing the proportion of total variance of all the sentiment proxies captured in each principal component. And, Panel B is representing the part of variance of each sentiment proxy coming into each principal component. Compared to the results of conventional PCA (in Table 2) the direction of explanation from sentiment proxies such as $NIPO_t, RIPO_{t-1}$ and CCI_t is changed from negative to positive.

Table 5: Correlation matrix of first principal component

	sPC_t	$TURN_t$	$NIPO_t$	$RIPO_t$	P_t^{D-ND}	$ESNI_t$	BCI_t
sPC_t	1.0000						
$TURN_t$	0.8692	1.0000					
$NIPO_t$	0.6792	0.5259	1.0000				
$RIPO_t$	0.3419	0.2296	0.1517	1.0000			
P_t^{D-ND}	0.7345	0.6557	0.3575	0.2061	1.0000		
$ESNI_t$	0.0318	0.0175	-0.2795	0.0819	0.1618	1.0000	
BCI_t	0.4238	0.4995	-0.0615	0.1308	0.4651	0.2166	1.0000
CCI_t	0.5257	0.2809	0.4441	0.3402	0.2065	-0.0974	-0.1506
$TURN_{t-1}$	0.9020	0.8709	0.5526	0.1133	0.7338	0.082	0.4586
$NIPO_{t-1}$	0.6567	0.5499	0.7716	0.0773	0.3142	-0.1409	-0.0287
$RIPO_{t-1}$	0.4133	0.2166	0.1763	0.5440	0.1513	0.0672	0.1560
P_{t-1}^{D-ND}	0.7265	0.6052	0.3812	0.2435	0.4634	0.1545	0.2763
$ESNI_{t-1}$	-0.0072	-0.0132	-0.0733	0.1530	0.0531	0.2224	0.1170
BCI_{t-1}	0.4715	0.4065	-0.0821	0.0921	0.5962	0.2966	0.7754
CCI_{t-1}	0.4944	0.3051	0.4556	0.3092	0.1367	-0.1789	-0.1499

Table 5 *(continued)*

	CCI_t	$TURN_{t-1}$	$NIPO_{t-1}$	$RIPO_{t-1}$	P_{t-1}^{D-ND}	$ESNI_{t-1}$	BCI_{t-1}	CCI_{t-1}
sPC_t								
$TURN_t$								
$NIPO_t$								
$RIPO_t$								
P_t^{D-ND}								
$ESNI_t$								
BCI_t								
CCI_t	1.0000							
$TURN_{t-1}$	0.3410	1.0000						
$NIPO_{t-1}$	0.4310	0.5269	1.0000					
$RIPO_{t-1}$	0.3649	0.2272	0.1506	1.0000				
P_{t-1}^{D-ND}	0.2788	0.6639	0.3577	0.2061	1.0000			
$ESNI_{t-1}$	-0.1582	-0.0215	-0.2972	0.076	0.1656	1.0000		
BCI_{t-1}	-0.0995	0.4916	-0.066	0.128	0.4673	0.1985	1.0000	
CCI_{t-1}	0.7386	0.2702	0.4427	0.3387	0.2071	-0.1237	-0.1622	1.0000

Notes: Table 5 presents the pairwise correlation among first principal component in first stage with set of scaled sentiment variables. Where, sPC_t is first principal component , $TURN_t$ is share turnover, $NIPO_t$ is number of IPOs, $RIPO_t$ is first-day returns of IPOs, P_t^{D-ND} is dividend premium, $ESNI_t$ is equity shares in new issues, BCI_t is business confidence index, CCI_t consumer confidence index. Additionally, t and t-1 are representing level and lagged values of each variable.

Table 6: Principal components

	Eigen values		Difference	Proportion explained		Cumulative proportion explained	
Panel A: Variance in principal components							
sC_1	2.6628		0.9696	0.3804		0.3804	
sC_2	1.6932		0.6501	0.2419		0.6223	
sC_3	1.0431		0.3787	0.149		0.7713	
sC_4	0.6644		0.1941	0.0949		0.8662	
sC_5	0.4703		0.2098	0.0672		0.9334	
sC_6	0.2604		0.0549	0.0372		0.9706	
sC_7	0.2056		-	0.0294		1.0000	
Panel B: Variance form variables							
Variable	sC_1	sC_2	sC_3	sC_4	sC_5	sC_6	sC_7
$TURN_{t-1}$	0.5558	0.0407	-0.1678	0.0900	0.0853	0.2558	-0.7619
$NIPO_t$	0.3814	-0.4458	-0.2494	0.2069	0.4980	0.2691	0.4800
$RIPO_{t-1}$	0.2590	-0.1400	0.7375	-0.5016	0.3309	-0.0856	-0.0319
P_t^{D-ND}	0.5144	0.2153	-0.2218	-0.0243	-0.0400	-0.7811	0.1660
$ESNI_t$	0.0578	0.5126	0.4433	0.6849	0.2409	0.0395	0.0931
BCI_{t-1}	0.3418	0.5238	-0.0553	-0.3585	-0.3025	0.4922	0.3786
CCI_t	0.3062	-0.4434	0.3420	0.3151	-0.6957	0.0279	0.0931

Notes: Table 6 is representing the results of sPCA. Where, Panel A is representing the eigen values, differences between current eigen value and next eigen value, the proportion of all the proxies explained by each principal component in percentage and cumulative percentage of explanation in components. Additionally, $sC_1$to sC_7 are representing the number of scaled principal components.

Following the study by Baker and Wurgler (2007), first principal component (sC_1) generated by sPCA is used as IPO sentiment index ($\mathrm{SENT}_t^{\mathrm{sPCA}}$). The first principal component carries 38.04% of the explanation in the scaled proxy variables, leading author to conclude that first captures significant portion of the shared variation. Table 7 below is representative of correlation matrix, representing the correlation of $SENT^{sPCA}$ with proxies of sentiments. Where, all the proxies are positively correlated with $SENT^{sPCA}$ depicting that the index is explaining all the proxies in same direction instead of different directions compared to basic PCA index in Table 3.

Table 7: Correlation of $SENT^{sPCA}$

	$SENT_t^{sPCA}$	$TURN_{t-1}$	$NIPO_t$	$RIPO_{t-1}$	P_t^{D-ND}	$ESNI_t$	BCI_{t-1}	CCI_t
$SENT_t^{sPCA}$	1.0000							
$TURN_{t-1}$	0.9070	1.0000						
$NIPO_t$	0.6224	0.5526	1.0000					
$RIPO_{t-1}$	0.4227	0.2272	0.1763	1.0000				
P_t^{D-ND}	0.8393	0.7338	0.3575	0.1513	1.0000			
$ESNI_t$	0.0943	0.0820	-0.2795	0.0672	0.1618	1.0000		
BCI_{t-1}	0.5578	0.4916	-0.0821	0.1280	0.5962	0.2966	1.0000	
CCI_t	0.4996	0.3410	0.4441	0.3649	0.2065	-0.0974	-0.0995	1.0000

Notes: Table 7 is representing detailed correlation of $SENT_t^{sPCA}$ sentiment index generated by sPCA method with $TURN_{t-1}$ lag of share turnover, $NIPO_t$ number of IPOs, $RIPO_{t-1}$ lag of closing returns of IPOs day, P_t^{D-ND} dividend premium, $ESNI_t$ equity shares in new issues, BCI_{t-1} lag of business confidence index and CCI_t consumer confidence index.

4.2.1(c) Partial Least Squares Analysis

Here, we used first lag of sentiment factor as dependent variables. We use the one-quarter-ahead of initial returns as the target variable and the orthogonalise sentiment proxies $(X_1, X_2, \dots, X_N)$ to construct market sentiment using PLS method are as follows:

Step 1: Let $(X_{1,t}, X_{2,t}, \dots, X_{N,t})$be the $T \times N$ matrix of orthogonalise sentiment proxies. The key idea is to use the PLS method to extract the unobservable IPO investor sentiment $SENT_t$ from the cross-section according to its covariance with future initial returns. In the first step, N time-series regressions are conducted.

$$X_{i,t-1} = \pi_{i,0} + \pi_i(MAIR_t) + \mu_{i,t-1}; \qquad where\ i = 1,2,\dots,T \tag{7}$$

Table 8: Predictions for each sentiment proxy for PLS

	$TURN_t$	$NIPO_t$	$RIPO_t$	P_t^{D-ND}	$ESNI_t$	BCI_t	CCI_t
$\widehat{\pi_\iota}$	0.2315	5.2514	3.0125	-6.0614	-1.2344	-18.9348	45.8383
	(0.87)	(0.95)	(5.48)	(-1.38)	(-0.27)	(-0.89)	(2.90)
$R^2(\%)$	0.94	1.10	27.07	2.30	0.09	0.98	9.39

Notes: Table 8 is representing results of estimated slopes of MAIR as π_i. The dependent variable used in all regression models is lag of variables mentioned as columns header. Values in parenthesis are *t*-statistics and R-squared is represented in percentage.

The coefficient π_i presents how each sentiment measure.

Step 2: We use the estimated loading from Step 1, and $x_{i,t}$ to run T cross-sectional regressions: for each period t, we run a cross-sectional regression of $x_{i,t}$ on the corresponding loading $\hat{\pi}$i.

$$x_i = c_i + \widehat{\pi_\iota} SENT^{PLS} + v_i; \qquad where\ i = 1,2,\dots,N \tag{8}$$

sentiment index we mentioned above. This approach uses time t+1 initial returns to extract $SENT^{PLS}$ from individual sentiment proxies, therefore, $SENT^{PLS}$ is only relevant for predicting initial returns and separated from the component that is irrelevant for predictions.

4.3 Robustness Checks on Construction of MIMSI

The significance of robustness checks in this study is to maintain consistency in variable selection. Besides, the conduct robustness checks is to ensure the validity and robustness of results. Table 9 shows the robustness checks for the construction of MIMSI using PCA, sPCA and PLS methods.

Table 9: Robustness checks in the construction of MIMSI using PCA, sPCA and PLS methods

	(1)	(2)	(3)	(4)
	$TURN_t$	$NIPO_t$	$RIPO_t$	P_t^{D-ND}
Panel A: Robustness for PCA				
Term	-1.2222***	-.1498***	-.9327***	.3299***
	(-4.67)	(-19.52)	(-8.54)	(38.29)
Constant	-.8261***	.9200***	-.5524***	-4.0682***
	(-12.07)	(8.68)	(-7.39)	(-44.60)
Panel B: Robustness for sPCA				
Term	1.2222***	.1498***	.9327***	-.3299***
	(4.67)	(19.52)	(8.54)	(-38.29)
Constant	.8261***	-.9200***	.5524***	4.0682***
	(12.07)	(-8.68)	(7.39)	(44.60)
Panel C: Robustness for PLS				
Term	-.1294	.0155***	.2152***	-.0411***
	(-.25)	(8.69)	(10.56)	(-15.65)
Constant	.8488***	.6625***	-.7760***	1.2473***
	(63.29)	(26.74)	(55.61)	(44.87)
Observations (N)	564	564	564	564

	(5)	(6)	(7)
	$ESNI_t$	BCI_t	CCI_t
Panel A: Robustness for PCA			
Term	.3826***	.0335***	-.0645***
	(4.48)	(12.38)	(-15.50)
Constant	-9.1795***	-4.0642***	5.9878***
	(-4.94)	(-15.31)	(13.42)
Panel B: Robustness for sPCA			
Term	-.3826***	-.0335***	.0645***
	(-4.48)	(-12.38)	(15.50)
Constant	9.1795***	4.0642***	-5.9878***
	(4.94)	(15.31)	(-13.42)
Panel C: Robustness for PLS			
Term	-.0859***	-.0086***	.0160***
	(-5.27)	(-18.92)	(23.81)
Constant	2.7151***	1.6768***	-.8577***
	(7.65)	(37.26)	(-11.87)
Observations (N)	564	564	564

4.4 Multiple Regression Model

Aggarwal and Conroy (2000); Barry and Jennings (1993); Bradley *et al.* (2009); Chorruk and Worthington (2010); and Schultz and Zaman (1994) used initial returns (IR), and market adjusted initial returns (MAIR) to measure short-run IPO share performance using the following equation:

Initial return:

$$\mathrm{IR_{it}} = \frac{P_{i1} - P_{i0}}{P_{i0}} \times 100 \tag{9}$$

where:

$\mathrm{IR_{it}}$ = the initial return of the stock$_i$ at period$_t$;
P_{i0} = the IPO offer price of the stock$_i$ as stated in the IPO prospectus; and
P_{i1} = the closing price of the stock$_i$ at the end of the first day of trading.

Market adjusted initial return:

$$\mathrm{MAIR_{it}} = \left(\frac{P_{i1} - P_{i0}}{P_{i0}} - \frac{MI_{i1} - MI_{i0}}{MI_{i0}}\right) \times 100 \tag{10}$$

where:

$\mathrm{MAIR_{it}}$ = the initial return of stock_i adjusted to the market effect of the corresponding stock exchange for period_t;

MI_{i0} = the closing price of the general market index of the stock exchange where stock_i is listed at offering day of the stock; and

MI_{i1} = the closing price of the general market index of the stock exchange where stock_i is listed at the end of the first day of trading.

The formula for computing IR does not account for changes in market conditions or stock exchanges, which could impact on the accuracy of the results. Consequently, many researchers opt for an alternative formula that adjusts the returns based on market fluctuations. This study adopts IPO's MAIR as a dependent variable to investigate the short-run IPO share performance. In addition, other independent variables and description are explained in Table 10.

Besides, this study estimates the IPO underpricing by using multiple regression model and binary regression model as set out in the following equation:

Ordinary least square regression model:

$$\begin{aligned}\mathrm{MAIR_{it}} = {} & \beta_0 + \beta_1\,\mathrm{SENT_{it}} + \beta_2\,\mathrm{IPOP_{it}} + \beta_3\,\mathrm{PRICE_{it}} + \beta_4\,\mathrm{OSIZE_{it}} + \beta_5\,\mathrm{ICOR_{it}} \\ & + \beta_6\,\mathrm{BOOK_{it}} + \beta_7\,\mathrm{FAGE_{it}} + \beta_8\,\mathrm{MVL_{it}} + \beta_9\,\mathrm{OVER_{it}} + \beta_{10}\,\mathrm{D_{UREPit}} \\ & + \beta_{11}\,\mathrm{D_{HOTit}} + \beta_{12}\,\mathrm{D_{BLISTit}} + \varepsilon_{it}\end{aligned} \tag{11}$$

where, $\mathrm{MAIR_{it}}$ is the market adjusted first-day initial returns of $\mathrm{firm_i}$. $\mathrm{SENT_{it}}$ is the Malaysian IPO market sentiment index was constructed using three different methods including PCA, sPCA, and PLS methods. $\mathrm{IPOP_{it}}$ is calculated as the period from opening to closing days of the offer (in calendar days). $\mathrm{PRICE_{it}}$ is calculated as the offer price of the IPO share. $\mathrm{OSIZE_{it}}$ is the natural log offer size calculated as total gross proceeds from the IPO. $\mathrm{ICOR_{it}}$ is calculated as the total issue costs relative to the total offer proceeds such as professional fees, brokers' fees, printing and other costs. $\mathrm{BOOK_{it}}$ is calculated as the total equity capital divided by the number of equity shares (equivalent to net assets per share). $\mathrm{FAGE_{it}}$ is calculated as the age of the firm since incorporation. $\mathrm{MVL_{it}}$ is calculated as the standard deviation of the daily FTSE Bursa Malaysia Kuala Lumpur Composite Index for the first one month (30 calendar days) prior to the IPO. $\mathrm{OVER_{it}}$ is calculated as the magnitude of response from investors to an IPO, which is estimated as the ratio of the application size to the issue size (in volume). $\mathrm{D_{UREPit}}$ {underwriter dummy equals '1' if the lead underwriter includes one of the Tier 1 financial institutions, CIMB Bank, Maybank and RHB Bank and '0' if otherwise}. $\mathrm{D_{HOTit}}$ {hot issue market was identified as issue year using IPO volume and first-day return, where number of IPOs and average first-day return are greater than the sample's average. Dummy variable, which denotes '1' for hot issue market and '0' for otherwise}. $\mathrm{D_{BLISTit}}$ {board listing is to determine Main Market (established listing company) and ACE Market (young and growing company). Dummy variable, which denotes '1' for Main Market and '0' for ACE Market}. β_0 is the intercept of the equation. ε_{it} is the error term of the equation.

Table 10: Summary of variables for short-run IPO share performance

Factors	Variables	Variables measurements	Authors (year)	Expected sign	Theory
Dependent variable	Market adjusted initial return (MAIR): First-day initial returns	$MAIR_{it} = \left(\frac{P_{i1} - P_{i0}}{P_{i0}} - \frac{MI_{i1} - MI_{i0}}{MI_{i0}}\right) \times 100$ MI_{i0} = the closing price of the general market index of the stock exchange where $stock_i$ is listed at offering day of the stock MI_{i1} = the closing price of the general market index of the stock exchange where $stock_i$ is listed at the end of the first day of trading	Aggarwal and Conroy (2000); Barry and Jennings (1993); Bradley *et al.* (2009); Chang *et al.* (2008); and Chorruk and Worthington (2010)	-	-
Independent variables	(i) Behavioral Characteristics				
	Malaysian IPO Market Sentiment Index (SENT)	Market sentiment constructed using PCA, sPCA, and PLS methods using sentiment proxies including share turnover, number of IPOs, first-day returns of IPOs, dividend premium, and equity shares in new issues, consumer confidence index, and business conditions index.	Firth *et al.* (2015); Boulton *et al.* (2011); Ritter and Welch (2002); and Song *et al.* (2014)	+ve	Ex-ante uncertainty / Signalling hypothesis
	(ii) Issue Characteristics				
	IPO period (IPOP)	Period from opening to closing days of the offer (in calendar days)	Lee *et al.* (1996); How (2000); How *et al.* (2007); and Ekkayokkaya and Pengniti (2012)	-ve	Winner's curse / Rock hypothesis
	Offer price (PRICE)	Offer price of the IPO share	Guo and Brooks (2008); Dimovski *et al.* (2011); Certo *et al.* (2001); and Kutsuna *et al.* (2008)	-ve	Ex-ante uncertainty / Signalling hypothesis
	Offer size (OSIZE)	Natural log of total gross proceeds from the IPO	Alanazi and Al-Zoubi (2015); and Yu and Tse (2005)	-ve	Ex-ante uncertainty hypothesis
	Issue cost ratio (ICOR)	Natural log of total issue costs relative to the total offer proceeds. Total issue costs such as professional fees, brokers' fees, printing and other costs	Ritter (1998); and Dimovski and Brooks (2004)	+ve	Ex-ante uncertainty hypothesis
	Underwriter reputation (UREP)	Underwriter dummy equals '1' if the lead underwriter includes one of the Tier 1 financial institutions, CIMB Bank, Maybank and RHB Bank and '0' if otherwise	Dimovski and Brooks (2004); and Aggarwal and Conroy (2000)	+ve	Ex-ante uncertainty / Signalling hypothesis

Table 10 *(continued)*

Factors	Variables	Variables measurements	Authors (year)	Expected sign	Theory
Independent variables	(iii) Firm Characteristics				
	Book value per share (BOOK)	Total equity capital divided by the number of equity shares (Equivalent to net assets per share)	Pukthuangthong Le and Varaiya (2007); and Klein (1996)	+ve	Signalling hypothesis
	Firm age (FAGE)	Age of the firm since incorporation	Ritter (1984); Kirkulak and Davis (2005); and Loughran *et al.* (1994)	-ve	Ex-ante uncertainty hypothesis
	(iv) Market Characteristics				
	Market volatility (MVL)	Standard deviation of the daily FTSE Bursa Malaysia Kuala Lumpur Composite Index for the first one month (30 calendar days) prior to the IPO	Omran (2005); and Paudyal *et al.* (1998)	+ve	Ex-ante uncertainty hypothesis
	Oversubscription ratio (OVER)	Indicates magnitude of response of the investors for an IPO. Estimated as the ratio of application size to the issue size (in volume)	Agarwal *et al.* (2008); Kandel *et al.* (1999); and Chowdhry and Sherman (1996)	+ve	Signalling / Ex-ante uncertainty / Winner's curse hypothesis
	Hot issue market (HOT)	Hot issue market was identified as issue year using IPO volume and first-day return, where number of IPOs and average first-day return are greater than the sample's average. Dummy variable, which denotes '1' for hot issue market and '0' for otherwise	Guo *et al.* (2008); Lowry *et al.* (2010); Samarakoon (2010); and Alli *et al.* (2010)	+ve	Ex-ante uncertainty / Window of opportunity hypothesis
	Board listing (BLIST)	Board listing is to determine Main Market (established listing company) and ACE Market (young and growing company). Dummy variable, which denotes '1' for Main Market and '0' for ACE Market	Chen et al. (2004); and Gounopoulos (2003)	-ve	Signalling / Ex-ante uncertainty hypothesis

4.5 Interaction Analysis

Additionally, interaction effects occur when the combined effect of two or more variables on a dependent variable differs from the sum of their individual effects. In other words, the relationship between one variable and the outcome is not constant but varies depending on the level or presence of another variable. It provides valuable insights into how variables related to each other.

To investigate whether the interaction terms may affect the regression result, the key determinant variables for short-run IPO share performance are extracted and added into the multiple regression model. The following is the multiple regression model with interaction terms:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \ldots + \beta_{10} X_{10} + \beta_{11} X_{11} + \beta_{12} X_{12} + \varepsilon_{it} \quad (12)$$

where Y_i is the predicted value of a dependent variable, in this case it refers to market sentiment (SENT), X_i is the key determinant of independent variables, β_i is the regression coefficients and ε_i = the error term of the model.

4.6 Binary Regression Model

The binary regression model holds greater significance for IPO investors compared to the multiple regression model due to several reasons. Firstly, it does not rely on assumptions of normal distribution and linearity. Secondly, it allows for the estimation of associated probabilities (risks) of determinants, which is particularly important given the dynamic nature of economic and financial factors in the market. Thirdly, the associated probability (risk) of a determinant, known as marginal probability, becomes crucial in identifying directional changes in IPO market performance. Lastly, the marginal probability can provide valuable information related to market timing, which is of utmost importance for investment decisions. However, binary regression models have generally received less attention in the IPO literature, including the specific context of Malaysia. Consequently, in order to identify the determinants of short-run IPO market performance, this study employed the logit regression model, which is binary regression model widely used in the field as set out in the following equation:

Logit regression model:

$$\left(\frac{P_i}{1-P_I}\right) = \beta_0 + \beta_1\,SENT_{it} + \beta_2\,IPOP_{it} + \beta_3\,PRICE_{it} + \beta_4\,OSIZE_{it} + \beta_5\,ICOR_{it} + \beta_6\,BOOK_{it} + \beta_7\,FAGE_{it} + \beta_8\,MVL_{it} + \beta_9\,OVER_{it} + \beta_{10}\,D_{UREPit} + \beta_{11}\,D_{HOTit} + \beta_{12}\,D_{BLISTit} + \varepsilon_{it} \quad (13)$$

Probit regression model:

$$P_i = \beta_0 + \beta_1\,SENT_{it} + \beta_2\,IPOP_{it} + \beta_3\,PRICE_{it} + \beta_4\,OSIZE_{it} + \beta_5\,ICOR_{it} + \beta_6\,BOOK_{it} + \beta_7\,FAGE_{it} + \beta_8\,MVL_{it} + \beta_9\,OVER_{it} + \beta_{10}\,D_{UREPit} + \beta_{11}\,D_{HOTit} + \beta_{12}\,D_{BLISTit} + \varepsilon_{it} \quad (14)$$

where, P_i = the probability of IPO underpricing occurs in the short-run IPO market, $-1 - P_i$ = the probability of IPO underpricing does not occur or the underperformance occurs in the short-run IPO market, $(\frac{P_i}{1-P_i})$ = the value of the odds ratios (in other words, the probability of occurring) for the event of IPO underpricing occurrence. The independent variables have the same explanation in Equation (2) above.

4.7 Marginal Probabilities Analysis

Additionally, marginal probability analysis was used to identify the directional changes between short-run underpricing and overpricing, due to change in probability (Δp) associated with the determinants. Marginal probabilities can be estimated only with the logit model because the logit model transforms the estimated function into a logistic probability using logistic distribution function. Following Maddala (2001) and Gujarati (2003), this study estimated the marginal probability (Δp) of each variable in the logit models as follows:

$$\Delta p = \beta_i\,P_i\,(1 - P_i) \quad (15)$$

where P_i = the probability of IPO underpricing occurs in the short-run market, Δp = marginal probability, β_i = coefficient of each explanatory variable and X_i = the average value of each explanatory variable.

5. Results and Discussion

As shown in Table 11, the findings show that the IPOs are underpriced across all the time periods from January 2000 to December 2020. This means that investors earned positive initial returns by investing in IPOs. The highest level of underpricing is recorded in 2000 where IPO's firm is on average underpriced at 63.67% in year 2000. The underpricing from year 2005 onwards shows a decreasing trend ranges from 8.52% to 36.68%. This implies that Malaysian investors could earn initial returns if they bought the IPO share at the offer price and sell it on the market price at the first trading day. This evidence is consistent with the previous Malaysian studies (Dawson, 1987; Yong and Isa, 2003; Mohamed *et al.*, 1994; Paudyal *et al.*, 1998; Jelic *et al.*, 2001). Nevertheless, the degree of underpricing varies significantly across markets. Ritter (1998) pointed out that the average initial return of new listings in 33 countries ranged from 13.60% to 388.00% in the developing market and 4.20% to 54.40% in the developed market. Initial underpricing of new listings on Bursa Malaysia was ranked among the top five in the list. It highlights that a more developed market registers a lower level of underpricing than an emerging market.

Table 11: IPO underpricing segmentation by listing year, industry, and board listing

By listing year	N	MAIR	*t*-statistic
2000	38	.6367	8.4866***
2001	20	.2369	1.9658***
2002	51	.1840	3.9953***
2003	58	.4006	6.4846***
2004	72	.3974	6.3379***
2005	75	.1629	2.6466***
2006	35	.2487	3.8091***
2007	22	.3233	4.3943***
2008	23	.2578	0.6702***
2009	14	.1255	2.2059***
2010	27	.0852	1.3657***
2011	25	.2280	2.9759***
2012	14	.3525	1.2384***
2013	16	.2656	2.7523***
2014	13	.1983	2.7815***
2015	9	.3051	2.6257***
2016	11	.1895	4.7333***
2017	10	.1466	3.7975***
2018	11	.3668	2.5991***
2019	15	.1590	1.6581***
2020	12	.3537	2.5165***
Overall	571	.2848	11.5416
By industry	N	MAIR	*t*-statistic
Industrial products & services	145	.2382	8.1487***
Trading & services	140	.3665	4.6781***
Technology	111	.3350	6.1291***
Consumer products & services	89	.2344	6.5240***
Property	23	.1433	2.2238***
Construction	22	.2310	3.6136***
Plantation	13	.1816	3.0421***
Financial services	10	.1104	1.8491***
Infrastructure	4	-.01599	-.1856***
Energy	2	.5862	1.4846***
Health care	1	-	-
Overall	571	.2848	11.5416
By board listing	N	MAIR	t-statistic
Main Market	364	.2467	8.3599***
ACE Market	207	.3518	8.0392***

Notes: Table 11 represents the year distribution of IPO underpricing for 571 Malaysian IPOs from January 2000 to December 2020. 'N' is the total number of firms per year, 'and 'MAIR' is market adjusted initial returns. *t*-statistic is given with significance level as follows: *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

For the industry sector, the highest IPO underpricing is recorded for energy industry where investors earned 58.62% returns on the first trading day followed by trading & services industry (36.65%), technology industry (33.50%), and industrial products & services (23.82%). However, the infrastructure industry generated significant negative initial returns of -1.59%. This indicates that on average investors lose the money by investing in IPO's belonging to the infrastructure industry. The industry distribution of IPO underpricing shows that, in Malaysia, industry performance varies in between 58.62% to -1.59% across different industries.

It can be observed that the phenomenon of IPO underpricing is greater in the ACE Market compared to the Main Market with MAIR of 35.18% and 24.67%, respectively. This means that investors can earn approximately 35.18% initial returns by investing in IPOs in the ACE Market.

Table 12 provides the estimation of equation at behavioral characteristics, issue characteristics, firm characteristics, and market characteristics for short-run IPO share performance determinants based on OLS regression model. Our result concludes that the behavioral characteristics plays a significant role in all models, followed by issue characteristics namely, offer price (PRICE), offer size (OSIZE), and issue cost ratio (ICOR). Further, our finding shows that Malaysian IPO market sentiment ($SENT^{PLS}$) is insignificant relates to the short-run IPO share performance with the appearance of market characteristics variables namely, hot issue market (HOT) and oversubscription ratio (OVER) which are commonly used as sentiment proxy in the past empirical study, Yong and Isa (2003), Derrien (2005) and Yong (2007), have outweighed the significance level of IPO market sentiment ($SENT^{PLS}$). This implies that the hot issue market (HOT) and oversubscription ratio (OVER) are absorbing some of the impact arising from these sentiment proxies.

Unlike PCA and sPCA methods, it shows that $SENT^{PCA}$ and $SENT^{sPCA}$ are significantly relates to short-run IPO share performance. Both $SENT^{PCA}$ and $SENT^{sPCA}$ have the same coefficients. $SENT^{sPCA}$ has adjusted for target variable, therefore the effects of $SENT^{sPCA}$ towards initial returns show negative as compared to $SENT^{PCA}$. For $SENT^{sPCA}$, even though we apply the market characteristics variables namely, hot issue market (HOT) and oversubscription ratio (OVER), it still shows significant results as compared to $SENT^{PCA}$ and $SENT^{PLS}$. Therefore, sPCA is a better method among these three methods. This is consistent with the study by Huang *et al.* (2022), Gong *et al.*, (2022), and Song *et al.*, (2023), sPCA is a more robust model for dimensionality reduction. Hence, it is giving more accurate results.

Our finding shows market sentiment (SENT) in all models has significantly relates to IPO underpricing. This statement is consistent with Leite (2005) state that the presence of sentiment investors in IPOs reduces the winner's curse problem (Rock's hypothesis) in the issue by increasing the relative probability for the least-informed (rational) investor to be allocated underpriced shares.

Besides, our finding shows that there is positive relationship between offer size (OSIZE) and IPO underpricing which implied that higher offer size can increase the ex-ante uncertainty on the newly listed firm among Malaysian investors. This contradicts with Ritter (1984), Corhay *et al.* (2002) report that a negative relationship between offer size and market return. They further explain that a smaller firm is subject to higher uncertainty and higher uncertainty in turn will generate greater differences in opinion, thus a negative relationship is expected for offer size (OSIZE).

Nonetheless, the investors always assume that companies which offered large size of IPO will have more guarantee towards their future financial performance. Therefore, issuers are encouraged to offer larger size to the investors, not only stabilise the offer price, but also raising more funds for company development. More firms have an incentive to go public following periods of high underpricing. This is because such periods are often associated with high investor enthusiasm and firms issue equity to take advantage of investors' optimism (Loughran, 1994; Baker and Wurgler, 2000; Ljungqvist and Wilhelm, 2003). Empirical evidence has proven otherwise, as argued by Lowry and Schwert (2002), if firms want to raise as much money as possible from their IPOs, it will only make sense that they would issue equity only when IPO underpricing is at the lowest.

Our finding also shows that there is a negative relationship between offer price (PRICE) and the degree of IPO underpricing. This is consistent with Benveniste and Busaba (1997) state that within the framework of fixed-price mechanism, offer price plays an important role in affecting investor demand during the pre-market period. The level of offer price has the potential of creating incidences of demand cascades (positive or negative) because the offer price is established without soliciting investor information. Additionally, Ljungqvist *et al.* (2006) state that it seems plausible that the presence of sentiment investors could lead to higher offer prices and a lower level of underpricing as rational issuers take advantage of them.

Last but not least, our finding shows that there is a negative relationship between issue costs ratio (ICOR) and IPO underpricing. However, there is no empirical evidence in Malaysia stock market which supports that issue costs ratio (ICOR) plays a significant factor in influencing the IPO underpricing.

The coefficient of each variable is given along with *t*-statistic in the parentheses. The *t*-statistic are computed by robust standard errors in order to avoid the heteroscedasticity problem. In OLS regression model, the F-statistics are used (instead of likelihood ratio (LR)) to evaluate the overall fitness of the models. The F-statistic result shows that OLS regression model as shown in Table 12, Model 4 are fit and significant at 1% level, which shows that all the models can be used for the analysis.

Table 13 provides the interaction analysis results between Malaysian IPO market sentiment with the key determinants independent variables with 5% significance level (in Table 12) i.e., SENT*PRICE, SENT*OSIZE, SENT*ICOR, and SENT*HOT.

However, when an interaction effect is considered, SENT*PRICE in all models appear to have no interaction effect. It implies that any changes in offer price (PRICE) will not influence the market sentiment (SENT). Additionally, the SENT^{PLS}*HOT has no interaction effect and this could be a consequence of the hot market (HOT) serving as a proxy for sentiment, absorbs some of the impact.

Overall, the interaction analysis results show that market sentiment (SENT) in all models interact significantly with offer size (OSIZE), issue cost ratio (ICOR), and hot market (HOT).

Table 12: Short-run IPO share performance determinants based on OLS with $SENT^{PCA}$, $SENT^{SPCA}$, and $SENT^{PLS}$

	PCA				sPCA				PLS			
	Dependent variable : MAIR				Dependent variable : MAIR				Dependent variable : MAIR			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Independent variables	Behavioral	Behavioral-and-Issue	Behavioral-Issue-and-Firm	(Overall) Behavioral-Issue-Firm-and-Market	Behavioral	Behavioral-and-Issue	Behavioral-Issue-and-Firm	(Overall) Behavioral-Issue-Firm-and-Market	Behavioral	Behavioral-and-Issue	Behavioral-Issue-and-Firm	(Overall) Behavioral-Issue-Firm-and-Market
SENT	.297	.554***	.551***	.381**	-.297	-.554***	-.551***	-.381***	-1.836***	-1.850***	-1.809***	-.486
	(1.49)	(2.77)	(2.76)	(2.24)	(-1.49)	(-2.77)	(-2.76)	(-2.24)	(-2.62)	(-2.70)	(-2.64)	(-.84)
IPOP		-.000408	-.00643	-.00176		-.000408	-.000643	-.00176		-.00143	-.00164	-.00205
		(-.10)	(-.15)	(-.51)		(-.10)	(-.15)	(-.51)		(-.34)	(-.39)	(-.59)
PRICE		-.0407***	-.0387***	-.0227***		-.0407***	-.0387***	-.0227**		-.0347***	-.0327***	-.0189***
		(-4.54)	(-4.30)	(-2.89)		(-4.54)	(-4.30)	(-2.89)		(-4.03)	(-3.79)	(-2.45)
OSIZE		.0449***	.0504***	.0700***		.0449***	.0504***	.0700***		.0457***	.0510***	.0700***
		(2.79)	(3.10)	(5.01)		(2.79)	(3.10)	(5.01)		(2.83)	(3.12)	(4.97)
ICOR		-.0792***	-.0734***	-.0748***		-.0792***	-.0734***	-.0748***		-.0771***	-.0715***	-.0750***
		(-5.63)	(-5.12)	(-6.18)		(-5.63)	(-5.12)	(-6.18)		(-5.47)	(-4.98)	(-6.17)
UREP		-.0121	.0167	-.0122		-.0121	.0167	-.0122		-.0191	.000903	-.00106
		(-.20)	(.27)	(-.24)		(-.20)	(.27)	(-.24)		(-.32)	(.15)	(-.21)
BOOK			-.0991*	-.0252			-.0991*	-.0252			-.0951	-.0179
			(-1.60)	(-.42)			(-1.60)	(-.42)			(-1.53)	(-.30)
FAGE			-.00284	.000891			-.00284	.000891			-.00282	.000763
			(-1.20)	(.45)			(-1.20)	(.45)			(-1.19)	(-.39)
MVL				.0281				.0281				.0526
				(.37)				(.37)				(.70)
OVER				.000826*				.000826*				.00102**
				(1.59)				(1.59)				(1.99)
HOT				.681***				.681***				.672***
				(13.90)				(13.90)				(13.58)
BLIST				-.0749				-.0749				-.0789
				(-1.31)				(-1.31)				(-1.37)
Constant	.241***	.662***	.579***	-.0405	.241***	.662***	.579***	-.0405	.230***	.631***	.553***	-.0402
	(8.16)	(2.41)	(2.09)	(-.17)	(8.16)	(2.41)	(2.09)	(-.17)	(8.00)	(2.28)	(1.98)	(-.16)
F-statistics (F)	2.21	9.27***	7.54***	28.08***	2.21	9.27***	7.54***	28.08***	6.88***	9.19***	7.45***	27.48***
R-squared (R^2)	.0044	.1008	.1088	.4075	.0044	.1008	.1088	.4075	.0135	.1001	.1076	.4023
Adjusted R^2	.0024	.0899	.0944	.3930	.0024	.0899	.0944	.3930	.0115	.0892	.0932	.3876
Observations (N)	503	503	503	503	503	503	503	503	503	503	503	503

Notes: Table 12 shows the short-run IPO share performance at each level of behavioral-issue-firm-and-market characteristics by using OLS regression model. The above table consists of four models: Model 1 consist of behavioral characteristics, Model 2 consist of behavioral-and-issue characteristics, Model 3 consist of behavioral-issue-and-firm characteristics, Model 4 consist of behavioral-issue-firm-and-market characteristics (overall). The dependent variable dichotomous takes the value of '1' if the firm is underpriced and takes the value '0' if the firm is overpriced. *t*-statistic is given with significance level as follows: *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Table 13: Short-run IPO share performance interaction analysis between SENT with PRICE, OSIZE, and HOT

Independent variables	PCA Dependent variable : MAIR				sPCA Dependent variable : MAIR				PLS Dependent variable : MAIR			
	Model 1 SENT*PRICE	Model 2 SENT*OSIZE	Model 3 SENT*ICOR	Model 4 SENT*HOT	Model 1 SENT*PRICE	Model 2 SENT*OSIZE	Model 3 SENT*ICOR	Model 4 SENT*HOT	Model 1 SENT*PRICE	Model 2 SENT*OSIZE	Model 3 SENT*ICOR	Model 4 SENT*HOT
SENT	.2740	-10.2100***	8.9100***	.1380	-.2740	10.2100***	-8.910***	-.1380	-.350	20.67***	-24.92***	-.380
	(1.43)	(-5.26)	(12.08)	(.70)	(-1.43)	(5.26)	(-12.08)	(-.70)	(-.55)	(3.44)	(-7.96)	(-.58)
IPOP	-.00191	.00110	-.00225	-.00138	-.000191	.00110	-.00225	-.00138	-.00207	-.00197	-.000741	-.00210
	(-.55)	(.32)	(-.74)	(-.40)	(-.55)	(.32)	(-.74)	(-.40)	(-.59)	(-.57)	(-.23)	(-.60)
PRICE	-.0443**	-.0211***	-.0171**	-.0206***	-.0443**	-.0211***	-.0171**	-.0206***	-.0214**	-.0184**	-.0187***	-.0187**
	(-2.29)	(-2.76)	(-2.45)	(-2.61)	(-2.29)	(-2.76)	(-2.45)	(-2.61)	(-2.30)	(-2.42)	(-2.58)	(-2.43)
OSIZE	.0733***	.0462***	.0448***	.0677***	0.0733***	.0462***	.0488***	.0677***	.0705***	.0339**	.0746***	.0697***
	(5.15)	(3.24)	(3.58)	(4.86)	(5.15)	(3.24)	(3.58)	(4.86)	(4.99)	(1.96)	(5.62)	(4.94)
ICOR	-.0760***	-.0594***	-.0494***	-.0725***	-.0760***	-.0594***	-.0494***	-.0725***	-.0752***	-.0760***	-.0328***	-.0747***
	(-6.26)	(-4.91)	(-4.53)	(-6.00)	(-6.26)	(-4.91)	(-4.53)	(-6.00)	(-6.18)	(-6.32)	(-2.60)	(-6.12)
UREP	-.0124	-.0227	-.0000101	-.00883	-.0124	-.0227	-.0000101	-.00883	-.0113	.00117	-.00279	-.0115
	(-.24)	(-.46)	(-.00)	(-.17)	(-.24)	(-.46)	(-.00)	(-.17)	(-.22)	(.23)	(-.58)	(-.22)
BOOK	-.0163	-.0419	-.0129	-.0292	-.0163	-.0419	-.0129	-.0292	-.00178	-.0109	-.0196	-.0188
	(-.27)	(-.72)	(-.24)	(-.49)	(-.27)	(-.72)	(-.24)	(-.49)	(-.30)	(-.18)	(-.35)	(-.31)
FAGE	.000819	.000488	.000544	.000486	.000819	.000488	.000544	.000486	.000739	.000101	.000311	.000755
	(.42)	(.26)	(.31)	(.25)	(.42)	(.26)	(.31)	(.25)	(.37)	(.52)	(.17)	(.38)
MVL	.0389	-.000531	.0529	.0394	.0389	-.000531	.0529	.0394	.0610	.0566	.0764	.0517
	(.51)	(-.01)	(.79)	(.52)	(.51)	(-.01)	(.79)	(.52)	(.79)	(.76)	(1.08)	(.69)
OVER	.000858	.00119**	.000960**	.000690	.000858	.00119**	.000960**	.000690	.00103**	.000994*	.00114**	.00101**
	(1.65)	(2.33)	(2.09)	(1.32)	(1.65)	(2.33)	(2.09)	(1.32)	(2.00)	(1.95)	(2.35)	(1.96)
HOT	.6790***	.6710***	.6560***	.628***	.6790***	.6710***	.6560***	.628***	.672***	.665***	.662***	.662***
	(13.84)	(14.09)	(15.15)	(11.71)	(13.84)	(14.09)	(15.15)	(11.71)	(13.57)	(13.60)	(14.21)	(11.64)
BLIST	-.0702	-.0777	-.0498	-.0747	-.0702	-.0777	-.0498	-.0747	-.0693	-.0740	-.0792	-.0764
	(-1.22)	(-1.39)	(-.98)	(-1.31)	(-1.22)	(-1.39)	(-.98)	(-1.31)	(-1.20)	(-1.29)	(-1.37)	(-1.33)
SENT*PRICE	.0831	-	-	-	-.0831	-	-	-	-.0766	-	-	-
	(1.22)				(-1.22)				(-.48)			
SENT*OSIZE	-	.6020***	-	-	-	-.0602***	-	-	-	-1.206***	-	-
		(5.47)				(-5.47)				(-3.53)		
SENT*ICOR	-	-	-.6000***	-	-	-	.6000***	-	-	-	1.693***	-
			(-11.81)				(11.81)				(7.92)	
SENT*HOT(1)	-	-	-	.8660**	-	-	-	-.8660**	-	-	-	-.452
				(2.39)				(-2.39)				(-.34)
SENT*HOT(0)	-	-	-	-	-	-	-	-	-	-	-	-
Constant	-.0698	.154	.00131	-.0242	-.0698	.154	.00131	-.0242	-.0470	.592***	-.760***	-.0368
	(-.29)	(.65)	(.01)	(-.10)	(-.29)	(.65)	(.01)	(-.10)	(-.19)	(1.97)	(-3.07)	(-.15)
F-statistics (F)	26.06***	29.76***	43.98***	26.61***	26.06***	29.76***	43.98***	26.61***	25.81***	26.16***	25.33***	24.68***
R-squared (R^2)	.4093	.4417	.5390	.4144	.4093	.4417	.5390	.4144	.4069	.4102	.4024	.4145
Adjusted R^2	.3936	.4268	.5267	.3988	.3936	.4268	.5267	.3988	.3911	.3945	.3865	.3977
Observations (N)	503	503	503	503	503	503	503	503	503	503	503	503

Notes: Table 13 shows the short-run IPO share performance interaction analysis between sentiment with key determinants short-run IPO share performance. The above table consists of four interactions: Model 1 consist of SENT*PRICE, Model 2 consist of SENT*OSIZE, Model 3 consist of SENT*ICOR, and Model 4 consist of SENT*HOT. *t*-statistic is given with significance level as follows: *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

The binary regression models have an advantage of being more realistic than OLS regression model because of its dichotomous in nature. Moreover, binary regression models do not assume the data normality assumption of regressions. Table 14 shows the frequency of dummy for short-run dependent variable, i.e. MAIR. In running the binary regression model, hot market (HOT) has been dropped from independent variables due to the lack of number of observations, which prevents the generation of meaningful binary results.

Table 14: Frequency of dummy for short-run dependent variable

Dummy variable for MAIR	Observations (N)	
IPO underpricing denotes '1'	394	78.33%
IPO overpricing denotes '0'	109	21.67%
Total	503	100.00%

Based on OLS regression model, the key determinants such as market sentiment (SENT), offer price (PRICE), offer size (OSIZE), and issue cost ratio (ICOR) are within the realm of IPOs as discussed in Table 12. Separately, in binary regression model, the significant key determinant are offer price (PRICE), offer size (OSIZE), underwriter reputation (UREP), book value per share (BOOK), and oversubscription ratio (OVER), distinct from the factors considered in an OLS regression model, influencing IPO underpricing in Malaysia. This means in the event of IPO underpricing, investors also examine the underwriter reputation and book value per share of IPO firms.

The overall result of binary regression model in terms of *t*-statistic and significance level of each parameter are relatively better than the probit model. In binary regression, the likelihood ratio (LR) tests are used (instead of F-statistic) to evaluate the overall fitness of the models. The LR result shows that all the models (in Table 15 and Table 16) are fit and significant at 1% level, which shows that all the models can be used for the analysis.

Marginal analysis was used to identify the most important explanatory variables that contributed to the change in the short-run share performance of the Malaysian IPOs. Marginal analysis measures the likelihood of change in probability (Δp) associated with short-run share performance due to a change in the explanatory variables. Table 17 shows the calculated changes in probability associated with the short-run IPO share performance based on probit regression model. For the logit regression model, no marginal probability analysis is present in this study because the result of probit regression model is similar or close to the result of logit regression model.

As shown in Table 17, there is no significant explanatory for market sentiment (SENT). The marginal analysis indicates that offer price (PRICE), underwriter reputation (UREP), and oversubscription ratio (OVER) are the most important explanatory variables (with 5% significance level) in Malaysian IPO market as compared with the others due to the highest probability associated with IPO underpricing used to measure the short-run IPO share performance. The results are consistently apply in all models.

Table 15: Short-run IPO share performance determinants based on logit with $SENT^{PCA}$, $SENT^{SPCA}$, and $SENT^{PLS}$

	PCA				sPCA				PLS			
	Probability occurrence : $\ln(\frac{P_i}{1-P_i})$				Probability occurrence : $\ln(\frac{P_i}{1-P_i})$				Probability occurrence : $\ln(\frac{P_i}{1-P_i})$			
Independent variables	Model 1 Behavioral	Model 2 Behavioral-and-Issue	Model 3 Behavioral-Issue-and-Firm	Model 4 (Overall) Behavioral-Issue-Firm-and-Market	Model 1 Behavioral	Model 2 Behavioral-and-Issue	Model 3 Behavioral-Issue-and-Firm	Model 4 (Overall) Behavioral-Issue-Firm-and-Market	Model 1 Behavioral	Model 2 Behavioral-and-Issue	Model 3 Behavioral-Issue-and-Firm	Model 4 (Overall) Behavioral-Issue-Firm-and-Market
SENT	-.1330	.8730	.8280	-.7320	.1330	-.8730	-.8280	.7320	-4.0070	-4.1510	-4.0320	-.0469
	(-.16)	(1.00)	(.94)	(-.68)	(.16)	(-1.00)	(-.94)	(.68)	(-1.41)	(-1.40)	(-1.35)	(-.01)
IPOP		.0255	.0249	.0319		.0255	.0249	.0319		.0229	.0225	.0317
		(1.37)	(1.34)	(1.51)		(1.37)	(1.34)	(1.51)		(1.23)	(1.21)	(1.50)
PRICE		-.1380***	-.1470***	-.0896**		-.1380***	-.1470***	-.0896**		-.1300***	-.1390***	-.0976**
		(-3.76)	(-3.81)	(-2.14)		(-3.76)	(-3.81)	(-2.14)		(-3.75)	(-3.82)	(-2.41)
OSIZE		.1220	.0917	.1990*		.1220	.0917	.1990*		.1280	.0967	.2040*
		(1.40)	(1.07)	(1.66)		(1.40)	(1.07)	(1.66)		(1.46)	(1.13)	(1.74)
ICOR		-0.1130	-.1190	-.1950		-.1130	-.1190	-.1950		-.1070	-.1140	-.2000
		(-1.14)	(-1.28)	(-1.35)		(-1.14)	(-1.28)	(-1.35)		(-1.09)	(-1.23)	(-1.42)
UREP		.7570**	.6140**	.7430**		.7570**	.6140**	.7430**		.7320**	.5870**	.7270**
		(2.54)	(2.01)	(2.24)		(2.54)	(2.01)	(2.24)		(2.45)	(1.91)	(2.20)
BOOK			.6690**	.8900**			.6690**	.8900**			.6700**	.8870**
			(2.16)	(2.29)			(2.16)	(2.29)			(2.16)	(2.27)
FAGE			-.0002	.0129			-.0002	.0012			-.0003	.0013
			(-.02)	(1.11)			(-.02)	(1.11)			(-.03)	(1.21)
MVL				.5210				.5210				.4530
				(1.09)				(1.09)				(.97)
OVER				.0435***				.0435***				.0425***
				(4.53)				(4.53)				(4.46)
BLIST				.4230				.4230				.4120
				(1.25)				(1.25)				(1.22)
Constant	1.2960***	.4590	.8170	-2.1330*	1.2960***	.4590	.8170	-2.1330*	1.2280***	.3050	.6770	-2.1360*
	(10.70)	(.40)	(.68)	(-1.60)	(10.70)	(.40)	(.68)	(-1.60)	(10.70)	(.26)	(.55)	(-1.59)
Likelihood ratio (LR)	-263.148	-249.225	-246.684	-216.840	-263.148	-249.225	-246.684	-216.840	-262.170	-248.746	-246.206	-217.093
Chi^2	.0300	27.38***	32.471***	92.15***	.0300	27.38***	32.47***	92.15***	1.98	28.34***	33.42***	91.65***
Pseudo R^2	.00205	.0521	.0617	.1753	.0001	.0521	.0617	.1753	.0038	.0539	.0636	.1743
Observations (N)	503	503	503	503	503	503	503	503	503	503	503	503

Notes: Table 15 shows the short-run IPO share performance at each level of behavioral-issue-firm-and-market characteristics by using logit regression model. The above table consists of four models: Model 1 consist of behavioral characteristics, Model 2 consist of behavioral-and-issue characteristics, Model 3 consist of behavioral-issue-and-firm characteristics, Model 4 consist of behavioral-issue-firm-and-market characteristics (overall). The dependent variable dichotomous takes the value of '1' if the firm is underpriced and takes the value '0' if the firm is overpriced. *t*-statistic is given with significance level as follows: *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Table 16: Short-run IPO share performance determinants based on probit with $SENT^{PCA}$, $SENT^{SPCA}$, and $SENT^{PLS}$

	PCA				sPCA				PLS			
	Probability occurrence : P_i				Probability occurrence : P_i				Probability occurrence : P_i			
Independent variables	Model 1 Behavioral	Model 2 Behavioral-and-Issue	Model 3 Behavioral-Issue-and-Firm	Model 4 (Overall) Behavioral-Issue-Firm-and-Market	Model 1 Behavioral	Model 2 Behavioral-and-Issue	Model 3 Behavioral-Issue-and-Firm	Model 4 (Overall) Behavioral-Issue-Firm-and-Market	Model 1 Behavioral	Model 2 Behavioral-and-Issue	Model 3 Behavioral-Issue-and-Firm	Model 4 (Overall) Behavioral-Issue-Firm-and-Market
SENT	-.0757	.5250	.4960	-.4470	.0757	-.5250	-.4960	.4470	-2.2730	-2.2860	-2.2410	.0168
	(-.16)	(1.03)	(.97)	(-.71)	(.16)	(-1.03)	(-.97)	(.71)	(-1.39)	(-1.34)	(-1.31)	(.09)
IPOP		.0142	.0137	.0187		.0142	.0137	.0187		.0126	.0121	.0185
		(1.32)	(1.27)	(1.47)		(1.32)	(1.27)	(1.47)		(1.17)	(1.12)	(1.45)
PRICE		-.0828***	-.0886***	-.0554**		-.0828***	-.0886***	-.0554**		-.0776***	-.0838***	-.0603**
		(-3.89)	(-4.04)	(-2.27)		(-3.89)	(-4.04)	(-2.27)		(-3.84)	(-4.03)	(-2.56)
OSIZE		.0705	.0544	.1180		.0705	.0544	.1180		.0723	.0564	.1210
		(1.45)	(1.13)	(1.71)		(1.45)	(1.13)	(1.71)		(1.49)	(1.18)	(1.77)
ICOR		-.0648	-.0704	-.1170		-.0648	-.0704	-.1170		-.0609	-.0668	-.1200
		(-1.19)	(-1.36)	(-1.41)		(-1.19)	(-1.36)	(-1.41)		(-1.13)	(-1.03)	(-1.47)
UREP		.4270***	.3520**	.4460**		.427***	.352**	.4460**		.4120***	.3360**	.4390**
		(2.63)	(2.12)	(2.30)		(2.63)	(2.12)	(2.30)		(2.54)	(2.01)	(2.26)
BOOK			.3930**	.5380**			.3930**	.5380**			.3960**	.5330**
			(2.12)	(2.40)			(2.28)	(2.40)			(2.30)	(2.37)
FAGE			.0002	.0084			.0002	.0084			.00007	.00912
			(.03)	(1.19)			(.03)	(1.19)			(.01)	(1.30)
MVL				.3170				.3170				.2780
				(1.12)				(1.12)				(.99)
OVER				.0261***				.0261***				.0254***
				(4.79)				(4.79)				(4.74)
BLIST				.2600				. .2600				.2550
				(1.28)				(1.28)				(1.24)
Constant	.7900***	.3100	.5120	-1.2690	.7900***	.3100	.5120	-1.269	.7500***	.2380	.4410	-1.2570
	(11.31)	(.46)	(.76)	(-1.68)	(11.31)	(.46)	(.76)	(-1.68)	(11.18)	(.35)	(.65)	(-1.66)
Likelihood ratio (LR)	-263.148	-249.185	-246.414	-216.061	-263.148	-249.185	-246.414	-216.061	-262.192	-248.817	-246.020	-216.406
Chi^2	.0300	27.46***	33.01***	93.71***	.0300	27.46***	33.01***	93.71***	1.94	28.20***	33.79***	93.02***
Pseudo R^2	.0000	.0522	.0628	.1782	.0000	.0522	.0628	.1782	.0037	.0536	.0643	.1769
Observations (N)	503	503	503	503	503	503	503	503	503	503	503	503

Notes: Table 16 shows the short-run IPO share performance at each level of behavioral-issue-firm-and-market characteristics by using probit regressions. The above table consists of four models: Model 1 consist of behavioral characteristics, Model 2 consist of behavioral-and-issue characteristics, Model 3 consist of behavioral-issue-and-firm characteristics, Model 4 consist of behavioral-issue-firm-and-market characteristics (overall). The dependent variable dichotomous takes the value of '1' if the firm is underpriced and takes the value '0' if the firm is overpriced. *t*-statistic is given with significance level as follows: *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

Table 17: The change in probability (Δp) due to a change in explanatory

	Model 1		Model 2		Model 3	
(Overall) behavioral-issue-firm-and-market	Change in probability	p-value	Change in probability	p-value	Change in probability	p-value
$SENT^{PCA}$	-0.1303	0.4940	-	-	-	-
$SENT^{sPCA}$	-	-	0.1303	0.4940	-	-
$SENT^{PLS}$	-	-	-	-	-0.0083	0.9890
IPOP	0.0056	0.1260	0.0056	0.1260	0.0056	0.1300
PRICE	-0.1595***	0.0028	-0.0159***	0.0280	-0.0174***	0.0130
OSIZE	0.0353**	0.0920	0.0353**	0.0920	0.0363**	0.0780
ICOR	-0.0347**	0.1740	-0.0347**	0.1740	-0.0355*	0.1520
UREP	0.1323***	0.0220	0.1323***	0.0220	0.1296***	0.0250
BOOK	0.1584**	0.0190	0.1584**	0.0190	0.1581**	0.0200
FAGE	0.0022	0.2650	0.0022	0.2650	0.0024	0.2240
MVL	0.0926**	0.2720	0.0926**	0.2720	0.0808	0.3310
OVER	0.0077***	0.0000	0.0077***	0.0000	0.0075***	0.0000
BLIST	0.0753	0.2060	0.0753	0.2060	0.7351	0.2190

Notes: Table 17 shows the change in probability due to a change in explanatory at (overall) behavioral-issue-firm-and-market characteristics by marginal analysis. The above table consists of three models: Model 1 with $SENT^{PCA}$, Model 2 with $SENT^{sPCA}$, and Model 3 with $SENT^{PLS}$. p-value is given with significance level as follows: *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

5. Conclusion

The study findings indicate that sentiment factor plays a significant role in explaining IPO underpricing. The results support the study done by Leite (2005) states that the presence of the sentiment investor reduces the winner's curse problem in the issue by increasing the relative probability for the least-informed (rational) investor to be allocated underpriced shares. A reduction in the participation probability of the sentiment investor increases the winner's curse problem in the issue, and this forces the issuer to reduce the IPO price and thereby leave more money on the table for investors. According to Rock (1986), the winner's curse argument accounts for the empirical evidence of underpricing in IPOs as compensation to uninformed investors for being allocated a disproportionately large fraction of overpriced issues. The findings also demonstrate there is significant impact of fundamental factors, particularly issue characteristics, on predicting IPO underpricing in Malaysia. Specifically, the offer price and issue cost ratio exhibit a negative correlation with IPO underpricing whereas offer size exhibits positive correlation with IPO underpricing, indicating their significant relationship in the context of Malaysian IPOs.

Nevertheless, this study has certain limitations. Our analysis primarily focused on examining the relationship between IPO underpricing and a composite measure of Malaysian IPO market sentiment using various proxies. in the future study, it would be interesting to explore the impact of individual investors' sentiment and retail investors' sentiment separately on IPO underpricing. This would help determine if the previously observed non-significant relationship between Malaysian IPO market sentiment and underpricing holds true for specific investor groups.

It is able to facilitate the country's long-term economic growth to be in line with Malaysia's national development plans. Combining with the reality of IPO underpricing in Malaysia stock market, this study puts forward some countermeasures and suggestions in order to weaken the problem of Malaysian IPO market in respect of market sentiment to promote a healthy development of Malaysia stock market. With this, the regulators are able to implement some forms of policy to pay more attention on investor education so as to reduce the proportion of investors who make decisions in selling or buying securities in the stock market without the support of professional advice, or fundamental and technical analysis. It helps investors to avoid psychology traps.

The findings of this study indicate that in the Malaysian IPO market, sentiment factors plays a significant role while fundamental factors, particularly issue characteristics have some degree of influence on predicting IPO underpricing. Given this insight, policymakers should concentrate on creating an environment that promotes transparency, efficient information dissemination, and fair valuation practices in the IPO market. This can help reduce information asymmetry and enhance market efficiency, ultimately leading to more accurate pricing of IPOs and minimising the extent of underpricing. Furthermore, since the study found that sentiment does interact with offer size (OSIZE), issue cost ratio (ICOR) and hot market (HOT), policymakers should monitor the impact of offer size (OSIZE), issue cost ratio (ICOR) and hot market (HOT) on market sentiment. Considering this interaction can be crucial in tailoring policies to address potential issues related to market sentiment and offer size (OSIZE), issue cost ratio (ICOR) and hot market (HOT), leading to more informed investment decisions and better IPO pricing outcomes.

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Stock Market Reactions to COVID-19 Announcement: Developed Versus Emerging Markets and Large Versus Small Firms

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Abstract: Research Question: How do stock markets around the world react to the World Health Organization (WHO)'s announcement on 11 March 2020 declaring COVID-19 as a global pandemic? Are there any differences in the reaction between developed and emerging markets? Are there any differences in the reaction between large and small firms? **Motivation:** There is a need to have a better understanding on whether different markets react differently to COVID-19 announcement. It is also important to know what factors make some markets more resilient than others. **Idea:** We envisage that developed markets, large firms, large stock markets, and markets with international exposure would demonstrate greater degree of resiliency than their respective counterparts. The results of this study would have profound implications on the ability of markets to withstand against global pandemic such as the COVID-19. **Data:** The sample consists of 30 world's largest stock markets based on their market capitalization on 31 December 2019, consisting of 18 developed markets and 12 emerging markets. For each market, we collect two indices: the main index representing large firms and the small-firm index representing small firms. **Method/Tools:** This is an event study using the market model and market-adjusted model to estimate abnormal returns. We then use the OLS and feasible GLS for cross-sectional regression analysis of the CARs. **Findings:** This study finds that the WHO's pandemic announcement negatively impacts stock market returns around the world in the short-term, while in the intermediate-term the markets recover some of the losses. Developed markets are less affected than emerging markets and large firms are better able to withstand the pandemic impact. The multiple regression results show that stock market size is positively related to CARs, and a country's international exposure is negatively associated with short-run CARs but is positively associated with intermediate-term CARs. **Contributions:** This study documents evidence of stock market reactions around the world to the announcement of the COVID-19 pandemic by the WHO. The study focuses on the difference in the reaction by developed versus emerging markets and by large versus small firms. Further, this study provides several institutional factors that influence the extent of the impact of the COVID-19 pandemic on share prices. Knowing these factors would be useful to governments, policymakers and companies to design strategies to

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help markets becoming more resilient to systemic risks such as the COVID-19 pandemic.

Keywords: Abnormal returns, COVID-19, event study, market model, stock market reaction.
JEL Classification: G10, G14, G18

1. Introduction

The World Health Organization (WHO) officially declared the COVID-19 outbreak to be a global pandemic on 11 March 2020. Since the outbreak, many studies have been conducted focusing on the economic impact of the pandemic. These studies include Fernandes (2020), He *et al.* (2020b), Sayed and Eledum (2021), Bannigidadmath *et al.* (2021), Harjoto *et al.* (2021a, 2021b), Liu *et al.* (2020a), Mishra *et al.* (2020), and Rahman *et al.* (2021). Generally, all these studies document the negative reaction of the stock markets to the announcements of the pandemic. These results are to be expected because the immediate reaction to the pandemic is economic and social lockdowns, thereby putting a break to all economic activities and business operations. However, very few studies explore the differences in the market reaction between developed and emerging countries, and between large and small firms.

The few studies that investigate the global pandemic impact on emerging countries include Huo and Qiu (2020), and Topcu and Gulal (2020). Topcu and Gulal (2020) indicate that the negative effect of COVID-19 is greatest in Asian emerging markets compared to European emerging markets. Harjoto *et al.* (2021b) show that investors from developed countries react differently compared to emerging countries. The evidence relating to how different sizes of firms react to COVID-19 is even more limited. Harjoto *et al.* (2021a) in the US and Rahman *et al.* (2021) in Australia find that small firms are more vulnerable to the COVID-19 pandemic compared to large firms. Harjoto *et al.* (2021a) analyse the response of MSCI World Index (MXWO), MSCI Emerging Markets Index (MXEF), and large and small cap index of US market due to the COVID-19 pandemic. They analyse the CARs of two event windows (-5, 5) and (-10, 10), and find that CAR of developed markets is positive while the CAR of emerging markets is negative. In another study, Harjoto *et al.* (2021b) use multiple regression to investigate whether COVID-19 cases and mortality rates are related to returns, volatility, and trading volume.

In this study we bring new evidence concerning the impact of the COVID-19 pandemic on stock markets around the world, focusing on developed versus emerging markets and on large versus small firms. Drawing inferences from institutional theory (Harjoto *et al.* 2021b), we argue that there are sound reasons to expect developed markets to be more resilient compared to emerging markets in facing the COVID-19 onslaught. Developed markets are generally characterised by traits such as large companies, good governance, market depth and width, price efficiency, large number of analysts and informed traders. These institutional characteristics necessarily lead to market strength and stability. Therefore, developed markets are expected to be able to withstand a global pandemic better than emerging markets. A similar argument can also be applied to large firms versus small firms; one may hypothesize that large firms are likely to be less impacted by the pandemic compared to smaller firms.

The objective of this study is to examine the impact on stock prices around the world of the 11 March 2020 WHO announcement declaring COVID-19 a global pandemic. Specifically, the study focuses on the differences in the market reaction in developed versus emerging countries as well as by firm size. We also analyse several factors that may influence the impact of COVID-19 on stock returns in the short-run and in the intermediate period. These factors include stages of a country's economic development, firm size, size of stock market, and the country's international trade exposure. This study contributes in the following ways. Firstly, it brings additional evidence on the impact of COVID-19 on stock markets. We focused on a single event, that is, the WHO announcement on 11 March 2020. We use event study methodology to trace market reactions before, during, and after the announcement; this allows us to identify the period markets are worse hit and the period recovery starts taking place. Secondly, we explore four factors that possibly determine the degree of impact of the announcement to stock markets. These factors are stages of a country's economic development, firm size, stock market size and a country's international trade exposure. We hope this will give us a deeper understanding on why some markets are more resilient than others facing the onslaught of the pandemic.

The rest of the paper is organized as follows. Section 2 discusses the literature review and describes in greater detail issues studied. Section 3 presents our data and methodology. This is followed by presentation and discussion of results in Section 4. Section 5 concludes the paper.

2. Literature Review

In general, prior studies on the COVID-19 pandemic report a negative reaction to the news of the pandemic. This is to be expected because the immediate reactions of many countries, such as economic lockdown, border closures, travel restrictions, and stay-at-home orders, brought economic activities to an immediate halt. Among the studies documenting a negative impact on stock markets are Fernandes (2020), Liu *et al.* (2020a), Huo and Qiu (2020), He *et al.* (2020a), Harjoto *et al.* (2021a, 2021b), Fernandes (2020), Bannigidadmath *et al.* (2021), Singh *et al.* (2020), Sayed and Eledum (2021), Mishra *et al.* (2020), and Rahman *et al.* (2021). These studies suggest that the degree of the negative effect of COVID-19 on the stock markets around the world varies. For example, Bannigidadmath *et al.* (2021) examine the top-25 most influenced economies in terms of the total number of infected and death cases. They find that country lockdown announcements have adverse effects on stock market returns, but only in 14 out of 25 countries, while in some countries stock market returns are statistically positive. This suggests that equity markets respond differently to the pandemic announcement and some markets are more resilient than others.

2.1 Developed Versus Emerging Markets

There are many reasons to expect that developed markets are better able to withstand the COVID-19 pandemic as opposed to emerging markets. One reason is to argue based on the institutional set-up of firms and markets. The institutional theory (North, 1990; North, 2005) assumes that business organizations and management practices are the product of the social characteristics of the society rather than economic considerations. The institutional theory considers the processes by which structures, including schemes, rules, norms, and procedures, become established as authoritative guidelines for business conduct. Harjoto *et al.* (2021b) and Khanna and Palepu (1997) state that emerging countries are generally saddled with weak institutional contexts in the regulatory systems, labour, and product markets. Using institutional theory, Harjoto *et al.* (2021b) argue that the stock markets of developed and emerging economies respond differently to COVID-19 shocks. The authors use multivariate regression to examine the impact of coronavirus death rates and new cases on stock prices in developed and emerging markets. They indicate that COVID-19 deaths and infections increase trading volume and volatility, and negatively influence stock returns in emerging markets whereas developed markets are generally unaffected. Studies like ElBannan (2017), Khanna *et al.* (2005), and Bhagat *et al.* (2011) state that capital markets in emerging economies usually have more information asymmetry and lower liquidity than markets in developed countries. Thus, any unanticipated global economic shock to emerging countries intensifies the variability and negatively impacts their equity market returns (Tran *et al.*, 2018). Based on these discussions, it is reasonable to assume that in developed markets, business organizations are better structured than those in emerging markets. This implies that firms in developed markets should be more resilient in facing a pandemic compared to those in emerging markets.

Further studies focusing on emerging countries, specifically China, show that COVID-19 has a negative impact on stock returns in the short-run (Huo and Qiu, 2020; Liu *et al.*, 2020b; He *et al.*, 2020a). In another study, Singh *et al.* (2020) focus on G20 countries and find that the pandemic negatively affects the equity markets in developed and developing economies, but that the impact is uneven across the G20 stock markets, with countries close to China, geographically or economically, suffering more than others. The authors also find that emerging stock markets experience more negative effects of COVID-19 than those in developed markets. Djankov and Panizza (2020) reason that the damage caused by the pandemic is more serious in emerging countries because of the generally weak economic condition and high policy uncertainties. Topcu and Gulal (2020) and Arellano *et al.* (2020) state that emerging countries usually have less advanced monetary and fiscal policies, and lower capacity to weather the negative effect of the global pandemic. This is because emerging countries have poor healthcare infrastructure (McKibbin and Fernando, 2021; Hsiang *et al.* 2020). Thus, any unexpected global shocks will significantly increase the uncertainties and negatively impact the emerging stock markets (Tran *et al.*, 2018). Harjoto *et al.* (2021a) find that the shock from the 11 March 2020 WHO announcement creates significant negative stock returns for emerging countries but positive returns for developed economies.

2.2 Large Versus Small Firm

Harjoto *et al.* (2021a) also look at the firm size effect and find that small firms are more vulnerable while large firms are more resilient to the pandemic shock. They find that the impact of the Fed stimulus announcement on 9 April 2020 is negative for small firms, while it is positive for large firms. The firm size effect is consistent with the findings of Rahman *et al.* (2021). The results show that firm size is negatively related to the CARs, indicating that small firms react more strongly towards the COVID-19 event. Similarly, Harjoto *et al.* (2021a) indicate that small firms suffer more negative impacts compared to large firms. The authors reason that, unlike large firms, small firms generally lack capital cushions and have limited access to the capital market to weather significant and sustained pandemic shocks. In China, Yan (2020) investigates the stock reactions of A-shares to COVID-19 between 20 January 2020 and 7 April 2020. Yan's results indicate that larger businesses are more resilient to the pandemic shock because they suffer less from the supply chain break and have greater monopoly power on resources.

2.3 Stock Market Size

Incidentally, developed markets are generally dominated by large stock markets, measured by total market capitalization (Bayraktar, 2014). Large capitalization markets tend to be more mature and consist of large and stable firms that have already experienced a great deal of growth and captured a large market share. Large and developed markets are also, in turn, dominated by institutional traders dealing with huge volumes of securities. Badhani *et al.* (2023) find that institutional investors tend to invest in high market capitalization and low-risk stocks. In contrast, institutional investors are relatively low in emerging markets. Given these arguments, it is expected that large markets are better able to withstand the impact of the COVID-19 pandemic.

2.4 International Exposure

Au Yong and Laing (2021) examine the US equity market response to the COVID-19 announcement, focusing on firms' international exposure. They discover that companies with more international exposure through exports and imports are negatively related to stock returns in the short-term, while the reverse is true in the long-term. The authors conclude that international trade and globalization make multinational companies more resilient to economic shocks from COVID-19. Our focus in this study is on the country's level. One may argue that the more exposed a country is to international trade, the more susceptible and vulnerable it becomes to global pandemics. But conversely, a well exposed country is also well-diversified in terms of its imports and exports, with many suppliers and buyers, thereby reducing its dependence on and vulnerability to any unique shock from any particular supplier or buyer. Given these opposing arguments, we tend to agree with the findings of Au Yong and Laing (2021) that international exposure leads to a market being more resilient towards the COVID-19 pandemic.

3. Data and Methodology

3.1 Data

The data for this study consists of 30 world's largest stock markets based on their market capitalization as of 31 December 2019, of which 18 are classified as developed markets and 12 are emerging markets, based on the MSCI classification. For each market, we collect two indices, the main index of the market, and the small-firm index. The main market indices usually consist of top largest firms in the market, and based on this premise we consider the main market index to represent large firms; in this way we can compare and contrast large firms versus small firms based on the indices.

Table 1 presents an overview of our data. The table shows the markets represented, classification of the markets into developed and emerging markets, market capitalization and the two indices for each market representing the large firms and small firms respectively. All daily stock indices are obtained from the DataStream database. The stock market capitalization of the countries as of 31 December 2019 are obtained from the World Bank database. The country's international exposure is obtained from World Bank data by adding the country's total imports and total exports and dividing them by the country's GDP for the year 2019.

Table 1: The data used in this study consists of the 30 largest markets based on market capitalization as at 31 December 2019

Country	Market capitalization as at 31/12/2019 (USD million)	Main index (proxy for large firm index)	Small firm index
Panel A Developed Markets			
United State	33905.98	DJUS large-cap total stock market	DJUS small-cap total stock market
Japan	6191.07	TOPIX 100	TOPIX small-cap
United Kingdom	5204.79	FTSE 100	FTSE small-Cap
Hong Kong	4899.23	Hang Seng Index	Hang Seng Comp small
Canada	2409.00	TSX Composite	TSX small-cap
France	2365.95	CAC40	CAC small-cap
Germany	2098.17	DAX 30	SDAX small-cap
Switzerland	1834.45	SMI	Swiss small-cap
Australia	1487.60	ASX 50 Index	ASX small-cap
Netherlands	1372.00	AEX index	AEX small-cap
Sweden	850.20	Stockholm 30	Stockholm small-cap
Spain	797.29	IBEX 35	IBEX small-cap

Table 1 *(continued)*

Country	Market capitalization as at 31/12/2019 (USD million)	Main index (proxy for large firm index)	Small firm index
Singapore	697.27	STI	STI small-cap
Italy	534.58	FTSEMIB	FTSEMIB small cap
Denmark	392.89	OMXC25	OMX small-cap
Belgium	321.10	BFX20	BEL small-cap
Norway	295.55	MSCI Norway large-cap	MSCI Norway small-cap
Finland	245.93	OMXH25	OMXH small-cap
Panel B: Emerging Markets			
China	8515.50	SSE 50	SSE small-cap
Saudi Arabia	2406.82	MT 30 index	MSCI Saudi small-cap
India	2179.78	BSE 30	BSE small-cap
South Korea	1463.00	KOSPI 200	KOSPI small-cap
Brazil	1187.36	BOVESPA	MSCI Brazil small-cap
South Africa	1056.34	MSCI S.Africa large-cap	MSCI S.Africa small-cap
Russia	791.52	MOEX	MSCI MVIS small-cap
Thailand	569.23	SET	SET small-cap
Indonesia	523.32	IDX LQ45	MSCI Indonesia small-cap
Mexico	413.62	IPC	FTSE Mexico small-cap
Malaysia	403.96	FTSEBM KLCI	FTSEBM small-cap
Philippines	275.30	PSEi	FTSE PHI small-cap

Notes: The sample consists of 18 developed markets and 12 emerging markets.

3.2 Methodology

This paper uses the event study method to analyse the stock market reaction to the WHO's announcement on 11 March 2020 that declares COVID-19 as a global pandemic. This date is chosen as the event date (day 0) for this study because it sends an unambiguous message to the world that we are facing a global pandemic from COVID-19. Following Harjoto *et al.* (2021a), and Au Yong and Laing (2021), this study uses the market model and market-adjusted model to estimate the abnormal return. However, the analysis shows remarkably similar results between the two abnormal return models, so we only present the market model in this paper. Our study uses the S&P 500 Index as the market benchmark for the US market. The Dow Jones global world emerging index and Dow Jones global world developed index (excluding the US) are used as market benchmarks for the emerging and developed markets, respectively.

The daily abnormal return (AR_{it}) of the market model is estimated using the following procedure:

$$AR_{it} = R_{it} - (\widehat{\alpha}_i + \hat{\beta}_i R_{mt}) \tag{1}$$

where $\widehat{\alpha}_i$ and $\hat{\beta}_i$ are OLS values estimated over a 90-day period, from day -130 to -41 before the event. The 90-day estimation period follows Liu *et al.* (2020a) and Ho *et al.* (2022). The estimates of α_i and β_i are obtained by equation (2):

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{2}$$

For each given day t during the event window, the cross-section average AR_t is calculated as:

$$AR_t = 1/n \sum_{i=1}^{N} AR_{it} \tag{3}$$

where n denotes the total number of indices. The CAR is calculated over a particular event period as below:

$$CAR_{(t_1,\,t_2)} = \sum_{t=t_1}^{t_2} AR_t \tag{4}$$

To test the significance of AR_t, the AR_{it} is divided by its estimated standard deviation, $S(AR_{it})$ to derive a standardized abnormal return, AR'_{it}.

$$AR'_{it} = \frac{AR_{it}}{S(AR_{it})} \tag{5}$$

where $S(AR_{it}) = \sqrt{\left(\frac{1}{90-1}\right)\sum_{T_1}^{T_2}(AR_{it} - AR_i^*)^2}$ and $AR_i^* = \frac{1}{90}\sum_{t_1}^{t_2} AR_{it}$, where T_1 and T_2 denote the beginning and ending days of the estimation window. The t-test statistic for any specific day is:

$$T_t = \left(\sum_{i=1}^{N_t} AR'_{it}\right) * (N_t)^{-1/2} \tag{6}$$

The t-test for CAR is as below equation:

$$t(CAR_w) = \frac{\widehat{CAR}_w}{\sigma(CAR_w)\sqrt{N}} \tag{7}$$

where the $\sigma(CAR_w)$ is the standard deviation and $\widehat{CAR}_w$ is the cross-sectional average of the CAR for a particular window, w.

The CARs are calculated over various event windows: (-35, -1), (-10, 10), (0, 30) and (0, 60), where 0 denotes the day of the WHO announcement. The event windows are chosen to capture the pre-event (-35, -11) period, and the short-term (-10, 10), the intermediate-term (0, 30) and the longer-term (0, 60) effect of the announcement.

This study also extends the analysis to examine factors that may influence the degree of impact of the pandemic on stock returns, as shown by the CARs. For this analysis, we run the following regression model:

$$\begin{aligned} CARs_{(t1,t2)} = {} & \beta_0 + \beta_1(EMD) + \beta_2(Small\text{-}capD) + \beta_3(EMD*Small\text{-}capD) \\ & + \beta_4(LnMV) + \beta_5(International\ exposure) + \varepsilon_t \end{aligned} \tag{8}$$

where $CARs_{(t1,t2)}$ is the cumulative abnormal returns of the specified windows. *EMD* is the emerging market dummy variable that carries the value of 1 if the index is from an emerging stock market and 0 otherwise, *Small-capD* is the dummy variable and equals 1 for small capitalization index and 0 otherwise, *EMD*Small-capD* dummy is an interaction variable, *LnMV* is the natural logarithm of stock market capitalization, and *International exposure* is the sum of total exports and imports divided by the total GDP of the country for the year 2019.

4. Results

4.1 Daily Returns Analysis

Table 2 presents the daily average abnormal returns (ARs) and cumulative abnormal returns (CARs) around the event date (day 0), for the developed markets and emerging markets, and, within each market, for the large-firm index and the small-firm index. The CARs are also drawn in Figure 1. Day 0 is the day of the WHO announcement (11 March 2020) declaring COVID-19 as a global pandemic. Our event window starts on day -35, which corresponds with the announcement of the Wuhan coronavirus outbreak (23 January 2020). Table 2 shows that on this day (day -35) there do not seem to be much reaction in the stock market, except for the small firm index of the emerging markets. Five days after that, on 30 January 2020 (day -30), WHO made an announcement declaring COVID-19 as a public health emergency of international concern (PHEIC). The table shows that all ARs are significantly negative on this day. As can be seen in Figure 1, from day -35 to about day -10, there is a mild reaction in the world stock markets, with some markets even showing a positive trend, particularly the large firms in developed markets, while the small companies in emerging markets seem to show a mild decline. On the whole, it seems that global markets are not taking serious heed of the Wuhan coronavirus outbreak announcement or the WHO's PHEIC announcement.

Our main focus in Table 2 is the daily movements of stock prices within the window (-10, 10) that captures the short-term market movements around the WHO's 11 March 2020 announcement. As can be seen in Table 2, as well as in Figure 1, there is a clear downward movement for all the markets over the (-10, 10) window. It can be assumed that by day -10, the disease has spread to other geographical areas and our results show that stock markets around the world are beginning to show negative reactions to the pandemic. The downward trend continues for about 20 days, until day +10. We also notice that there is a significant drop for all markets on day 0, which is the WHO announcement day. Table 2 shows that within the short-term window (-10, 10) there are more negative ARs than those with positive signs and without exception all the significant ARs are negative. The large drops in all markets within this window could be due to the market reactions to the immediate lockdowns implemented by many countries.

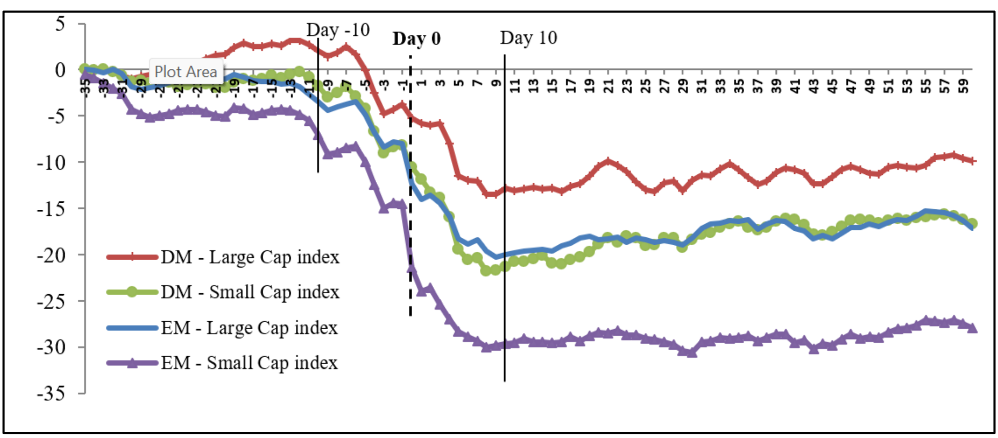
Across Table 2, we can see that the impact of the WHO announcement is felt greatly by emerging markets, showing the largest single day drop on day 0 in the entire window. But for developed markets the day 0 drop is rather mild. Table 2 and Figure 1 also clearly indicate that emerging stock markets are much more negatively impacted compared to developed markets. Within the developed and emerging markets, small firms seem to suffer greater negative returns than large firms. This is consistent with the findings of prior studies on the vulnerability of small firms compared to large firms. In sum, our short-term results indicate that there is a clear global negative reaction of stock markets around the world to the COVID-19 global pandemic announcement by WHO.

Figure 1 also captures market movements in the intermediate-term (0, 30) and in the longer-run (0, 60). The Figure shows that the longer-run effect of the pandemic seems to be fading away shortly after day 10. The graphs show that after day 10, stock markets remain more or less stable with a slight uptrend until the end of our study window. Looking at Table 2, day 60 CARs are lower than day 10 CARs, which indicates that most markets are on a recovery trend, possibly due to the many incentives and initiatives taken by governments around the world to revive their respective economies.

Table 2: Daily ARs and CARs of developed and emerging markets, large-firm and small-firm indices

Day	Panel A: Developed markets				Panel B: Emerging markets			
	Large market cap		Small market cap		Large market cap		Small market cap	
	AR	CAR	AR	CAR	AR	CAR	AR	CAR
-35	0.034	0.034	0.046	0.046	0.028	0.028	-0.519**	-0.519
-30	-0.394***	-0.983	-0.677**	-1.290	-1.479*	-1.876	-1.678**	-4.261
-20	0.088	1.622	-0.023	-1.940	0.105	-0.991	-0.099	-5.046
-10	-0.626*	2.067	-0.933**	-1.736	-0.769*	-3.487	-1.490**	-7.037
-9	-0.651**	1.417	-1.221***	-2.957	-0.877**	-4.364	-2.101***	-9.138
-8	0.402	1.819	0.496	-2.460	0.336	-4.028	0.241	-8.897
-7	0.656	2.474	0.593	-1.867	0.263	-3.765	0.483	-8.414
-6	-0.783***	1.692	-1.015***	-2.882	0.309	-3.455	0.162	-8.252
-5	-1.706***	-0.015	-1.338**	-4.220	-1.430***	-4.886	-1.719**	-9.971
-4	-2.506***	-2.520	-2.413***	-6.633	-1.898***	-6.784	-2.484***	-12.455
-3	-2.296***	-4.816	-2.396***	-9.029	-1.567***	-8.351	-2.521***	-14.977
-2	0.553	-4.263	0.693	-8.336	0.534	-7.817	0.581	-14.396
-1	0.547	-3.716	0.122	-8.215	-0.156	-7.973	-0.140	-14.536
0	-1.534*	-5.250	-2.304**	-10.518	-4.369***	-12.342	-6.843***	-21.379
1	-0.604	-5.854	-1.331*	-11.849	-1.717**	-14.059	-2.565**	-23.944
2	-0.168	-6.022	-1.376*	-13.225	0.548	-13.511	0.357	-23.587
3	0.222	-5.800	-0.647	-13.872	-0.913	-14.424	-1.804***	-25.391
4	-2.165**	-7.965	-2.075***	-15.947	-1.372**	-15.796	-1.569***	-26.961
5	-3.525*	-11.49	-3.462***	-19.409	-2.499***	-18.295	-1.362***	-28.322
6	-0.431	-11.921	-1.116	-20.525	-0.512	-18.807	-0.507	-28.830
7	-0.150	-12.071	0.167	-20.359	0.419	-18.387	-0.518	-29.347
8	-1.361***	-13.432	-1.427***	-21.786	-1.194**	-19.581	-0.638**	-29.985
9	-0.048	-13.481	0.103	-21.683	-0.690	-20.271	0.160	-29.825
10	0.639	-12.842	0.367	-21.316	0.258	-20.014	0.252	-29.573
20	1.084***	-10.394	0.822**	-18.866	-0.381	-18.332	0.343	-28.401
30	1.111**	-11.941	0.810	-18.365	0.667**	-18.227	-0.140	-30.533
40	0.408*	-10.661	0.323	-16.079	-0.054	-16.397	-0.019	-28.612
50	-0.065	-11.307	-0.236	-16.532	-0.318	-17.004	-0.010	-28.912
60	-0.303	-9.883	-0.467*	-16.696	-0.869**	-17.127	-0.504	-27.940

Notes: Large market cap and small market cap denote large and small market capitalizations, respectively. *, ** and *** represent significance at the 10%, 5% and 1% levels, respectively.



Notes: Day 0 denotes the (11 March 2020) WHO announcement.

Figure 1: CARs for developed and emerging markets, large-firm and small-firm indices

4.2 CARs Analysis

Table 3 presents the results on CARs for various sub-windows. The windows are designed to cover market reactions in the pre-event period, in the short-run period around the announcement, and in the longer-run period after the announcement. In the pre-event period, as shown by CAR (-35, -11), the developed markets are doing better than the emerging markets in response to the Wuhan coronavirus outbreak. In fact, the large companies in the developed markets are showing positive returns. It seems the developed markets are not really concerned about the disease, particularly investors of large companies. However, market reactions among emerging markets are entirely different; both large and small firms react negatively, more so for small firms. Columns 7 and 8 of Table 3 show our analysis on the difference between developed markets and emerging markets for large firms and small firms, respectively. The results clearly show that emerging markets suffered a greater loss in market value compared to developed markets, both for large as well as for small firms. This means developed markets are more resilient facing the onslaught of COVID-19 pandemic.

The short-term period around the WHO announcement is represented by CAR (-10, 10). It can be seen during this period, all markets are suffering great losses. As we have presented in the previous section, beginning from day -10, which is about 2 weeks before the WHO's announcement, markets are already showing negative reaction. The negative reaction of the markets continues rapidly after day 0 due to many countries taking immediate action by implementing lockdown measures in an effort to prevent the spread of the disease. Our results show that the biggest losers are the small firms in emerging markets, followed by small firms in the developed markets. The difference in the losses between small firms and large firms is statistically significant in both the developed and emerging markets. Large firms seem to be less affected compared to small firms in both, developed and emerging markets. Firm size seems to play a critical role in determining the extent of losses suffered by the companies. Comparing developed versus emerging markets for large and small firms, column 7 and 8 show that developed markets suffered less compared to emerging markets during the 20 day period around the WHO announcement. Although all markets suffered a great loss in value during this short-term period, it seems that emerging markets are clearly more vulnerable.

After the announcement we focus on market recoveries in the intermediate period CAR (0, 30) and the longer-term period CAR (0, 60). For the CAR (0, 30) the results indicate that there is some amount of recovery in the market indices. The net cumulative abnormal losses are lowest in the developed markets. Comparing the CAR figure of days (-10, 10) and days (0, 30) the largest recovery is the small firms index in the developed markets, recovering about 10% of the losses incurred in the CAR (-10, 10) window, followed by small firms in emerging markets. Market recoveries during the days (0, 30) may be due to market overreaction during the WHO announcement, as well as due to various incentives implemented by governments to revive their economies. In the longer-term period, the CAR (0, 60) shows they are still negative indicating that the world stock markets have not fully recovered three months after the WHO announcement. However, there are signs of further recovery in the last 30 days in our study period because all the CARs (0, 60) are less negative than CARs (0, 30). As for the firm size effect, the results show that small firms recover faster than large firms in both developed and emerging markets. Between markets it our results show that developed markets demonstrate faster recoveries than emerging markets, for both large-cap and small-cap indices.

Overall, our negative results on the short-term market reaction to the pandemic announcement are consistent with many prior studies, such as Singh *et al.* (2020), He *et al.* (2020b), Rahman *et al.* (2021), and Huo and Qiu (2020). Our results on the market recovery in the intermediate and longer-run periods are also consistent with the findings of Topcu and

Gulal (2020), and Singh *et al.* (2020). We also document unambiguously that emerging markets are more affected compared to developed markets and that small firms are worse affected compared to large firms. These results are in line with the findings of Harjoto *et al.* (2021a). These findings support the argument of Tran *et al.* (2018) that unexpected shock adversely affects emerging stock markets. Our evidence is also consistent with the argument that the effect of an adverse event is greater on small stocks (Lanfear *et al*., 2019).

Table 3: CARs around WHO announcement (11 March 2020)

Event window	Panel A: Developed markets			Panel B: Emerging markets			(1)-(4)	(2)-(5)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Large-cap	Small-cap	Diff	Large-cap	Small-cap	Diff	Diff	Diff
CAR	2.693***	-0.802	3.495***	-2.718***	-5.546***	2.828**	5.411***	4.744***
(-35, -11)	(3.729)	(-0.931)	(3.109)	(2.973)	(-6.189)	(2.209)	(3.220)	(4.780)
CAR	-15.536***	-20.514***	4.978**	-17.296***	-24.027***	6.731**	1.760*	3.513**
(-10, +10)	(-5.058)	(-6.039)	(1.994)	(-4.782)	(-5.640)	(2.022)	(1.815)	(2.190)
CAR	-8.224**	-10.150***	1.926	-10.254**	-16.016***	5.762	2.030***	5.866***
(0, +30)	(-2.067)	(-2.649)	(0.494)	(-2.363)	(-3.048)	(1.169)	(2.374)	(4.745)
CAR	-6.166	-8.481**	2.315	-9.153*	-13.404**	4.251	2.987***	4.923***
(0, +60)	(-1.496)	(-2.311)	(0.563)	(-1.792)	(-2.005)	(0.723)	(3.341)	(3.098)

Notes: Large-cap and small-cap denote large and small market capitalizations. Figures in parentheses are *t*-statistics. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. Column 7 shows the difference between large-cap developed markets and large-cap emerging markets. Column 8 shows the difference between small-cap developed markets and small-cap emerging markets.

4.3 Regression Results

In this section, we extend the analysis to examine possible factors that may influence the impact of COVID-19 on stock returns. We run the OLS multiple regression Equation (8) cross-sectionally with CARs for various windows as dependent variables. The independent variables are chosen based on a survey of previous studies on the possible factors that can influence CARs. Specifically, this analysis focuses on four factors; these are: (1) developed versus emerging markets, (2) large versus small firms, (3) size of stock market capitalization, and (4) the extent of the country's international trade exposure. Our results are presented in Table 4. The mean-centred variance inflation factor (VIF) for the independent variables specified is 2.07. This indicates that there is no collinearity issue in the regression model.

In Table 4 we find that the dummy variable for emerging market (EMD) has a negative coefficient for all CARs. This means emerging markets are more severely impacted than developed markets. Hence emerging markets is an important factor determining the impact of COVID-19 pandemic on stock prices. As for firm size, the coefficient for small-capD dummy and for the interaction term, EMD*Small-capD, are negative for pre-event (-35, -11) and short-term (-10, 10) CARs, but insignificant for the intermediate-term (0, 30) and longer-term (0, 60) CARs. This means small firms are more severely affected compared to large firms, and more so for emerging markets. Hence firm size is an important factor during the early stage of the pandemic, possibly due to increased uncertainty especially for small firms.

The third factor analysed in the regression is the stock market valuation, which is a proxy for stock market size. It is expected that large markets are better able to withstand systemic events such as the COVID-19 pandemic. Table 4 shows that the coefficients for stock market size (LnMV) are significantly positive for all regressions, which means that market size would reduce the negative impact of the pandemic on stock values. The last factor analysed is the international exposure. Table 4 shows that international exposure is insignificant for the pre-event CAR, it is negative for short-term CAR (-10, 10) but it is positive for CAR (0, 30) and CAR (0, 60). The results indicate that international trade exposure would worsen the impact of the pandemic when it was first announced. But after the initial shock, international trade exposure helps to recover from previous losses. This finding is consistent with Au Yong and Laing (2021) who argue that countries with higher trade openness or companies with greater international exposure are more able to withstand the impact of the global pandemic in the longer-run due to the benefits of geographical diversification.

In summary, our analysis indicates that four factors are important in determining the severity of the impact of COVID-19 pandemic on the stock market in the short-run; these are: stages of economic development, firm size, size of stock market, and country's international trade exposure. During the recovery period, it is found that only three factors are significant: stages of economic development, size of stock market and country's international trade exposure.

As a robustness check to our OLS regression, and following Liu *et al.* (2020a), we rerun the regression using feasible generalized least squares (FGLS) estimation with heteroscedastic error correction. The results (not presented) are qualitatively similar to the OLS results presented in Table 4.

Table 4: Regression results

	(1) CAR(-35,-11)	(2) CAR(-10,+10)	(3) CAR(0,30)	(4) CAR(0,60)
EMD	-6.045***	-6.154**	-3.522***	-5.928**
	(0.858)	(2.489)	(1.197)	(2.842)
Small-capD dummy	-1.642**	-4.021**	-2.916	-2.928
	(0.915)	(1.966)	(3.562)	(2.842)
EMD*Small-capD dummy	-3.178**	-3.739*	-5.285	-1.611
	(1.162)	(2.070)	(4.751)	(1.176)
LnMV	0.482*	4.903***	2.848*	4.393**
	(0.257)	(1.322)	(1.740)	(1.971)
International exposure	0.433	-1.024*	1.794**	1.212**
	(0.546)	(0.554)	(0.869)	(0.535)
Intercept	6.589**	-31.125***	-18.210	-18.425
	(2.948)	(10.024)	(13.192)	(16.615)
R-squared	0.527	0.355	0.243	0.189
F-statistic	13.926***	5.834***	3.405**	2.463**
N	60	60	60	60

Notes: Figures in parentheses are standard errors. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

5. Conclusion

On 11 March 2020, the World Health Organization (WHO) officially announced that COVID-19 was considered a global pandemic. This study examines the impact of this announcement on stock markets around the world. Specifically, we select 30 world's largest stock markets for analysis, consisting of 18 markets in developed countries and 12 markets in emerging economies. This study focuses on the differences in the market reaction in developed versus emerging markets as well as by firm size. Our study also analyses several factors that may influence the impact of COVID-19 on stock returns in the short-run and intermediate-run. This study uses the standard event methodology and the market model, to analyse market reaction around the announcement.

Our findings indicate that the COVID-19 pandemic has a negative impact on stock market returns around the world. In the 20-days around the announcement (short-run period), evidence shows that all markets suffer great losses, with emerging markets losing more than developed markets. Within the developed and emerging markets, small firms seem to suffer greater negative returns than large firms. In the longer-run, the study finds that all markets are recovering from the initial losses, but that the net effect is still negative.

The results show that developed markets recover faster than emerging markets. Our cross-sectional multiple regressions reveal that stock markets in developed countries and markets with large capitalization are better able to cope with the pandemic compared to markets in emerging countries and smaller capitalization markets. The results also show that larger firms suffer less than smaller firms in the short-term. Country's international trade exposure is an interesting factor. We find that international exposure hurts stock markets in the short-term, but helps in market recovery in the intermediate and longer-term.

This study has several practical implications. Firstly, the findings suggest that emerging markets are worse affected than developed markets. The implication is that the authorities of emerging markets should take the necessary steps to strengthen themselves, particularly in areas that lead to their vulnerability to international shocks such as the COVID-19 pandemic. Secondly, our results indicate that large firms are more resilient than small firms. The size effect is present in both the developed and emerging markets. Being small means increased vulnerability. The implications for the management of small firms are to focus on the company's strength to develop resilience to the pandemic. Thirdly, the results show that international diversification contributes positively to the market's recovery. Countries that are more open in terms of international trade should stand to benefit from this finding. This has implications for governments as well as for individual companies as proper diversification strategies will help cushion the impact of pandemics as well as help in the recovery stages. Lastly, the findings have practical implications for investors. It is clear from our results that markets are negatively affected, particularly in the short-run period. The worse hit are emerging markets and small firms. These findings represent an opportunity to investors who can take positions in appropriately selected stocks. These shares are due to recover as the pandemic subsides and recovery plans take effect.

One possible extension of this study is to focus on government incentives and recovery plans. In facing this systemic calamity, all governments have devised and implemented various recovery plans in their efforts to revive the economy. However, our analysis reveals that only partial recovery took place after three months. For further studies, an event-study methodology may be adopted focusing on the effectiveness of the plans. The extent of the effectiveness of the incentive plans will provide important feedback to authorities concerned in planning follow-up strategies. Another possible extension of this research is to look at the long-term recovery phase. The question of interest is how long does it take for the markets to fully recover from the impact of the COVID-19 pandemic? In this paper, our analysis runs for only 60 days after the event. Future research on this issue should consider a much longer period for analysis, for example, over a one to two-year calendar period, in order to capture the actual recovery phase of the markets. Analysis may also be made to determine the micro and macro factors that contribute to the recovery of these companies.

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The Role of Institutional Investors in The Indian Stock Markets During the Pandemic

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Abstract: Research Question: The study evaluates the behaviour of the FIIs and DIIs on the returns and volatility of the four major Indian stock indices namely, Nifty 50, Nifty Next 50, BSE Sensex, and BSE 100 before and during the pandemic of COVID-19. To capture the volatility, exogenous variable, India VIX has been used. **Motivation:** Due to the stringent measures taken by several countries in response to the COVID-19 pandemic, there was an initial downturn in the global economic prospects and a meltdown in the financial markets. **Idea:** It made the individual investors curious about the behaviour of institutional investors to take a position amidst the highly uncertain environment. **Data:** The daily data of buying and selling of FIIs and the DIIs and the four indices have been obtained from the period January 1, 2011, to April 3, 2020. Further, the study is divided into three sub-periods that is full, before COVID and during COVID. **Method/Tools:** Various analysis were performed using correlation, rolling correlation, Granger causality, GARCH, GJR-GARCH and EGARCH to gauge the relationship between activities of FIIs and DIIs and the market returns. **Findings:** The outcome of the analysis reveals that both the FIIs and DIIs play significant role in generating the returns and volatility in the Indian stock market. However, during the pandemic of COVID-19, the FIIs led the market returns and DIIs led the volatility. This is due to the fact that the DIIs were the net buyers during this period and the distribution of their net position was positively skewed. The leverage effect is also observed. The persistence of the volatility is highest during COVID-19. **Contributions:** The study is one of a kind adding to the existing body of knowledge related to the behaviour of FIIs and DIIs during the global epidemic. It is the most recent and closely related to the literature on capturing FII and DII investment patterns during a global pandemic.

Keywords: FIIs, DIIs, Indian stock markets, COVID-19, GARCH.
JEL Classification: C52, C58, G01, G23, G17, G41

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1. Introduction

Indian economy is one of the best places to invest due to its demographic growth, expanding productivity, and long-term economic growth potential[1] (IBEF, 2019). It has been ranked as one of the world's top emerging economies due to its striking Gross Domestic Product (GDP) at around 6% during Fiscal Year (FY) 2019 among other emerging economies in the world[2]. It not only appeals to domestic investors (institutional as well as retail) to invest for lucrative returns but also fascinates foreign participants. The emerging Indian economy, which offers a relatively higher growth rate than many other developed economies[3], has been the focus of foreign investors since 1991 after the announcement of LPG as a part of the new economic policies. The Indian stock market was kept open for foreign investors in September 1992 and gained popularity as an attractive investment destination for Foreign Direct Investments (FDIs) and Foreign Institutional Investors (FIIs). Other than retail investors, institutional investors include asset management companies, banks, insurance companies, hedge funds, pension funds and portfolio management companies, to name a few. As investors, they generate more volatility in the stock market since they hold a substantial fraction of financial assets, huge trading volume, and larger investment funds (Baral and Patra, 2019; Roy and Deb, 2019; Reddy, 2017; Naik and Padhi, 2015). They are also considered to have better information access compared to retail investors (Ghosh and Srinivasan, 2014). They are the driving force for any economy as they inject global liquidity into the capital markets of the host country, increase the efficiency of these markets by raising the price-to-earnings ratios, and lower the cost of capital (Srikanth and Kishore, 2012). As a result, retail investors are more likely to follow institutional investment strategies and herd around foreign investors (Chong *et al.*, 2019).

Institutional investors are mostly classified into two broad categories: (a) Domestic Institutional Investor (DII) is defined as the institutional investors registered in the home country who are investing in the financial markets of the same country. The DIIs channel domestic savings into the financial markets (Naik and Padhi, 2015). b) Foreign Institutional Investor (FII) is defined as an entity incorporated outside India that proposes to invest in India and is registered as an FII under SEBI (Foreign Institutional Investors) Regulations, 1995. They include investment companies incorporated and registered outside India that make investments in a large pool of investments created by small investors (Goyal and Singh, 2013). Recent years have witnessed an increase in investments by FIIs and DIIs in the Indian stock market, which has resulted in an increase in the value of the Indian stock indices such as the BSE Sensex and Nifty (Roy and Deb, 2019). Some studies suggest that DIIs invest in the market when FIIs take an exit call and help stabilize the market (Baral and Patra, 2019; Murthy and Singh, 2013). However, according to a study conducted by moneycontrol.com[4], it has been observed that in the long run, there is no correlation between domestic and foreign institutional investments and market returns. With improvement in the economy's global linkages, foreign capital also makes the host country's markets more vulnerable to global shocks (Ghosh and Srinivasan, 2014). In 2019, the global economy was already going through turmoil and the outbreak of COVID-19[5] created a high risk of converting this slowdown into

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a crisis at the beginning of 2020. Many developed and developing economies are forced to go for a shutdown of economic activities to curtail the spread of the pandemic (Mishra *et al.*, 2022). It has shaken powerful economies like the United Kingdom, the United States, Japan and China to name a few. Indian economy is no exception to this. Indian real GDP has also gone down to the lowest in over 6 years in the third quarter of FY 2019-20. It has affected the three major contributors to GDP, i.e., private consumption, investments, and external trade[6].

In this backdrop, the objectives of the study are to (a) examine the investment patterns of FIIs and DIIs before and during the period of a pandemic, (b) appraise the influence of FIIs and DIIs activities on the returns and volatility of the Indian stock market using GARCH tests before and during the global crisis of COVID-19, and (c) get an answer to the question "who drives the market-FIIs or DIIs?" This article consists of five sections, starting from the introduction. The next section discusses a detailed review of related literature. It is followed by the third section on data and research methodology. The fourth section deals with data analysis and discussions. The concluding remarks of the study are provided in section five.

2. Literature Review

Substantial amounts of foreign capital have been attracted to India as a result of the opening of the Indian stock market to foreign investors in September 1992, the market's stellar performance since around 2001, an increase in the number of profitable corporate houses, and a gradual improvement in the rate of overall economic growth. (Poshakwale and Thapa, 2010). The two major factors attracting inflows of FIIs are (a) positive interest rates and (b) growth in the Index of Industrial Production (IIP). Ultimately, it leads to a surge in foreign exchange reserves of the country (Srikanth and Kishore, 2012). Mohanamani and Sivagnanasithi (2012) suggested that the FIIs positively affect the economic factors at a macro level and are likely to have an impact on the overall economic development of the country. On the contrary, Kaur and Dhillon (2010) observed that the flows of FIIs are greatly influenced by both macroeconomic factors and returns from the stock market. Based on the study, evaluating the relationship between FIIs and organisation-specific factors like shareholding pattern, financial performance, and returns from stock, it is observed that the companies operating in emerging economies generate huge profits and that attract institutional investment (Goyal and Singh, 2013). One study has also noted that FIIs prefer to invest in companies where the public holds a higher portion of shares. It suggests that there is a negative relationship between the promoters' holdings and foreign investments (Prasanna, 2008).

Mostly the studies referred to consider only FIIs as institutional investors and the literature targeting the impact of both the FIIs and the DIIs is scarce. Moreover, a limited number of studies have considered the overall DIIs category, while some have taken investments by mutual funds as a proxy of DIIs (Naik and Padhi, 2015; Murthy and Singh, 2013; Kumar, 2007). The FIIs also influence the actions of the DIIs (Gahlot, 2019). Many researchers have highlighted that institutional investors typically follow their past investment strategies. (Naik and Padhi, 2015). For example, they normally buy the added shares in the index and sell out the deleted shares within several days (Ng and Zhu, 2016). Shaharuddin *et al.* (2017) confirm that due to institutional investors' preference for growth stocks from blue-chip companies, the growth style is more sensitive to fresh information than the value style. Gupta and Gordon (2003) observed that the flows of the FIIs are resilient and it is positively influenced by the performance of the shares listed on the indices of the emerging markets. They found a surprising negative relationship between domestic market performance and FIIs flows. In emerging economies, FIIs play a more crucial role in setting the market trend and in

[6] https://home.kpmg/content/dam/kpmg/in/pdf/2020/04/potential-impact-of-covid-19-on-the-Indian-economy.pdf Accessed on April 5, 2020

generating liquidity and volatility in stock returns as compared to DIIs (Shukla *et al.*, 2011; Baral and Patra, 2019; Roy and Deb, 2019). The volatility in the stock market is the rate and magnitude at which the prices of securities, indices, and derivative products change. In finance, volatility has been referred to as risk (Ibrahim and Ahmad, 2008; Kuhe, 2018). In India, the index that measures expected volatility in the stock market over the near term based on the order book of the underlying index options i.e., Nifty Index Option prices is the India VIX Index[7]. French *et al.* (1987) observed that the expected excess return on a stock portfolio over the risk-free investment in a government treasury bill is positively related to the volatility of stock returns. The stock market volatility can be modelled using GARCH models proposed by Engle (1982), Bollerslev (1986), etc. Recently, it has gained the interest of researchers, academicians and financial analysts. The GARCH models have also been more successful in analysing statistical facts of financial time series such as volatility clustering, volatility shock persistence, volatility mean reversion, leverage effect and risk premium, etc. (Kuhe, 2018).

Despite the associated volatility, the increase in foreign capital results in enhanced performance of the economy as a whole and the stock returns. On the other hand, improved stock returns and economic performance attract more foreign capital. The increase in the inflow of foreign capital due to an increase in stock returns is known as 'positive feedback' trading, while the increase in foreign capital inflow due to a decline in stock returns is termed 'negative feedback' trading (Inoue, 2009). The FIIs invest in the stock markets for opportunistic gain, as they involve more in trading activities and do not intend to cause a fundamental change in the market (Baral and Patra, 2019; Murthy and Singh, 2013) i.e., FIIs are considered as 'return chasers' or 'feedback traders'. They follow positive feedback trading while buying in the Indian stock market -cash and futures- whereas their sales are the outcome of negative feedback trading (Dhingra *et al.*, 2016). Samarakoon (2009) observed a similar outcome while evaluating the institutional investment flows and past returns. However, in times of crisis, he found a reversal trend. Examining the relationship between the returns and the past flows, it was observed that there is a significant positive correlation between purchases of the DIIs and future returns, while no significant correlation was observed between purchases of the FIIs and future returns. The sales by the DIIs have no correlation with future returns, while sales by the FIIs have a strong positive relationship with future returns. The impact of flows on future returns was found to be indifferent between stressed and normal periods.

During a time of crisis, in the home country or the host country, or at the world level, foreign investors are the first to leave. From the analysis of the worst twenty-five crashes at BSE, it was found that the FIIs have been highly bearish in all the cases (Loomba, 2012). Further, investigating the reason for the sudden fall in the Indian stock market during 2008-2009, it was understood the rapid fall was a drop in the investment of the FIIs and the DIIs (Roy and Deb, 2019). Other studies noted a negative correlation between the FIIs and the DIIs investment activities, i.e., the DIIs play a defending role by buying in a falling market when the FIIs withdraw, but their buying does not seem to be enough to restore the falling market (Jalota, 2017; Reddy, 2017). Kaur and Dhillon (2010) explored the determinants of FIIs in the Indian stock market. They observed that the inflows of the FIIs in India are dependent on both stock market movements and macroeconomic factors. Among the factors, returns on investment from the Indian stock market significantly influence the flows of FIIs in India, while returns on investment from the US stock market do not play any significant role. Apart from that risk factor associated with the stock market, the market capitalization of the Indian market has a substantial positive effect on the inflows of the FIIs to India, while market turnover has a considerable positive effect on the latter. However, this significance has been

[7] https://www1.nseindia.com/products/content/equities/indices/india_vix.htm Accessed on 18th March, 2020

found only in the short run. Among macroeconomic factors, the investments by the FIIs are positively related to the economic growth of the Indian economy in the long run as well as in the short run. The other macro-economic factors like inflation in the US, positively influence the investments of the FIIs in India only in the long run. While the inflation rate in India negatively affects the latter. Moreover, the interest rates in the US negatively affect the investments by the FIIs while the liberalization policy announcements in India encouraged more inflow of the FIIs.

Kotishwar and Alekhya (2015) undertook research to examine the correlation between Nifty returns and the FIIs and the DIIs and the mutual funds' inflows and outflows. The study was conducted for the period from 2006 to 2014. The outcome of the regression analysis indicates that Nifty is affected by the DIIs, not the FIIs. Moreover, it was also observed that mutual funds' inflows have a negative correlation with Nifty. However, Bansal and Rao (2018) observed a strong negative correlation between the DIIs and the Nifty returns, while Atif (2016) noted that there is a unidirectional relationship where Sensex movement drives the DIIs flows. Bose (2012) witnessed similar outcomes related to the negative correlation between the market returns and the investment flows by the DIIs. Loomba (2012), based on daily data for a period from January 2001 to December 2011, concluded that a significant positive correlation was observed between the activities of FIIs and the Indian stock market. Bohra and Dutt (2011) found a strange outcome that BSE Sensex is indifferent to the FIIs' inflows. Further, they probed the relationship between the flows of the FIIs and the turnover of different indices in BSE like small-cap and mid-cap indices. The analysis concluded that a positive correlation was observed between the investments by the FII and the stock market except in the years 2005 and 2008. They also observed that the FIIs' movement plays a major role in framing domestic investors' sentiments in the market. Moreover, the flow of the FIIs also significantly affects the share prices and the trading volume of the companies in mid-cap and small-cap indices. Ultimately, it results in an increase in volatility in the indices (Shukla *et al.*, 2011).

Studies have checked the causality between the investments by institutional investors and the stock market returns. The study conducted by Sonawane (2020) had an objective to analyse the long-term and short-term causality between the Indian stock market with the FIIs and DIIs. The period covered under the study was from April 2007 to December 2013 based on the monthly data of the two leading stock indices, namely, Sensex and Nifty. The study concluded that there is unidirectional causality from the FIIs to the Indian stock market both in the long run as well as short run. However, the DIIs have unidirectional long-run causality with the market. Gahlot (2019) examined the effect of FIIs and DIIs on the selected Indian stock indices. They used the Granger causality test and TGARCH model, and concluded that historical volatility is statistically significant, and it takes a long time to discover the same. As an outcome of Granger causality test, they found that the investment activities of the DIIs depend upon the investment activities of the FIIs. The results of ARCH and GARCH suggest that based on recent and historical news investors can make profitable investment strategies. The leverage coefficient indicates irregular movement between the return shock and volatility adjustment and due to that irregularity, it was suggested to the investors be more conscious of negative news in the market. However, according to the efficient market hypothesis, the news should quickly adapt to the entry of fresh information into the market Fama (1970). As a result, the active trader, such as institutional investors, takes a position utilising their knowledge and high-frequency data analysis (Danak and Patel, 2020).

Roy and Deb (2019) found as an outcome of the Granger causality test that the index value granger cause over the FIIs and the DIIs. Srikanth and Kishore (2012) observed a bidirectional causal relationship between the FIIs' inflows and BSE Sensex during their 8 yearlong study from April 2003 to March 2011. The results of Granger causality tests conducted by Murthy and Singh (2013) suggest that the FIIs and the DIIs have a significant influence on the stock market, while the mutual funds are the passive players. Kumar (2007) investigated the combined impact of the FII and the mutual funds on the Indian stock market. The result of the Granger causality check shows that mutual funds are leading the movement of the market and that the FIIs are trailing them. Naik and Padhi (2015), with the help of the structural Vector Auto-Regression (VAR) framework, attempted to empirically check the relationship between institutional investment (both foreign and domestic) and the Indian stock market. On applying the causality test, it was found that there exists bidirectional causation between the net flows of the FIIs and market volatility, whereas flows of the mutual funds do not cause volatility. Bansal and Rao (2018) explored the relationship between investments by the DIIs and the FIIs with Nifty returns. They observed a strong negative correlation between the DIIs and Nifty returns, and the opposite for the FIIs and Nifty returns. The results of the Granger causality test revealed a unidirectional causality from the FIIs to Nifty returns and the DIIs to Nifty returns.

The current study is one of a kind adding to the existing body of knowledge related to behaviour of FIIs and DIIs during the global pandemic. As the pandemic of COVID-19 has resulted in a slowdown in the overall global economy, it has led individual investors curious about the behaviour of institutional investors to take a position amidst the highly uncertain environment. In such a scenario, the study evaluates the behaviour of the FIIs and DIIs on the returns and volatility of the four major Indian stock indices before and during the pandemic of COVID-19. It is the most recent and closely related to the literature on capturing FII and DII investment patterns and their impact on returns and volatility during the global pandemic. It attempts to examine the behaviour of the FIIs and the DIIs on the volatility of the stock market in India before and during the global crisis of COVID-19. We also check the causal relationship between the FIIs and the DIIs on the selected indices in India before and during the COVID-19 crisis. To achieve the objective, the study period was divided into three parts: the first (full) period: the entire period from January 1, 2011, to April 3, 2020; the second (pre-COVID) period: January 1, 2011, to December 31, 2019; and the third (during COVID) period: January 1, 2020, to April 3, 2020.

3. Data and Methodology

3.1 Objective of The Study

Through this research, we attempt to analyse the behaviour of the FIIs and the DIIs on the volatility of the Indian stock market before and during the global crisis of COVID-19. The study further tries to check the causal relationship between the FIIs, the DIIs, and the selected indices in the Indian stock market. The objectives of the study are to (a) examine the investment patterns of FIIs and DIIs before and during the period of an economic slowdown, (b) appraise the influence of FIIs and DIIs on the returns and volatility of the Indian stock market using GARCH tests before and during the global crisis of COVID-19, and (c) get an answer to the question “who drives the market-FIIs or DIIs?”

3.2 The Data

For capturing the behaviour of the investment pattern of the FIIs and the DIIs, we have taken four broad indices, namely, Nifty 50, Nifty Next 50, BSE Sensex, and BSE 100 because most of the investment of the FII and the DII lies with companies listed on these four indices (Gahlot, 2019). Broadly, these indices are considered the yardstick of the Indian economy and rightly explain the economic performance. The daily data of the FIIs purchases, the FIIs sales, the DIIs purchases, the DIIs sales, and the four indices have been obtained. In order to capture the volatility aspect, we have also taken the India VIX index as an exogenous variable.

3.3 Period of Study

The overall period of the study is from January 1, 2011, to April 3, 2020. We try to check the long-term pattern of investment by the FIIs and the DIIs as well as the effect of COVID-19 on the investment behaviour of the FIIs and the DIIs. Hence, the short-term period captures the COVID-19 effect, which allows investigation of the behavioural aspects of the institutional investors in the financial markets. The study covers the following three sub-periods:

(I) First (full) period: the entire period from January 1, 2011, to April 3, 2020.
(II) Second (pre-COVID) period: January 1, 2011, to December 31, 2019.
(III) Third (during COVID) period: January 1, 2020, to April 3, 2020.

The specific reason behind dividing the study period into three is to capture the effect of COVID-19 on the investment patterns of institutional investors. The first period investigates the overall behaviour and its impact on the volatility of the market. The second period is a normal period, which captures the behaviour before the COVID-19 outbreak. The third period was intentionally broken from January 1, 2020, because the national authorities in China informed the World Health Organization on December 31, 2019, regarding pneumonia of unknown etiology in Wuhan[8].

3.4 Data Source

The indices data are obtained from ProwessIQ, whereas the investment data of the FIIs and the DIIs are sourced through the two depository services in India, namely, the NSDL and CDSL and from the NSE website.

3.5 Returns Convertibility

It is essential to convert the price series into the returns series to take care of the unit root. Therefore, all the index series have been converted into the returns series by taking the first difference to their logarithmic value. We employed the following formula to convert the daily prices to the continuously compounded daily returns:

$$r_{A,t} = ln\left(\frac{P_{A,t}}{P_{A,t-1}}\right) \times 100 \tag{1}$$

where $r_{A,t}$ is the continuously compounded daily returns in percentage. $P_{A,t}$ and $P_{A,t-1}$ are the price series of an asset for the period of t and $t-1$, respectively.

3.6 Econometric Methodology

3.6.1 GARCH Model

The GARCH (p, q) model, the most widely used tool to estimate volatility in financial markets, was originally proposed by Bollerslev (1986). He proposed this model by adding lags of the variance terms in the variance equation in addition to the ARCH term. In simple words, GARCH (p, q) refers to the p ARCH term and q GARCH term. The ARCH term refers to the lag on the squared error term and the GARCH term refers to lagged variance. The mean equation for all GARCH models is the same; however, the dummy variable is removed when it is not applicable, i.e., more precisely, the dummy is only possible for the full sample period to be broken into before and during the COVID-19 outbreak. The dummy variable was

[8] https://www.who.int/csr/don/05-january-2020-pneumonia-of-unkown-cause-china/en/ Accessed on February 18, 2020

introduced in the mean as well as the variance equation. The net FII and net DII investments are added to the variance equation to check the impact of the net position of the institutional investors on the volatility as proposed in objective (b).

$$R_i|I_{t-1} = \alpha + \beta_1 R_{i-1} + \beta_2 GP_{FII} + \beta_3 GS_{FII} + \beta_4 GP_{DII} + \beta_5 GS_{DII} + \beta_6 IND_{VIX} + \beta_7 D_{Covid} + \varepsilon_t \quad (2)$$

where α represents the intercept, R_{i-1} represents the lagged returns of different indices, GP_{FII} represents the gross purchase of FIIs, GS_{FII} represents gross sales of FIIs, GP_{DII} represents the gross purchase of DIIs, GS_{DII} represents gross sales of DIIs, IND_{VIX} represent the returns of the India VIX Index, D_{Covid} represents the dummy variable (0 before the COVID-19 outbreak and 1 during the COVID-19 outbreak), and ε_t represents error term.

Variance equation:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 FII + \beta_3 DII + \phi D_{Covid} \quad (3)$$

where ε_{t-1}^2represents ARCH term (lagged squared error of mean equation), σ_{t-1}^2represents the GARCH term (lagged variance), FII represents the net position of foreign institutional investors, DII represents the net position of domestic institutional investors, and D_{Covid} represents the dummy variable.

3.6.2 Threshold GARCH (GJR-GARCH) Model

The above GARCH specifications are symmetric, which is a major restriction. It indicates that the GARCH term must have the absolute value of the innovation because it considers the squared residuals and variance. The GJR-GARCH model was proposed by Glosten *et al.*, (1993). This model postulates the effect of negative and positive shocks on volatility. This model helps us to find the leverage effect which means that negative shocks (or ‘bad news’) in the market have a larger impact on volatility than positive shocks (or ‘good news’) of the same magnitude.

We specify the GJR-GARCH (1, 1) model for the conditional variance as shown below:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \beta_1 \sigma_{t-1}^2 + \beta_2 FII + \beta_3 DII + \phi D_{Covid} \quad (4)$$

where d_t= 1 if ε_t< 0 and d_t= 0 otherwise.

In this model, the good news (when $\varepsilon_t > 0$) and the bad news ($\varepsilon_t < 0$) have differential effects on the conditional variance. Hence, if there is good news, it has an impact on α_1, while the bad news has an impact on α_1 and γ. If $\gamma > 0$, it implies that the bad news increases the volatility and creates the leverage effect. Hence, we conclude that there is asymmetry, while if γ = 0, the news impact is symmetry.

3.6.3 Exponential GARCH

Nelson (1991) proposed the exponential GARCH (EGARCH) model by converting variance into the natural log variance that makes the leverage effect exponential and conditional variance nonnegative. The EGARCH captures the asymmetric effect between the positive and the negative returns.

$$ln(\sigma_t^2) = \omega + \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}^2}\right| + \gamma \left[\frac{\varepsilon_{t-1}}{\sigma_{t-1}^2}\right] + \beta_1\, ln(\sigma_{t-1}^2) + \beta_2 FII + \beta_3 DII + \phi D_{Covid} \quad (5)$$

where γ represents the asymmetric coefficient in the model and β_1 coefficient represents the measure of shock persistence. If $\gamma = 0$, symmetry exists and if $\gamma < 1$, the leverage effect exists.

4. Results and Discussions

4.1 Descriptive Statistics

Figure 1 depicts the price and returns series of four indices along with FII and DII purchases and sales during the sample period. It can be seen that all the price series of the indices follow a trend. However, after January 2020, the trend of all indices suddenly started falling when the first case of COVID-19 was reported in Kerala, India, on January 30, 2020[9]. It should be noted that the volatility in the returns during the COVID-19 outbreak is tremendous in all indices. The FIIs' purchases and sales are smoother than those of DIIs'. During the COVID-19 period, the FIIs' sales are higher than purchases; whereas, in the case of DIIs, the situation seems reversed. The sales of DII after 2017 seem more volatile. The descriptive statistics are computed based on the returns series and are reported in Table 1.

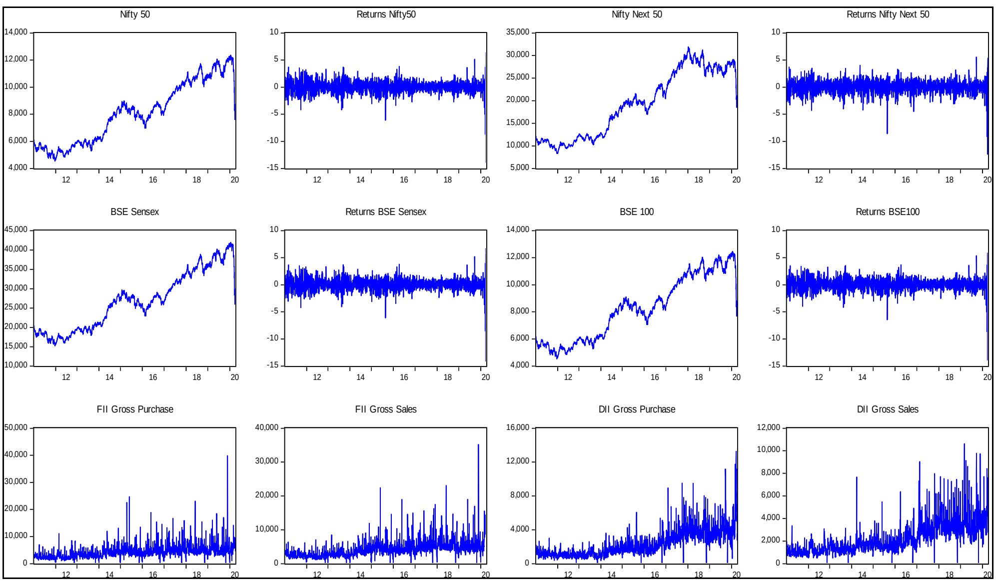

Figure 1: Price & return series of four indices along with FII and DII Purchases and Sales

Table 1 shows descriptive statistics of the different indices for three different periods. It is generally believed that the stock market offers the highest returns. During the full period, which also covers the turbulent period due to the COVID-19 outbreak, Nifty Next 50 offered the highest returns (0.0226%) with the highest standard deviation (1.167%), which was also consistent with the pre-COVID period. It offered the highest returns (0.0383%) with the highest standard deviation (1.087%). In all the returns series, the null hypothesis of normal distribution was rejected at a 1% level of significance based on the Jarque-Berra test. The series was also tested for autocorrelations. Not all the returns series demonstrate the autocorrelations before and during the COVID-19 period. The Ljung-Box Q statistic for autocorrelation is reported up to lag 6 in Table 1. The ordinary regression model presumes that the variance of the residual remains constant. This assumption is called homoskedasticity.

[9] https://economictimes.indiatimes.com/news/politics-and-nation/coronavirus-crisis-heres-total-number-of-confirmed-cases-in-india-as-per-health-ministry/articleshow/74589499.cms?from=mdr Accessed on April 16, 2020

In the case where the null hypothesis of homoskedasticity is rejected, the series is called heteroskedastic, and hence ordinary regression does not offer the best linear unbiased estimator (BLUE). In order to check this assumption, we performed the ARCH-LM test at lag 1 on the residuals. The null hypothesis of no heteroskedasticity in the residuals was rejected in most of the variables, except BSE100 in the full sample period and Nifty Next 50 and BSE 100 in the third period.

Table 1: Descriptive statistics for indices

Descriptive	NIFTY50	NNEXT50	SENSEX	BSE100
Panel-1: Full period sample Jan 1, 2011 to April 3, 2020				
Mean	0.0121	0.0226	0.0131	0.0122
Median	0.0303	0.1013	0.0394	0.0447
Maximum	6.41	5.57	6.75	5.89
Minimum	-13.90	-12.37	-14.10	-13.88
Std. Dev.	1.093	1.167	1.085	1.085
Skewness	-1.290	-1.096	-1.346	-1.354
Kurtosis	19.750	12.441	21.291	19.799
Jarque-Bera	26962.9*	8818.7*	32087.3*	27180.3*
Q(6)	35.085*	40.376*	34.992*	32.647*
ARCH-LM	78.40*	15.76*	83.20*	68.99
Observations	2253	2253	2253	2253
Panel-2: Pre-COVID period Jan 1, 2011 to December 31, 2019				
Mean	0.0311	0.0383	0.0318	0.0310
Median	0.0335	0.1064	0.0492	0.0546
Maximum	5.18	5.57	5.19	5.38
Minimum	-6.10	-8.59	-6.12	-6.49
Std. Dev.	0.972	1.087	0.957	0.967
Skewness	-0.040	-0.418	-0.028	-0.120
Kurtosis	5.189	5.701	5.232	5.263
Jarque-Bera	437.1*	728.4*	454.3*	471.9*
Q(6)	19.245*	48.575*	17.790*	22.365
ARCH-LM	10.69*	11.96*	11.00*	9.77*
Observations	2187	2187	2187	2187
Panel-3: During-COVID period Jan 1, 2020 to April 3, 2020				
Mean	-0.6197	-0.4964	-0.6095	-0.6102
Median	-0.2967	-0.1818	-0.3653	-0.2902
Maximum	6.41	5.36	6.75	5.89
Minimum	-13.90	-12.37	-14.10	-13.88
Std. Dev.	3.033	2.678	3.097	2.993
Skewness	-1.491	-1.723	-1.438	-1.544
Kurtosis	8.333	8.938	8.254	8.517
Jarque-Bera	175.0*	171.4*	184.6*	181.1*
Q(6)	23.811*	16.910*	22.059*	22.538*
ARCH-LM	3.73***	0.20	2.82***	2.36
Observations	66	66	66	66

Notes: (a) Q(6) are Ljung-Box Q statistics for return series for six lags. (b) ARCH-LM test shows Engle (1982) test for conditional heteroskedasticity calculated for the first lag only. (c) * implies significance at 1% level, ** implies significance at 5% and *** implies significance at 10% level.

During the full sample period, the least returns were observed in Nifty 50 (0.0121%) with a moderate standard deviation of 1.093%. It should be observed that the median return for Nifty Next 50 is 0.1013%. It is noteworthy that during this period, the returns of all the assets are negatively skewed with the highest kurtosis in Sensex (21.291), followed by BSE100 (19.799). The higher kurtosis implies a greater likelihood of abnormal gains or losses. During the pre-COVID period, the average returns are positive in all the indices and even much higher than the full period, which is mainly because the full period includes the COVID-19 outbreak. The highest returns are observed in Nifty Next 50 (0.0383%) with a 1.087% standard deviation, which implies good returns as compared to the risk in other assets. The least returns are observed in BSE100 (0.0310%) with a standard deviation of 0.967%. It must be noted that as compared to the full period, in this period the skewness is relatively near zero and the kurtosis are slightly higher than the expected normal distribution. This clearly implies that the COVID-19 outbreak has really distorted the returns and the volatility of the returns during this period. The third period starts with the outbreak of COVID-19, which is prevalent in asset returns. The average returns in this period are negative in all the indices. The least returns are observed in Nifty 50 (-0.6197%) with a standard deviation of 3.033%. This was primarily because institutional investors invest more in these stocks. The volatility was highest as compared to the rest of the period. The skewness of all the asset returns is very negative, suggesting a negatively skewed distribution having abnormal negative returns and the kurtosis was relatively higher than prior to COVID-19.

Table 2: Descriptive statistics for FII and DII net investments

Descriptive	Panel-1: Full period sample Jan 1, 2011 to April 3, 2020		Panel-2: Pre-COVID period Jan 1, 2011 to December 31, 2019		Panel-3: During-COVID period Jan 1, 2020 to April 3, 2020	
	FIINET	DIINET	FIINET	DIINET	FIINET	DIINET
Mean	14.83	129.12	55.03	99.46	-1317.25	1111.79
Median	24.14	47.98	35.78	39.33	-693.58	418.59
Maximum	17488.73	7621.16	17488.73	5196.60	1495.25	7621.16
Minimum	-9690.84	-5631.99	-9690.84	-5631.99	-6595.56	-1419.85
Std. Dev.	1132.61	794.78	1079.23	719.12	1848.59	1866.47
Skewness	1.96	0.96	2.73	-0.05	-0.86	1.18
Kurtosis	37.68	13.79	44.40	10.00	3.05	4.13
Jarque-Bera	114319.7*	11279.01*	158886.7*	4467.93*	8.19**	18.91*
Observations	2253	2253	2187	2187	66	66

Notes: * implies significance at 1% level and ** implies significance at 5%.

Table 2 describes the statistics of the FIIs and the DIIs investments for three periods. In the full sample period, the average and median net investment by the DIIs is higher than the FIIs, which suggests that the scale of investment by the DIIs is larger than that of the FIIs; hence, the impact of investment of the DIIs may be higher in the stock market than the FIIs. However, the distribution of net investment by the FIIs was wider as compared to the DIIs. The maximum and minimum net investments of the FIIs are extreme as a result the standard deviation of the FIIs is higher than that of the DIIs. These observations are similar to the full sample period as well as the sample period before the COVID-19 outbreak. However, during the COVID-19 outbreak, the pattern of investments of the FIIs and the DIIs changed a lot. The average daily net investment during this period by the FIIs and the DIIs is -1317.25 crores[10] and 1111.79 crores, which indicates that during this period, the FIIs sold and the DIIs bought significant portions in the marketplace. This implies that the DIIs played an instrumental role in order to make the market less exposed to the COVID-19 outbreak. Moreover, it should be noted that the minimum net investment of the FIIs was -6595 crores as compared to -1419.85 crores, whereas the maximum net investment of the DIIs was 7621 crores as compared to 1495.25 crores of the FIIs. This further implies the instrumental role of the DIIs. The null hypothesis of a normal distribution is also rejected as per the Jarque-Berra test in all the periods. The skewness of the FIIs and the DIIs in the third period is negative and positive, respectively.

4.2 Regression Results

Generally, financial time series exhibit the trending behaviour in the price series, because their mean and standard deviation will not remain constant over the period. Unit root test is

[10] In India, 1 crore = 10 million

conducted to assess if the time series data are stationary or not. A time series is stationary if a change in time doesn't result in a change in the shape of the distribution. The existence of unit roots is a cause for non-stationarity. Hence, we checked the presence of the unit root using the Augmented Dicky-Fuller (ADF) unit root test.

Table 3: Unit Root Test

Sr. No.	Indices / Variables	Level		First difference	
		Intercept	Intercept and trend	Intercept	Intercept and trend
1	NIFTY 50	-1.108	-1.619	-17.00*	-17.02*
2	NIFTY NEXT 50	-1.051	-1.058	-42.73*	-42.73*
3	BSE Sensex	-1.084	-1.976	-17.14*	-17.15*
4	BSE 100	-1.082	-1.38	-16.87*	-16.89*
5	India VIX	-3.163**	-2.98	-43.77*	-43.78*
6	FII Purchase	-7.96*	-17.13*	-----	-----
7	FII Sales	-6.44*	-13.99*	-----	-----
8	FII Net	-11.20*	-11.62*	-----	-----
9	DII Purchase	-4.26*	-11.66*	-----	-----
10	DII Sales	-6.31*	-12.84*	-----	-----
11	DII Net	-11.05*	13.02*	-----	-----

Notes: * implies significance at 1% level and ** implies significance at 5% level.

Table 3 reports the results of the ADF tests. All the indices suffer from the problem of unit root in the log price series. Therefore, all the index series have been converted into the returns series by taking the first difference to their logarithmic value. The null hypothesis of the presence of unit root was rejected at a 1% level of significance using intercept and intercept and trend in all indices returns in all periods. Whereas purchases, sales, and net investments by the FIIs and the DIIs are stationary at the level.

4.3 Correlation Analysis

Correlation analysis is used to evaluate the strength of the relationship between variables under the study (Roy and Deb, 2019). Here, they are stock market return, the flow of FIIs and DIIs. The return series appears to have anomalous asymmetry during these three periods. The effect of diversification in an international portfolio investment can be explored using correlation, rolling correlation and cointegration (Joshi *et al.*, 2021; Modi *et al.*, 2010; Patel and Patel, 2022). As a result, correlation and rolling correlation were used to analyse the pattern of both institutional investors with regard to market and volatility index in order to identify the dynamic relationship of the FIIs and DIIs over time.

Table 4: Correlation analysis

		RNIFTY50	FIINET	DIINET
FIINET	Before	0.2702*	----	----
	During	0.3138*	----	----
DIINET	Before	-0.0816*	-0.6177*	----
	During	-0.221****	-0.8266*	----
INDIA VIX	Before	-0.5540*	-0.1090*	0.0491**
	During	-0.4754*	-0.3658*	0.4505*

Notes: (a) 'Before' includes the pre-COVID period from Jan. 1, 2011 to Dec. 31, 2019: n = 2187. (b) 'During' captures during the COVID from Jan 1, 2020 to Apr 3, 2020: n = 66. (c) * implies significance at 1% level, ** implies significance at 5% and *** implies significance at 10% level.

Table 4 discusses the pre-COVID and during COVID correlation of the net investment by the FIIs and the DIIs with the broad market index Nifty as well as the volatility index-India VIX in pre-COVID and during the COVID periods. The effect of the FIIs on the Indian stock market can be understood from the correlation analysis before and during the COVID-19 outbreak. The correlation of net investments by the FIIs with the Nifty 50 was positive and significant at a 1% level before and during COVID-19. However, the DIIs besides the bigger investment pools have negative and significant correlations at 1% and 10% with the market in pre and during COVID periods, respectively (Bansal and Rao, 2018). The market generally has a negative relationship with volatility, which implies higher volatility follows lower returns and vice versa (Cox and Ross, 1976; French *et al.*, 1987; Bekaert and Wu, 2000; Boyer *et al.*, 2010; Qadan *et al.*, 2019). This can be evident from the significant negative correlation between market returns and the volatility index at 1%. It should be important to note that the correlation between the net investment by the FIIs and the DIIs in the pre-COVID period is -0.6177 and significant at 1%; furthermore, this correlation even became stronger during the COVID period at -0.8266. This clearly implies that this is the period when the FIIs kept on selling and the DIIs kept on buying. The FIIs have a significant negative correlation with the India VIX index, which implies a decrease in volatility when the FIIs buy more than they sell and vice versa. The DIIs in the pre-COVID period have a positive correlation with the volatility index at 0.0491, which is significant at 5%; however, during COVID, the correlation became strongly positive with 1% significance. This clearly shows the opposite behaviour as compared to the FIIs net investment. However, it should be noted that when the FIIs sell, DIIs start purchasing and the market volatility starts increasing.

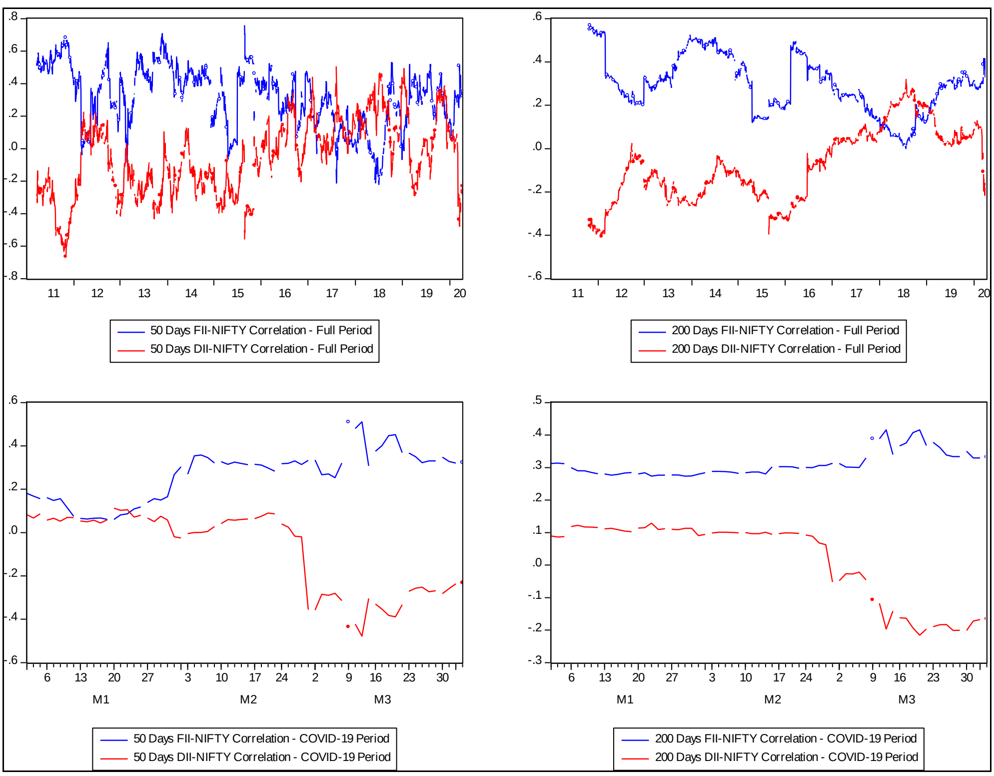

Figure 2: 50 Days and 200 Days Rolling correlations for full period and third period

Figure 2 portrays the rolling correlation of the FIIs and the DIIs with Nifty 50. Long-term investors rely more on longer day averages than day traders and swing traders, who typically use the shorter moving averages. In light of this, rolling correlations allow to comprehend the relationship's trend through time and eliminate the impact of temporal change on the relationship. To examine the short- and long-term evolution of the relationships, we have taken rolling correlations over 50 and 200 days. We have captured this correlation with only

Nifty 50 because of its high liquidity and well diversity. The top two figures are 50 days and 200 days rolling correlations for the full sample period and the bottom two figures capture the rolling correlations during the COVID-19 outbreak. The benefit of rolling correlation is that it removes the abnormal correlations. From figure 1, it seems that the behaviour of the net investments by the FIIs and the DIIs is negative in the long-term as well as short-term. This is obvious when comparing their 200 days rolling correlations. During the outbreak of COVID-19, this negative correlation became stronger, which is apparent in the bottom two figures, especially after February 2020.

Further, to investigate the relationship of the net investments by the FIIs and the DIIs with the market, we converted the time series into the ratio of purchase to sales. When the ratio is greater than one, it implies that the institution is buying more than selling and vice versa. The series of this ratio is then compared with the returns series of Nifty 50. This relationship was documented in the form of alpha and beta to understand the behaviour with the market index.

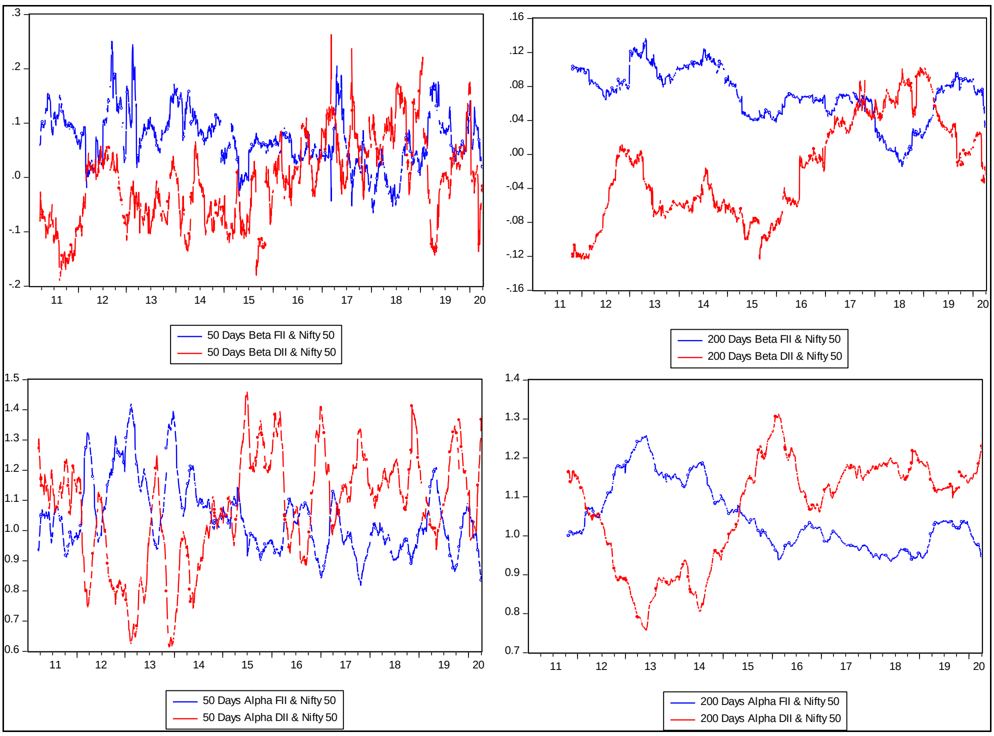

Figure 3: 50 Days and 200 Days Rolling alpha and beta for full period

From figure 3, it is quite apparent that the movement of the net investments by the FIIs and the DIIs seems the opposite. From the 50 days and 200 days rolling beta and alpha, it can be seen that the sensitivity of these institutions is opposite to each other with respect to Nifty 50, which looks candid in the 200 days rolling period.

4.4 Granger Causality Test

This test scrutinizes the direction of causality between the variables of the time series. After examining the unit root and correlation analysis, the next step is to know the direction of the causality. The test represents that for two variables (for example, X and Y); if X is influenced by its delayed values and/or the delayed values of Y, then we can say Y Granger cause of X and vice versa in case X Granger cause of Y. When both X and Y Granger cause each other, it is the case of bidirectional causality. When only one exists, then it is unidirectional causality. There may be cases of the existence of no causality between variables (Roy and Deb, 2019). The Granger causality test for each of the three periods is listed in Table 5. The lag length of two was identified based on the VAR unrestricted model with regard to the Schwarz information criterion (SIC) and the Hannan-Quinn Information Criterion (HQIC).

Table 5: Analysis of Granger Causality Test

Caused by ↓	Granger caused to ↓						
	NIFTY 50	Nifty Next 50	Sensex	BSE 100	India VIX	FII Net	DII Net
Panel 1: Jan 1, 2011 to Apr 3, 2020							
NIFTY 50	-----	1.526	5.602*	1.515	2.377***	47.351*	70.951*
Nifty Next 50	0.244	-----	0.198	0.161	5.047*	37.003*	72.312*
Sensex	5.587*	0.922	-----	0.782	2.260	47.069*	69.558*
BSE 100	1.175	1.261	1.137	-----	3.022**	48.243*	75.574*
India VIX	4.104**	4.509**	4.296**	4.042**	-----	21.882*	12.63*
FII Net	5.66*	6.586*	5.71*	6.338*	0.296	-----	30.05*
DII Net	3.69**	2.590***	3.621**	3.489**	2.303	50.989*	-----
Panel 2: Jan 1, 2011 to Dec 31, 2019							
NIFTY 50	-----	1.678	2.271	0.794	8.916*	39.059*	61.127*
Nifty Next 50	0.070	-----	0.137	0.079	12.863*	29.167*	64.397*
Sensex	2.44***	1.754	-----	0.584	8.481*	38.605*	60.465*
BSE 100	0.302	1.491	0.370	-----	10.495*	39.591*	66.111*
India VIX	0.963	2.421***	1.068	0.978	-----	14.812*	10.059*
FII Net	0.115	0.930	0.222	0.152	1.486	-----	25.795*
DII Net	0.738	0.155	0.901	0.689	1.707	39.808*	-----
Panel 3: Jan 1, 2020 to Apr 3, 2020							
NIFTY 50	-----	0.329	3.539**	0.577	1.637	2.978***	3.235**
Nifty Next 50	0.451	-----	0.519	0.309	2.202	4.044	3.192**
Sensex	3.434**	0.106	-----	1.715	1.652	3.082***	3.087***
BSE 100	0.683	0.326	2.151	-----	1.732	3.248**	3.218**
India VIX	1.988	1.125	1.973	1.759	-----	3.804**	0.563
FII Net	6.69*	5.959*	6.191*	6.836*	1.517	-----	2.263
DII Net	5.793*	3.66**	5.594*	5.612*	0.575	1.350	-----

Notes: * implies significance at 1% level, ** implies significance at 5% and *** implies significance at 10% level.

Panel 1 explores the Granger causality for the full sample period. It can be observed that Nifty 50 is (Granger) caused by Sensex, the net investment of the FIIs and the DIIs at 1% level of significance which is consistent with Roy and Deb (2019). Whereas, India VIX granger cause Nifty 50 at 5% level. Nifty Next 50 is caused by the net investment by the FIIs at 1% level; however, India VIX causes at 5%, whereas the net investment by the DIIs causes at 10% level of significance. Sensex is caused by the Nifty 50 as well as the net investment by the FIIs at 1%, which indicates a bidirectional relationship. The BSE 100 is caused by the net investment by the FIIs at 1%. India VIX is significantly caused by Nifty Next 50 at 1%. It should be noted that the net investments by the FIIs and the DIIs are caused by all the variables at 1%. Bhargava and Malhotra (2015) also observed that the activities of FIIs have a direct and positive impact on the Indian stock market. Moreover, it should be noted that India VIX causes both the net investment by the FIIs and the DIIs, whereas none of the institutions cause India VIX. This signifies the dependency of the returns and the volatility of the indices on the investment patterns of the FIIs and the DIIs.

Panel 2 summarizes the Granger causality for the second period, which is quite a normal period before COVID-19. In this period, the Nifty 50 is hardly caused by any variable except Sensex at a 10% level of significance. Moreover, the Nifty 50 causes India VIX as well as the net investments by the FIIs and the DIIs. This is similar to all the indices. India VIX is caused by all the other indices. The relationship between the net investments by the FIIs and the DIIs is consistent with the full sample period and they are caused by the returns and the volatility in the market.

Panel 3 discusses the sample period during the COVID-19 outbreak. It is worth noting that the India VIX is not caused by any of the variables. All the indices except the India VIX are caused by the net investments of the FIIs and the DIIs at a 1% level of significance. However, the indices, except Nifty Next 50, are also causing the net investments by the FIIs and the DIIs, but the magnitude of this cause was not significant at 1% level. They are significant either at 5% or at 10%. It is surprising to observe that during this period none of the institutional investors caused each other, which implies that the investment patterns of the FIIs and the DIIs are different. However, looking at the correlations during the pandemic, both institutions have significant and negative correlations and there is substantial evidence from Table 2 during this period.

4.5 GARCH (1,1)

The results of Table 6 report the parameter estimates of the symmetric GARCH (1,1) model with normal Gaussian distribution for Nifty 50 as a dependent variable in the three periods. We found similar results in the other three indices (results are available on request). In the symmetric GARCH (1, 1) model, all the parameters of the model are statistically significant at a 1% level of significance. In each of the models, R^2 is meaningful because of the regressors in the mean equation. The upper part of the model provides the output for the mean equation, the middle part provides the output for the variance equation, and the lower part provides the model diagnostics.

From the mean equation of GARCH (1, 1), it can be observed that the coefficients of gross purchases of the FIIs and the DIIs are positive and significant, while at the same time, the coefficients of gross sales of the FIIs and the DIIs are negative and significant. This implies that the purchases of institutional investors have a positive impact and sales have a negative impact on the market returns. Moreover, the India VIX has a significant negative relationship with the market returns, which implies that the volatility has a negative impact on the market returns. This can be the first evidence of the leverage effect. The COVID-19 dummy is not statistically significant in the return equation. In the variance equation, the α coefficient reflects the weight attached to the news assessed as the shock of the lagged period hence, a larger α indicates market reaction to the news. The β coefficient is the weight applied to the previous volatility forecast. The equation of GARCH (1, 1) in Table 6 clearly indicates that the current volatility is explained by the reaction of news as well as past volatility and as a result, this model showed evidence of the volatility clustering in full and sub-period. The sum of ARCH and GARCH terms is close to unity in GARCH and GJR-GARCH in all periods, which indicates a high degree of volatility persistence. This observation is common in all the indices under the study. Hence, we have not reported the results of all the indices; however, results are available on request. The higher value of $\alpha + \beta$ indicates that the shocks in the Indian market tend to have longer durations. The more important variable in the variance equation is the COVID-19 dummy variable applicable in the first period which breaks the two sub-periods. It can be observed that the coefficient of a dummy is positive (0.0622) and significant, which implies that the volatility has increased after this period. The net position of FIIs is statistically significant which indicates that the volatility is driven by the net position of FIIs. During the COVID period, the net position of DIIs drove the volatility. In the pre-COVID period, the results are quite similar. However, the β coefficient is higher than the full period and the α coefficient is lower than the first period. This clearly implies the COVID-19 effect in the first period has distorted the volatility in the market.

Table 6: GARCH (1, 1) estimates

	NIFTY 50					
	Panel-1: Full period sample Jan 1, 2011 to April 3, 2020		Panel-2: Pre-COVID period Jan 1, 2011 to December 31, 2019		Panel-3: During-COVID period Jan 1, 2020 to April 3, 2020	
Variable	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic
Mean equation						
Intercept	0.0485	1.521	0.0373	1.133	0.5758	0.897
Returns (-1)	0.0816*	4.357	0.0839*	4.563	-0.3928*	-2.947
FIIGP	0.0002*	25.292	0.0002*	24.762	0.0009*	4.687
FIIGS	-0.0002*	-24.318	-0.0002*	-22.768	-0.0007*	-2.844
DIIGP	0.0002*	8.894	0.0002*	8.626	0.0001	0.586
DIIGS	-0.0002*	-6.630	-0.0002*	-6.351	-0.0005**	-2.510
INDIA_VIX	-0.1005*	-39.525	-0.0983*	-38.845	-0.1199*	-4.420
COVID-19 Dummy	0.0068	0.036	-------	-------	-------	-------
Variance equation						
ω	0.0186*	4.164	0.0122*	3.790	0.2496**	2.414
α	0.0988*	11.235	0.0650*	8.730	0.4498***	1.909
β	0.8767*	71.245	0.9167*	94.712	0.4954*	2.972
FII	0.0347***	1.843	0.0088	0.549	0.1478	0.181
DII	0.0179	1.494	0.0028	0.276	0.8626**	2.436
COVID-19 Dummy	0.0622*	4.010	-------	-------	-------	-------
$(\alpha+\beta)$		0.9755		0.9818		0.9453
Model diagnostics						
R-squared		0.3237		0.3641		0.4563
Adj. R-squared		0.3216		0.3623		0.4019
Durbin-Watson stat		2.2056		2.0008		2.0984
Log likelihood		-2586.680		-2461.825		-106.989
AIC		2.3097		2.2633		3.5519
SIC		2.3452		2.2946		3.9468
Q(5) (P-value)		1.2681 (0.938)		0.3129 (0.997)		4.3473 (0.501)
$Q^2(5)$ (P-value)		3.1649 (0.675)		3.7475 (0.586)		2.4024 (0.791)
ARCH-LM Test (P-value)		1.5499 (0.2133)		1.4997 (0.2208)		2.4213 (0.1246)

Notes: (a) Q and Q^2 are Ljung-Box Q statistics up to five lags of the residuals in GARCH (1, 1) Model. (b) The results of ARCH-LM test for conditional heteroskedasticity in GARCH (1, 1) Model using the first lag of the residuals. (c) * implies significance at 1% level, ** implies significance at 5%, and *** implies significance at 10% level.

In the COVID period, the purchases and sales of the FIIs play a very important role in the mean equation and they are significant at 1%. However, the purchases of the DIIs did not affect the mean returns. This primarily indicates that the returns are driven by the purchases and sales of the FIIs during the COVID-19 outbreak period. The α coefficient and the β coefficient in all the market indices are close to each other. This implies that the increase in volatility is due to news surprises as well as lagged volatility in the marketplace. The $\alpha+\beta$ value is close to unity in Nifty 50. Figure 4 shows the conditional variance of the model that is dynamic, volatile, and the entire process becomes nonstationary with highly persistent variance after March 11, 2020. This implies that the COVID-19 outbreak in this period made the Indian market over-persistence of shocks, which can eventually explode to infinity. Lamoureux and Lastrapes (1990) argued that the high persistence might reflect the event specific variance. This result is also consistent with Bala and Asemota (2013). Hence, during this period, explosive-shocked stock markets are not conducive to long-term investing because investors in these stocks may lose or benefit forever (Kuhe, 2018).

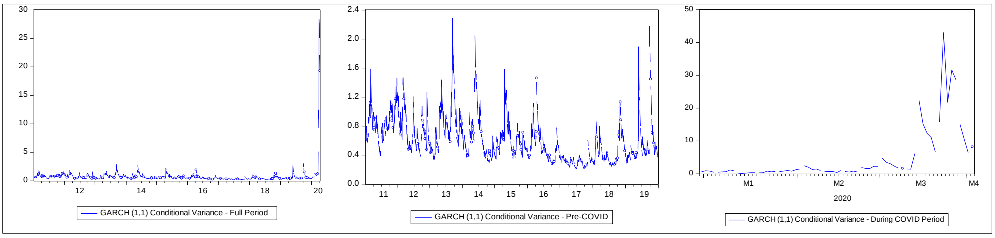

Figure 4: GARCH (1.1) Conditional variance

4.6 GJR-GARCH

Table 7 reports the parameter estimates of the asymmetric GJR-GARCH (1,1) model with normal Gaussian distribution for Nifty 50 as a dependent variable in the three periods. We found similar results in the other three indices (results are available on request). All the estimated parameters of the mean equation are significant, except COVID-19 dummy variables, which indicate that the market in normal conditions is driven by the activities of the FIIs and the DIIs. All the parameters in the variance equation are positive and statistically significant at 1%. The value of α coefficient (0.0667) is significant. It shows the effect of recent news on current market volatility. The significant and positive γcoefficient (0.1045) value shows a strong presence of the asymmetric effect of news that implies that the market is more sensitive toward negative shocks as compared to positive shocks in the returns. The historical volatility impact represented by the β coefficient (0.8454) is also significantly positive and much higher than the recent news impact. This means that in the Indian stock market, historical volatility takes a long time to wipe out (Gahlot, 2019). This is consistent with all the indices in the full period and sub-periods. The positive and significant γcoefficient (0.1045) indicates that the negative news (negative shocks) leads to increased volatility compared to the positive news (positive shocks) of the same magnitude. Thus, the study found empirical evidence for asymmetry with the leverage effect. These results are similar for the second period.

The third period is full of chaos due to the COVID-19 outbreak. It must be worth noting that the purchases and sales of the FIIs have a direct impact on the mean returns. However, purchases of the DIIs do not affect the returns in any of the market indices. The Indian VIX also has a negative impact on the mean returns and it is significant at 1%, this implies that the market returns decrease as volatility increases, which is prima facie evidence of the leverage effect.

The significant and negative γcoefficient (-0.0642) value shows the presence of the asymmetric effect of news which implies that the market is more sensitive toward positive shocks as compared to negative shocks in the returns. The historical volatility impact represented by the β coefficient (0.7083) is also significantly positive and much higher than the recent news impact. This means that in the Indian stock market, historical volatility takes a long time to wipe out (Gahlot, 2019). This is consistent with the empirical literature, which states that the lagged volatility influences the current volatility. Even the persistence of the volatility is highest in the third period, which indicates the explosion in the volatility to make abnormal gains and losses. Using the GJR-GARCH, it is also observed that during the COVID period, the net position of DIIs drove the volatility. This is consistent with the GARCH (1,1) model.

Table 7: GJR-GARCH (1, 1) estimates

	NIFTY 50					
	Panel-1: Full period sample Jan 1, 2011 to April 3, 2020		Panel-2: Pre-COVID period Jan 1, 2011 to December 31, 2019		Panel-3: During-COVID period Jan 1, 2020 to April 3, 2020	
Variable	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic
Mean equation						
Intercept	0.0586***	1.8346	0.0527	1.6173	0.8495**	2.3734
Returns (-1)	0.0817*	4.3309	0.0844*	4.5321	-0.1047	-0.7719
FIIGP	0.0002*	23.9409	0.0002*	23.4843	0.0005*	3.3140
FIIGS	-0.0002*	-23.4124	-0.0002*	-22.6092	-0.0005*	-2.8929
DIIGP	0.0002*	8.6468	0.0002*	8.2529	0.0001	1.2123
DIIGS	-0.0002*	-6.6030	-0.0002*	-6.0765	-0.0003*	-2.6614
INDIA_VIX	-0.0978*	-38.0174	-0.0960*	-37.8280	-0.1080*	-6.6502
COVID-19 Dummy	0.0288	0.1513	-------	-------	-------	-------
Variance equation						
ω	0.0276*	4.6475	0.0183*	4.2581	0.0635*	3.6649
α	0.0667*	6.4543	0.0491*	5.8117	0.3496	1.5934
γ	0.1045*	5.3524	0.0661*	4.2593	-0.0642	-0.1982
β	0.8454*	50.6013	0.8914*	70.4245	0.7083*	8.7257
FII	0.0522*	2.6258	0.0272	1.5499	-0.4684	-1.2150
DII	0.0104	0.7632	0.0017	0.1353	0.3654*	77.6947
COVID-19 Dummy	0.0595*	4.0787	-------	-------	-------	-------
$\alpha+\beta+\frac{\gamma}{2}$		0.9644		0.9736		1.0258
Model diagnostics						
R-squared		0.3218		0.3626		0.3320
Adj. R-squared		0.3197		0.3608		0.2641
Durbin-Watson stat		2.2046		2.0007		2.6126
Log likelihood		-2578.179		-2456.613		-95.1277
AIC		2.3030		2.2595		3.2766
SIC		2.3411		2.2933		3.7079
Q(5) (P-value)		0.8449 (0.974)		0.3115 (0.997)		4.8856 (0.43)
$Q^2(5)$ (P-value)		2.1795 (0.824)		3.6339 (0.603)		2.2451 (0.814)
ARCH-LM Test (P-value)		0.5491 (0.4588)		1.1577 (0.2821)		2.2702 (0.1369)

Notes: (a) Q and Q^2 are Ljung-Box Q statistics up to five lags of the residuals in GARCH (1, 1) Model. (b) The results of ARCH-LM test for conditional heteroskedasticity in GARCH (1, 1) Model using the first lag of the residuals. (c) * implies significance at 1% level, ** implies significance at 5%, and *** implies significance at 10% level.

4.7 EGARCH

The results of Table 8 report the parameter estimates of the asymmetric EGARCH (1,1) model with normal Gaussian distribution for Nifty 50 in the three periods. The results of EGARCH (1, 1) are also consistent with GJR-GARCH (1, 1). The γcoefficient (-0.0358) indicates that the negative news leads to increased volatility compared to the positive news. This is consistent in the pre-COVID period. However, γcoefficient (0.3715) in the COVID period indicates positive news increases volatility. In the third period, it is observed that the ARCH term is positive and significant at a 1% level in all the indices, which indicates that the recent news creates volatility in the market. The Q^2 of residuals also indicates the serial autocorrelation in the squared residuals.

Table 8: EGARCH (1, 1) estimates

	NIFTY 50					
	Panel-1: Full period sample Jan 1, 2011 to April 3, 2020		Panel-2: Pre-COVID period Jan 1, 2011 to December 31, 2019		Panel-3: During-COVID period Jan 1, 2020 to April 3, 2020	
Variable	Coefficient	z-Statistic	Coefficient	z-Statistic	Coefficient	z-Statistic
Mean equation						
Intercept	0.04813	1.572	0.04369	1.393	-0.01114	-0.047
Returns (-1)	0.08032*	4.539	0.08014*	4.487	-0.35877*	-18.601
FIIGP	0.00022*	25.373	0.00022*	25.007	0.00096*	8.830
FIIGS	-0.00024*	-26.088	-0.00024*	-25.718	-0.00071*	-11.957
DIIGP	0.00020*	9.584	0.00020*	9.314	0.00015	2.069
DIIGS	-0.00018*	-7.366	-0.00018*	-6.973	-0.00045*	-4.034
INDIA_VIX	-0.09916*	-38.296	-0.09883*	-37.581	-0.11232*	-8.180
COVID-19 Dummy	0.07319	0.294	-------	-------	-------	-------
Variance equation						
ω	-0.16247*	-11.217	-0.15457*	-9.951	-0.99139	-1.532
α	0.18798*	11.901	0.17224*	10.253	1.70567*	4.966
γ	-0.03579*	-3.610	-0.03455*	-3.407	0.37152***	1.677
β	0.96866*	141.293	0.96272*	115.706	-0.59529*	-6.140
FII	0.07526**	2.162	0.09424*	2.587	-0.25493	-0.119
DII	0.03795***	1.747	0.03625	1.632	3.17478*	4.233
COVID-19 Dummy	0.12703*	8.049	-------	-------	-------	-------
$(\alpha + \beta)$		1.15664		1.13496		1.11038
Model diagnostics						
R-squared		0.3236		0.3654		0.4549
Adj. R-squared		0.3215		0.3637		0.4004
Durbin-Watson stat		2.2041		1.9973		2.1867
Log likelihood		-2565.945		-2445.814		-113.074
AIC		2.2921		2.2496		3.7634
SIC		2.3302		2.2834		4.1912
Q(5) (P-value)		0.7497 (0.98)		0.375 (0.996)		0.039 (0.858)
$Q^2(5)$ (P-value)		5.3085 (0.379)		5.5423 (0.353)		0.197 (0.002*)
ARCH-LM Test (P-value)		3.0529 (0.081***)		2.4596 (0.1170)		0.053614 (0.8176)

Notes: (a) Q and Q^2 are Ljung-Box Q statistics up to five lags of the residuals in GARCH (1, 1) Model. (b) The results of ARCH-LM test for conditional heteroskedasticity in GARCH (1, 1) Model using the first lag of the residuals. (c) * implies significance at 1% level, ** implies significance at 5%, and *** implies significance at 10% level.

All GARCH models satisfy the assumptions in the first and second periods. Moreover, the null hypothesis of homoskedasticity in the residual is accepted using ARCH LM tests for ARCH effects of the estimated models. This shows that the conditional variance equations for GARCH (1, 1), GJR-GARCH (1, 1), and EGARCH (1, 1) models are well defined as the models captured all the ARCH effects and none was left in the innovation. In the first and the second periods, the sum of ARCH and GARCH terms and in GARCH and GJR-GARCH models is close to unity, which is required to have a mean-reverting process in the variance. However, this sum in the third period is more than unity, which indicates that the mean-reverting process in the variance is not taking place. This shows that the process of one-directional variance is still in the process and long-term investors may lose or gain in the market significantly.

5. Conclusion

The study examined the impact of activities of the FIIs and the DIIs on the returns and the volatility of the market indices in India prior to and during the COVID-19 outbreak using rolling correlation, Granger causality, GARCH, GJR-GARCH, and EGARCH. The current research divides the entire period into three sub-periods to capture the impact of activities of the institutional investors before and during the crisis due to the pandemic of COVID-19. The descriptive statistics suggest that COVID-19 skewed returns and volatility. The average and median net investment by the DIIs is higher than that of the FIIs, suggesting the scale of investment by the DIIs is greater than the FIIs. However, the pattern of the FIIs and the DIIs investments changed a great deal during the COVID-19 outbreak.

The average daily net investment during the COVID-19 period by the FIIs and the DIIs is -1,317.25 crores and 1,111.79 crores, respectively. It shows that during this period, the FIIs have sold and the DIIs have bought a significant portion in the marketplace. This implies that the DIIs played a very instrumental role to make the market less exposed to the COVID-19 outbreak, as referred to in various literature (Murthy and Singh, 2013; Baral and Patra, 2019). It was observed that the FIIs have been found to be net sellers during the time of crisis and DIIs have been defending players by buying in the falling market (Loomba, 2012; Murthy and Singh, 2013; Jalota, 2017; Reddy, 2017; Baral and Patra, 2019). The correlation of the net investments by the FIIs with the Nifty 50 was positive and significant at a 1% level before and during COVID-19. The DIIs, besides the bigger investment pools, have shown a negative and significant correlation at 1% before COVID-19. However, the correlation of the DIIs with the market was only significant at 10%. The correlation between the net investments by the FIIs and the DIIs in the long-term is -0.6177 in the normal course of action; however, during the outbreak of COVID-19, this correlation even reduced to -0.8266, which is significant at a 1% level, which implies this as a period when the FIIs kept on selling and the DIIs kept on buying. This finding is consistent with the rolling correlation analysis.

The result of Granger causality depicts that Sensex and the net investments by the FIIs and the DIIs cause Nifty 50 at a 1% level of significance. It should be noted that the net investments by the FIIs and the DIIs are influenced by all the variables at 1%. The results signify the dependency of the returns and the volatility of the indices on the investment pattern of the FIIs and the DIIs (Bansal and Rao, 2018; Roy and Deb, 2019). During the COVID-19 outbreak, the net investments by the FIIs and the DIIs caused all the indices except India VIX at a 1% level of significance. However, none of the indices causes the net investment by the FIIs and the DIIs at a 1% level. It is surprising to observe that during the pandemic period, none of the institutional investors caused each other, which implies that investment patterns of FIIs and DIIs are independent of each other.

The study modelled heteroskedasticity in the Indian stock market by employing three GARCH specifications, namely, symmetric GARCH (1,1), GJR-GARCH (1,1), and asymmetric EGARCH (1,1) models. The results of GARCH show that the current volatility is explained by the reaction to the news and the past volatility; and as a result, this model showed evidence of volatility clustering. The sum of ARCH and GARCH terms is less than one, which indicates high-volatility persistence. The more important variable in the variance equation is the COVID-19 dummy and the net position of institutional investors. It can be observed that the coefficient of the dummy is positive (0.0622) and significant, which implies that the volatility has exploded during the COVID-19 outbreak. Further, the volatility was due to the net position of FIIs. In the third period, the purchases and sales by the FIIs play a very crucial role in the mean equation and they are significant at 1%. However, during the COVID period, the net position of DIIs also drove the volatility. This largely shows that the returns are driven by the purchases and sales activities of the FIIs (Shukla *et al.*, 2011; Baral and Patra, 2019; Roy and Deb, 2019).

The α coefficient is lower than the β coefficient in all the market indices. This implies an increase in volatility due to lagged volatility in the marketplace. However, during the COVID period, these terms are close to each other which indicates that the volatility was due to news and previous volatility. This implies that the COVID-19 outbreak made the Indian market over-persistent to shocks, which can eventually explode to infinity. The GJR-GARCH reveals that negative news (negative shocks) leads to increased volatility compared to positive news (positive shocks) of the same magnitude. Thus, the study found empirical evidence for asymmetry with the leverage effect. However, during the COVID-19 outbreak, the volatility was mainly because of the negative news, which can be observed in γcoefficient in most of the indices. The results of EGARCH are consistent with GJR-GARCH. The asymmetric models showed evidence of asymmetry with leverage effect on the Indian stock market.

Our study is the most recent and is closely related to the literature on capturing FII and DII investment patterns and their impact on pandemic returns and volatility. None of the studies in the world examined how FIIs and DIIs acted during the global outbreak. As a result, our study is the first to look at this nexus, contributing to the body of knowledge. This research has policy implications for policymakers in terms of framing policies to decrease volatility that may develop as a result of unexpected pandemic news. Further, retail investors who become more sensitive during times of crisis should take cues from the activities of both FIIs and DIIs in taking their investment decisions. The leverage effect indicates an asymmetrical relationship between news and volatility in stock return, hence, investors are advised to play safe during such highly turbulent times especially when it is negative in nature. The increasing volume of institutional investment in the Indian capital market is a good signal for the growing economy. With many positive aspects, they also bring some risks for the markets and the overall economy. The outcomes of the Granger causality test for the period during the pandemic suggest that all the indices except the India VIX are caused by the net investments by the FIIs and the DIIs. Hence, the economy and the capital markets are highly dependent on the actions of institutional investors. However, as none of the institutional investors cause each other, indicating their independent investment patterns, they should be treated separately in such a way that it doesn't create a big impact on the capital markets of the economy. This research has a significant contribution to assessing how institutional investors react in the event of a pandemic. Future studies could look into the same relationship between developed and developing countries.

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Does Uncertainty Indices Impact the Cryptocurrency Market?

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Abstract: Research Question: Does uncertainty indices have impact on cryptocurrency? **Motivation:** Most of the previous study investigate the impact of geopolitical risk and economic policy uncertainty on Bitcoin only and less research investigate the long run and short run relationship between the uncertainty indices and cryptocurrency. Hence, this study investigates whether the economic policy uncertainty, geopolitical risk and US equity market uncertainty have an impact on Bitcoin, Ethereum and Binance Coin by the multivariate VAR Granger non-causality. **Idea:** This study applied three different uncertainty indices (geopolitical risk, economic policy uncertainty and US equity market uncertainty) and top three ranking cryptocurrency (Bitcoin, Ethereum and Binance Coin) to investigate and compare the impact of uncertainty indices on cryptocurrency with different uncertainty conditions and applied top three ranking cryptocurrency in cryptocurrency market to reinforce the result. **Data:** This study applied monthly data with 42 observations which cover the period of December 2017 until May 2021 and data for cryptocurrency extracted from investing.com, while the uncertainty indices from policyuncertainty.com. **Method/Tools:** This study utilize multivariate VAR Granger non-causality to examine the cointegration relationship between the cryptocurrency and uncertainty indices. **Findings:** The results show that the economic policy uncertainty, geopolitical risk and US equity market uncertainty cointegrated with Bitcoin, while Binance Coin cointegrated with geopolitical risk only. Hence, the economic policy uncertainty, geopolitical risk and US equity market uncertainty plays a vital role in the Bitcoin prediction and geopolitical risk plays an important role to forecast the Binance Coin. **Contributions:** The Bitcoin investors may focus on the changes in economic policy uncertainty, geopolitical risk and US equity market uncertainty to predict the Bitcoin return, and Binance Coin investors focus on the geopolitical risk.

Keywords: Geopolitical risk, economic policy uncertainty, US equity market uncertainty, cryptocurrency.
JEL Classification: G1, G4

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1. Introduction

The blockchain system facilitates trusted transactions between untrusted participants through its cryptographic-based distributed ledger (Taylor *et al.*, 2020). As blockchain technology grows in popularity, a variety of applications are being used by businesses and private users. For businesses, blockchain is primarily applied to optimize the data storage, as well as data sharing, whereas cryptocurrency is its most popular use among private users (Teichmann and Falker, 2020). In November 2008, Satoshi Nakamoto proposed Bitcoin during the global financial crisis. His whitepaper, 'Bitcoin: A Peer-to-Peer Electronic Cash System', describes Bitcoins and its payment systems with technical details. This would enable consumers to manage their payments without involving any financial intermediaries (Nakamoto, 2008). Bitcoins launch and take advantage of a highly uncertain environment after the global financial crisis. Bitcoin is one of the cryptocurrencies, which is a form of electronic money. It is a digital currency decentralized fully without central authority and intermediaries required but from the Bitcoin blockchain network. The worsening economic conditions is believed can affect the Bitcoin volatility and infect the Bitcoin returns directly (Chaim and Laurini, 2018). In some cases, it can act as a safe-haven asset. Hence, with this property, the Bitcoin has received a significant amount of critical attention in the global economy as an investment strategy.

The network economics play a critical role to cryptocurrencies. Development of technology and innovation are closely related to network economics in cryptocurrency. Economic policy uncertainty and geopolitical risk can affect the pace of cryptocurrency innovation and application development. Startups and developers may be hesitant to pursue cryptocurrency-related projects due to uncertain regulatory environments and slow down the technological advancements. Furthermore, cryptocurrency relies on the network effects, as more participants join the cryptocurrency network, its value and utility increase. The adoption, acceptance and liquidity of cryptocurrency can be enhanced by effective network effect but it is possible to disrupt by the economic policy uncertainty and geopolitical risk, which negative events or regulatory actions can reduce confidence and impede the growth of networks.

Besides, the economic policy uncertainty and geopolitical risk have contingent spillover effect on cryptocurrency. Economic policy uncertainty and geopolitical risk could spread negative sentiment and market disturbance across different markets, including cryptocurrency. The volatility can be amplified and affect investor behaviour when crisis or shocks occur. The risk perception and investor behaviour in cryptocurrency market could affected by economic policy uncertainty and geopolitical risk. In exhibiting herd behaviour, investors can intensify market movements and volatile the prices. As a result of uncertain circumstances, the cryptocurrency may also perceive as riskier by risk-averse investors, which may increase the demand for traditional safe-haven assets and decreasing participation in cryptocurrency.

Geopolitical risks can be defined as the risk of events such as wars, terrorist attacks, and political tensions threatening foreign relations' normal and peaceful nature (Caldara and Iacoviello, 2018).[1] Most previous studies investigate the impact of geopolitical risks on the stock markets and oil price. Kannadhasan and Das (2020), for instance, investigate the impacts of geopolitical risks and global economic policy uncertainty on the stock return. They find that both indicators have a negative impact on the stock return, with the impact of policy uncertainty is more substantial than geopolitical risk. Balcilar *et al.* (2017), on the other hand, find that geopolitical risk typically influences stock market volatility measures and not on

[1] The coronavirus disease (COVID-19) outbreak contains the potential to affect the geopolitical risk. Sharif *et al.* (2020), for example, find that the United States (US) geopolitical risk was more significant by the outbreak of COVID-19 than US economic uncertainty.

returns. The geopolitical risk also affects the oil price index. Antonakakis *et al.* (2017) discover that, in terms of average return and variability, the oil price index tends to be more strongly influenced negatively by the geopolitical tension index compared to the stock market.

Due to its characteristic as a highly volatile asset, Bitcoin becomes a major subject in the financial press and academia. Most of the study investigate the impact of geopolitical risk on stock or oil price. The geopolitical risk and economic policy uncertainty leads to weakening the investor's trust in the currencies or economy, especially the geopolitical risk in extreme times. Hence, we inspired to investigate whether different aspects of uncertainty indices have impact on cryptocurrency market. Apart from geopolitical risk and economic policy uncertainty, we decided to add an uncertainty index which is US equity market uncertainty to examine and compare the results in different aspects. For the cryptocurrency, we include the top 3 ranking cryptocurrency in cryptocurrency market which are Bitcoin, Ethereum and Binance Coin to reinforce the results. The market capitalization for BTC, ETH and BNB are $895.69 billion, $455.71 billion, and $88.64 billion respectively (according to the https://coinmarketcap.com/ and last search conducted on 2nd January 2022). Our findings suggest that portfolio managers who choose to invest Bitcoin should pay attention to economic policy uncertainty, geopolitical risk and US equity market uncertainty while Binance Coin investor recommend focus on the geopolitical risk trends. This study has been organized into five sections which are introduction, literature review, methodology, empirical finding, and conclusion.

2. Literature Review

2.1 Impact of Economic Policy Uncertainty on Bitcoin

EPU can be one of the determiners for dynamics of cryptocurrency (Koumba *et al.*, 2019). The EPU able to improve BTC prediction and influence long-term BTC volatility significantly (Fang *et al.*, 2019). Besides, the EPU has potential affect BTC (Hazgui *et al.*, 2022) with different frequencies (Al-Yahyaee *et al.*, 2019), especially in extreme market conditions (Mokni, 2021). Moreover, the economic uncertainty measure from internet-based index more predictive than the newspaper-based in BTC returns prediction (Bouri and Gupta, 2021). Before the BTC crash, the EPU have positive impact on BTC, but BTC affected negatively by EPU after the Bitcoin crash in December 2017 (Mokni et al, 2020). Qin *et al.* (2021) and Demir *et al.* (2018) found EPU have positive and negative effect on BTC. The BTC volatility and returns may increase when the uncertain times uprise (Paule-Vianez *et al.*, 2020; Singh *et al.*, 2022). The highest EPU days will generate greater BTC returns significantly compared to days of lowest EPU (Wang *et al.*, 2020). However, Kalyvas *et al.* (2020) and Hazgui *et al.* (2022) found EPU negatively related with BTC price crash risk which shown high EPU leads to low BTC crash risk.

When the unfavorable economic conditions, the global EPU and US EPU have greater effect on BTC (Al Mamun *et al.*, 2020). The returns of BTC in US, China and Japan are more responsive to EPU (Shaikh, 2020) but Cheng and Yen (2020) shown the EPU of US and other Asian countries have no predictive power. Besides, there has significant causal effect exists between the BTC and US EPU (Ben and Ben, 2023), as well the nonlinearity is one of the critical factors to examine the causal effect of US EPU and BTC shown by BDS test (Fasanya *et al.*,2021). The BTC/USD is more affected by the US EPU than BTC/GBP by the UK EPU (Wang *et al.*, 2020). The US EPU have both positive and negative effect on BTC (Umar *et al.*, 2021). Panagiotidis *et al.* (2019) found BTC have positive reaction to the changes of US EPU. The US EPU raise the BTC volatility and trading volume after the spike days of EPU (Wang *et al.*,2020). The US EPU also have negative effect on BTC which the US EPU shocks will reduce the volatility of BTC (Shaikh, 2020; Matkovskyy *et al.*, 2020). Furthermore, Cheng and Yen (2020) and Ben and Ben (2023) found China EPU able to predict the BTC returns but the results from Panagiotidis *et al.* (2019) is not significant. After China regulates the crypto trading, Cheng and Yen (2020) found the China EPU able to enhance its predictive power on BTC returns while Bouri and Gupta (2021) shown the China EPU might not have impact on the cryptocurrency volatility. Furthermore, Shaikh (2020) and Chen *et al.* (2021) found China EPU have positive impact on BTC. However, Yen and Cheng (2021) found the China EPU associated negatively with BTC volatility. The Japan EPU also have negative effect on BTC that the reduction of volatility of BTC market in Japan caused by the raising of Japan EPU (Matkovskyy *et al.*, 2020). The raising of European EPU also will leads to the BTC returns increase (Panagiotidids *et al.*, 2019).

Risk premiums are obtained by global EPU during the distress market conditions (Al Mamum *et al.*, 2020). The BTC have strong hedge against the EPU in average conditions (Wu *et al.*, 2019). BTC have a potential act as a hedging instrument against the risk of global EPU (Ali *et al.*, 2023; Demir *et al.*, 2018), US EPU (Matkovskyy *et al.*, 2020), and China EPU (Yen and Cheng, 2021; Chen *et al.*, 2021). The BTC able to hedge the EPU (Kalyvas *et al.*, 2020) and not limit to internet-based or newspaper-based measure of economic uncertainty (Bouri and Gupta, 2021). On the other side, Qin *et al.* (2021) found EPU cannot always hedge by BTC. The cryptocurrency market has a weak hedge against the EPU during the bull market conditions (Colon *et al.*, 2021; Wu *et al.*, 2019). Fasanya *et al.* (2021) also shown the US EPU cannot hedge by BTC. Furthermore, BTC behave more as a safe haven rather than speculative assets (Paule-Vianez *et al.*, 2020). BTC generally immune from EPU risk spillover effect indicate by MVQM-CAViaR approach while the result from Granger causality risk test is insignificant (Wang *et al.* 2019). When the EPU is high, BTC able act as a safe haven (Zhou, 2021) but the relationship tends to change from the short run to long run (Umar *et al.*, 2021). The BTC can be a safe haven under average market conditions (Wu *et al.*, 2019). However, BTC serve as a weak safe haven when the market is extremely bearish and bullish (Wu *et al.*, 2019; Colon *et al.*, 2021). Moreover, the BTC able function as a safe haven if the EPU have positive impact on BTC, but it cannot be sustained when the negative effect exists (Qin *et al.*, 2021). The BTC cannot serve as a safe haven against the US EPU (Fasanya *et al.*, 2021).

2.2 Impact of Geopolitical Risk on Bitcoin

The GPR have a potential forecast the BTC volatility and returns (Al-Yahyaee *et al.*, 2019; Aysan *et al.*, 2019; Bouri *et al.*, 2022; Singh *et al.*, 2022). The BTC able influence by GPR at different frequencies (Al-Yahyaee *et al.*, 2019). The GPR has greater impact on BTC volatility and risk premia compared to global EPU and US EPU (Al Mamun *et al.*, 2020). The impact of GPR on BTC more significant during the unfavorable economic conditions (Al Mamun *et al.*, 2020; Kyriazis, 2020). A positive and negative influence can be observed on BTC from GPR (Su *et al.*, 2020). The GPR have positive impact on BTC price volatility and influence BTC returns negatively (Aysan *et al.*, 2019). The BTC affect positively by GPR (Su *et al.*, 2020) at higher quantiles (Aysan *et al.*, 2019). However, Kyriazis (2020) found BTC affected by GPR negatively. The BTC seen as a valuable asset to immune from GPR when existing the positive effect while this view is invalid on the negative effect (Su *et al.*, 2020). The GPR acquired a risk premium during the distressed market conditions (Al Mamun *et al.*, 2020). The BTC can be served as a hedging tool against the GPR (Aysan *et al.*, 2019). GPR's extreme upsides can be hedged by BTC (Al-Yahyaee *et al.*, 2019). Although the cryptocurrency market provides a strong hedge against the GPR but in most of the cases it unable act as a safe haven (Colon *et al.*, 2021) but Kyriazis (2020) found BTC can serve as a safe haven against the GPR.

2.3 Short Summary

Most of the previous study applied quantile regression approach (eg: Umar *et al.*, 2021; Chen *et al.*, 2021; Colon *et al.*, 2021; Shaikh, 2020; Paule-Vianez *et al.*, 2020; Wu *et al.*, 2019; Demir *et al.*, 2018; Wang *et al.*, 2019) and GARCH-based approach (eg: Zhou, 2021; Malladi and Dheeriya, 2021; Bouri and Gupta, 2021; Mokni *et al.*, 2020; Wang *et al.*, 2020, Al Mamun *et al.*, 2020, Wu *et al*., 2019, Fang *et al.*, 2019; Kyriazis, 2020) to examine the influence of EPU or GPR on BTC. Earlier studies utilize quantile regression model to investigate effectiveness of BTC as a hedging tool, diversifier etc. For instance, Umar *et al.* (2021) modelled quantile regression approach to identify the time changing effect of the uncertainty on BTC. Moreover, Wang *et al.* (2019) evaluated the U.S. EPU index risk spillover effect to BTC by employed the multivariate quantile model. Similarly, Wu *et al.* (2019) applied both quantile regression and GARCH model to analyze and compared the Bitcoin and gold when perform as the hedging tools or safe haven against the EPU. Furthermore, most of the previous study applied GARCH-based models used to examine the conditional variance of Bitcoin. Malladi and Dheeriya (2021) applied EGARCH model to analyze the BTC returns to the EPU which it provides a better fit to the data than other GARCH models, according to standard goodness-of-fit measures. Moreover, Fang *et al.* (2019) examine the BTC long run volatility in response to EPU by GARCH-MIDAS model. Wang *et al.* (2020) and Mokni *et al.* (2020) applied dynamic conditional correlation (DCC)-GARCH and DCC-EGARCH to examine the dynamic correlation and time-varying correlation between BTC and EPU. In this study, we ascertain the cointegration between the uncertainty indices and cryptocurrency based on multivariate VAR Granger non-causality.

In this study, we adopt the top three ranking of cryptocurrency in the cryptocurrency market which are Bitcoin, Ethereum, and Binance Coin (based on the https://coinmarketcap.com/ and the searches conducted on 2nd January 2022) to denote the cryptocurrency instead of Bitcoin only to compare and examine whether the current result still valid. Besides, we expand the research by adding uncertainty indices in this study which is US equity market volatility to compare and reinforce the results in this study. Therefore, there have three uncertainty indices in different aspects included in this study which are economic policy uncertainty, geopolitical risk, and US equity market volatility. In summary, this study investigates the impact of economic policy uncertainty, geopolitical risk, and US equity market volatility on the Bitcoin, Ethereum, and Binance Coin by multivariate VAR Granger non-causality with monthly data.

3. Methodology

This empirical research investigates the impact of uncertainty risk on the cryptocurrency. Hence, this study adopted three cryptocurrency and uncertainty indices which Bitcoin (BTC), Ethereum (ETH) and Binance Coin (BNB) and uncertainty indices as independent variables which are Economic Policy Uncertainty (EPU), Geopolitical risk (GPR) and US equity market uncertainty (USEMV). The hypothesized functional relationship between the cryptocurrency and the uncertainty indices shown in Equation (1), Equation (2) and Equation (3). The Model 1 (BTC), Model 2 (ETH) and Model 3 (BNB) exhibits the BTC, ETH and BNB as the dependent variable and shown in Equation (1), Equation (2) and Equation (3) respectively. The usual log-linear equation for estimation is obtained by taking natural logarithms on both sides.

Model 1 (BTC):

$$LBTC_t = \beta_0 + \beta_1 LEPU_t + \beta_2 LGPR_t + \beta_3 LUSEMV_t + v_t \tag{1}$$

Model 2 (ETH):

$$LETH_t = \beta_0 + \beta_1 LEPU_t + \beta_2 LGPR_t + \beta_3 LUSEMV_t + v_t \tag{2}$$

Model 3 (BNB):

$$LBNB_t = \beta_0 + \beta_1 LEPU_t + \beta_2 LGPR_t + \beta_3 LUSEMV_t + v_t \quad (3)$$

where β_0 indicates constant and the error term, v_t should be independent and normally distributed.

This study aims to investigate the relationship and causal dynamics among cryptocurrency and uncertainty risk by multivariate Vector Autoregression (VAR) framework, specifically examining the non-causality between the variables. Non-causality analysis is essential for understanding the interdependencies and direction of influence among cryptocurrency and uncertainty risk, which can provide valuable insights for policymakers and researchers.

We employed a multivariate VAR model of order p to capture the dynamic relationships among the variables. The order of the VAR model was determined based on the VAR lag order selection criteria to indicate the optimal lag length which are sequential modified LR test statistic (LR), Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC) and Hannan-Quinn information criterion (HQ). To investigate the non-causality between the variables, the Granger causality test adopted to examines whether past values of one variable improve the forecast of another variable, thus indicating causal effect between the variables. The granger causality test tested based on the following hypothesis:

H_0: The variables absence causal relationship.
H_1: The variables presence causal relationship.

The causal relationship exists between the variables if the null hypothesis rejected. In addition, to ensure the reliability of our results, we assessed the statistical properties of the VAR model, including the presence of heteroscedasticity and autocorrelation. Model 1 (BTC), Model 2 (ETH) and Model 3 (BNB) passed the diagnostic test to ensure the robustness of the results.

Furthermore, the impulse response function (IRF) analysis adopted to examine the dynamic effects of uncertainty risk on cryptocurrency. In order to estimate the impulse response functions, we followed the Cholesky identification approach which identified structural shocks and provides robust standard errors to account for the uncertainty in the estimates. The estimated VAR coefficients used to compute the IRFs for each variable in response to a one-standard-deviation shock in each of the variables. It examines the impact of exogenous shocks on the system and understand the response patterns over time. In addition to IRFs, the variance decomposition analysis conducted to understand the relative contributions of each shock to the variability of the variables. The variance decomposition analysis was performed within the framework of a Vector Autoregression (VAR) model. This analysis provides insights into the proportion of forecast error variance attributed to each shock at different horizons.

3.1 Data

The monthly data of Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), geopolitical risk (GPR), economic policy uncertainty (EPU) and US equity market uncertainty (USEMV) cover the period of December 2017 until May 2021 comprising of 42 observations in total. The BTC, ETH and BNB are extracted from investing.com, while the GPR, EPU and USEMV are from policyuncertainty.com. The cryptocurrencies and uncertainty indices act as the dependent variable and independent variable, respectively. All data are transformed to natural logarithm to decrease the data variability. Model 1 (BTC), Model 2 (ETH), and Model 3

(BNB) indicates the BTC, ETH and BNB acts as the dependent variables in each models respectively.

Table 1: Descriptive statistics, 2017M12 - 2021M05

	BTC	ETH	BNB	EPU	GPR	USEMV
Observations	42	42	42	42	42	42
Mean	9.217	5.842	3.068	5.476	4.968	3.113
Median	9.121	5.616	2.836	5.508	4.897	3.052
Maximum	10.981	7.928	6.435	6.064	5.942	4.149
Minimum	8.142	4.670	1.633	4.818	4.181	2.514
Standard Deviation	0.700	0.878	1.039	0.282	0.367	0.344
Skewness	1.024	0.804	1.770	-0.163	0.286	0.667
Kurtosis	3.697	2.768	5.974	2.495	2.894	3.461
Jarque-Bera	8.195	4.622	37.396	0.631	0.594	3.484
Sum	387.118	245.367	128.839	229.986	208.649	130.77
Sum of Squared Deviation	20.064	31.597	44.248	3.257	5.509	4.853
Probability	0.017**	0.099*	0.000***	0.729	0.743	0.175

Notes: *, ** and *** denotes that H_0 is rejected at the 10%, 5% and 1% significance levels, respectively.

4. Empirical Findings

The optimal lag order needs to be determined before proceeding to the granger causality test. Table 2 shown the results of the criteria for Model 1 (BTC), Model 2 (ETH) and Model 3 (BNB). The table reveals final prediction error (FPE), Schwarz information criterion (SC) and Hannan-Quinn information criterion (HQ) suggests Model 1 (BTC) and Model 2 (ETH) indicates 1 lag. However, sequential modified LR test statistic (LR) and Akaike information criterion (AIC) reveals 4 lags and 5 lags respectively. For Model 3 (BNB), all criteria signify 1 lag only.

Table 2: VAR lag order selection criteria

Lag	LR	FPE	AIC	SC	HQ
Model 1 (BTC, EPU, GPR, USEMV)					
0	NA	0.00022	2.92285	3.09700	2.98425
1	129.5814	9.11e-06*	-0.26171	0.60906*	0.04528*
2	10.14227	1.56e-05	0.24093	1.80831	0.79351
3	9.93778	2.66e-05	0.69172	2.95572	1.48989
4	27.15721*	1.93e-05	0.19873	3.15934	1.24248
5	25.45041	1.28e-05	-0.52706*	3.13016	0.76228
Model 2 (ETH, EPU, GPR, USEMV)					
0	NA	0.00028	3.18387	3.35802	3.24527
1	120.9542	1.55e-05*	0.26892	1.13969*	0.57591*
2	13.40392	2.35e-05	0.65507	2.22245	1.20765
3	8.82865	4.21e-05	1.15208	3.41607	1.95024
4	29.50103*	2.72e-05	0.54189	3.50250	1.58564
5	21.37689	2.32e-05	0.07070*	3.72792	1.36004
Model 3 (BNB, EPU, GPR, USEMV)					
0	NA	0.00045	3.64485	3.81900	3.70625
1	111.8923*	3.26e-05*	1.01308*	1.88385*	1.32007*
2	10.47834	5.50e-05	1.50372	3.07110	2.05630
3	13.24388	8.19e-05	1.81676	4.08075	2.61492
4	20.47806	8.30e-05	1.65772	4.61833	2.70147
5	18.52520	8.47e-05	1.36476	5.02198	2.65410

Notes: * indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion.

Table 3: Results of Granger causality test

Dependent Variable	Independent Variable			
Model 1 (BTC)				
	BTC	EPU	GPR	USEMV
BTC	-	7.0584***	4.7194**	2.8031*
EPU	2.1184	-	1.0322	0.0371
GPR	2.4438*	1.2108	-	0.2672
USEMV	0.1036	1.4195	1.6164	-
Model 2 (ETH)				
	ETH	EPU	GPR	USEMV
ETH	-	1.5321	1.2068	3.52e-06
EPU	5.4310**	-	1.8883	0.0259
GPR	2.9333*	2.8143*	-	0.2394
USEMV	0.5172	0.7364	2.0538	-
Model 3 (BNB)				
	BNB	EPU	GPR	USEMV
BNB	-	0.0270	3.1069*	0.0275
EPU	0.4537	-	0.4404	0.0852
GPR	1.0057	1.0533	-	0.1875
USEMV	0.1655	1.4775	1.7173	-

Notes: The statistics are chi-squares of Wald tests. *, ** and *** denote that H_0 is rejected at the 10%, 5% and 1% significance levels, respectively. The optimal lag length selected is 1.

The Wald statistics of granger causality test for Model 1 (BTC), Model 2 (ETH) and Model 3 (BNB) exhibits in Table 3. There is bi-directional granger causality between BTC and GPR in Model 1 (BTC), and unidirectional granger causality running from EPU to BTC and from USEMV to BTC. For Model 2 (ETH), there is unidirectional granger causality from ETH to both EPU and GPR, as well as from EPU to GPR. Moreover, only GPR have granger causes on BNB for Model 3 (BNB).

Table 4: Decomposition of variance

	Period									
	1	2	3	4	5	6	7	8	9	10
Model 1 (BTC)										
Variance decomposition of BTC										
BTC	100.00	91.99	84.64	77.62	71.07	65.18	60.04	55.64	51.90	48.77
EPU	0.00	1.47	5.19	10.05	15.16	20.04	24.45	28.31	31.64	34.47
GPR	0.00	3.33	5.49	7.16	8.56	9.74	10.73	11.54	12.20	12.74
USEMV	0.00	3.21	4.68	5.18	5.21	5.03	4.78	4.51	4.25	4.02
Variance decomposition of EPU										
BTC	1.31	2.91	4.52	6.10	7.62	9.06	10.40	11.60	12.64	13.52
EPU	98.69	94.84	91.66	89.18	87.16	85.45	83.97	82.67	81.53	80.56
GPR	0.00	2.20	3.56	4.22	4.46	4.50	4.44	4.37	4.31	4.29
USEMV	0.00	0.05	0.25	0.51	0.76	0.99	1.19	1.37	1.51	1.63
Variance decomposition of GPR										
BTC	0.62	0.59	0.78	1.01	1.19	1.32	1.40	1.45	1.47	1.48
EPU	0.07	1.94	4.34	6.59	8.56	10.22	11.59	12.72	13.64	14.37
GPR	99.31	96.91	94.27	91.82	89.69	87.91	86.45	85.28	84.35	83.61
USEMV	0.00	0.55	0.61	0.59	0.57	0.56	0.55	0.55	0.54	0.54
Variance decomposition of USEMV										
BTC	5.55	5.67	5.67	5.68	5.73	5.80	5.88	5.98	6.08	6.17
EPU	12.16	14.15	16.19	17.77	18.85	19.53	19.94	20.15	20.26	20.29
GPR	13.70	20.08	21.67	21.99	21.99	21.92	21.85	21.79	21.74	21.70
USEMV	68.59	60.10	56.47	54.56	53.44	52.75	52.34	52.08	51.93	51.84

Table 4 *(continued)*

	Period									
	1	2	3	4	5	6	7	8	9	10
Model 2 (ETH)										
Variance decomposition of ETH										
ETH	100.00	97.20	92.92	88.13	83.35	78.89	74.85	71.28	68.14	65.40
EPU	0.00	1.01	3.18	5.92	8.79	11.57	14.14	16.45	18.51	20.31
GPR	0.00	1.79	3.89	5.93	7.79	9.44	10.88	12.11	13.16	14.07
USEMV	0.00	4.13e-06	0.01	0.03	0.06	0.10	0.13	0.16	0.19	0.22
Variance decomposition of EPU										
ETH	2.54	6.83	11.33	15.97	20.61	25.03	29.03	32.44	35.20	37.32
EPU	97.46	89.20	82.89	77.82	73.36	69.27	65.54	62.20	59.30	56.86
GPR	0.00	3.93	5.66	6.03	5.83	5.49	5.24	5.17	5.32	5.64
USEMV	0.00	0.04	0.12	0.18	0.20	0.20	0.20	0.19	0.18	0.17
Variance decomposition of GPR										
ETH	0.33	0.51	0.79	1.00	1.14	1.22	1.27	1.29	1.30	1.31
EPU	0.03	4.29	8.02	10.74	12.68	14.06	15.06	15.78	16.29	16.66
GPR	99.64	94.71	90.53	87.55	85.46	83.98	82.93	82.18	81.65	81.27
USEMV	0.00	0.48	0.65	0.70	0.73	0.74	0.75	0.75	0.76	0.76
Variance decomposition of USEMV										
ETH	5.12	5.84	6.33	6.82	7.37	7.97	8.61	9.25	9.87	10.46
EPU	10.67	11.69	13.12	14.13	14.66	14.86	14.86	14.78	14.68	14.59
GPR	14.81	22.41	24.11	24.38	24.30	24.13	23.95	23.77	23.62	23.48
USEMV	69.40	60.07	56.45	54.67	53.67	53.04	52.58	52.20	51.83	51.46
Model 3 (BNB)										
Variance decomposition of BNB										
BNB	100.00	95.22	91.05	87.89	85.44	83.45	81.79	80.37	79.13	78.04
EPU	0.00	0.02	0.02	0.06	0.17	0.33	0.52	0.74	0.96	1.18
GPR	0.00	4.73	8.83	11.86	14.13	15.90	17.31	18.48	19.45	20.29
USEMV	0.00	0.03	0.10	0.18	0.26	0.32	0.37	0.42	0.46	0.50
Variance decomposition of EPU										
BNB	12.39	13.68	14.80	15.86	16.87	17.86	18.80	19.70	20.55	21.36
EPU	87.61	85.07	82.94	81.33	80.08	79.05	78.14	77.30	76.50	75.72
GPR	0.00	1.13	2.02	2.49	2.68	2.71	2.67	2.61	2.56	2.54
USEMV	0.00	0.12	0.24	0.32	0.37	0.39	0.40	0.40	0.39	0.39
Variance decomposition of GPR										
BNB	0.34	0.33	0.36	0.42	0.51	0.63	0.77	0.94	1.13	1.34
EPU	0.16	1.35	2.91	4.21	5.17	5.87	6.36	6.72	6.97	7.16
GPR	99.50	97.94	96.15	94.70	93.60	92.76	92.11	91.57	91.12	90.72
USEMV	0.00	0.38	0.58	0.67	0.71	0.74	0.76	0.77	0.78	0.79
Variance decomposition of USEMV										
BNB	6.80	7.05	7.40	7.75	8.06	8.35	8.61	8.84	9.06	9.27
EPU	8.87	10.72	12.69	14.27	15.40	16.15	16.62	16.92	17.09	17.19
GPR	15.78	22.37	23.90	24.02	23.83	23.60	23.41	23.26	23.14	23.04
USEMV	68.55	59.86	56.01	53.96	52.71	51.90	51.36	50.98	50.71	50.50

The variance decomposition results for Model 1 (BTC), Model 2 (ETH) and Model 3 (BNB) are summarized in Table 4 over 10-months period. For Model 1 (BTC), the results indicate EPU and GPR are the most exogenous variables compared to USEMV and BTC as they have high proportion of shocks to explained their own innovations. The forecast error variance for EPU and GPR explained its own innovation at the end of 10 months are 80.56% and 83.61%, while USEMV and BTC are 48.77% and 51.84% respectively. At the end of period, EPU have greater impact on BTC compared to GPR and USEMV where forecast error variance of EPU (34.47%) higher than GPR (12.74%) and USEMV (4.02%). Furthermore, the GPR is strongly endogenous compared to ETH, EPU and USEMV in the Model 2 (ETH). After 10 months, the forecast error variance for GPR, ETH, EPU and USEMV to predict its own are 81.27%, 65.40%, 56.86% and 51.46% respectively. The EPU and GPR forecast error variance in explaining the ETH are 20.31% and 14.07%. However, the ETH is insignificant explained by USEMV. The Model 3 (BNB) shown GPR, BNB, and EPU strongly influences itself with forecast error variance of 90.72%, 78.04% and 75.72% respectively in comparison with USEMV which 50.50%. The GPR have 20.29% forecast error variance in explaining BNB, while EPU and USEMV are weak influence in predicting BNB.

Besides, impulse response function can provide information on the relations between variables in addition to variance decomposition. Figure 1-3 presents the impulse response functions for Model 1 (BTC), Model 2 (ETH) and Model 3 (BNB) respectively. BTC, ETH and BNB response to EPU are lying on the positive region and shown increase gradually over the period when shocks occur which EPU have gradual positive effect on BTC, ETH and BNB. In contrast, GPR has gradual negative effect as the response of BTC, ETH and BNB to GPR are gradually decrease in the negative region. For USEMV, the response of ETH and BNB are slightly increase in the positive region, but BTC lying in the negative region and increase gradually over the period.

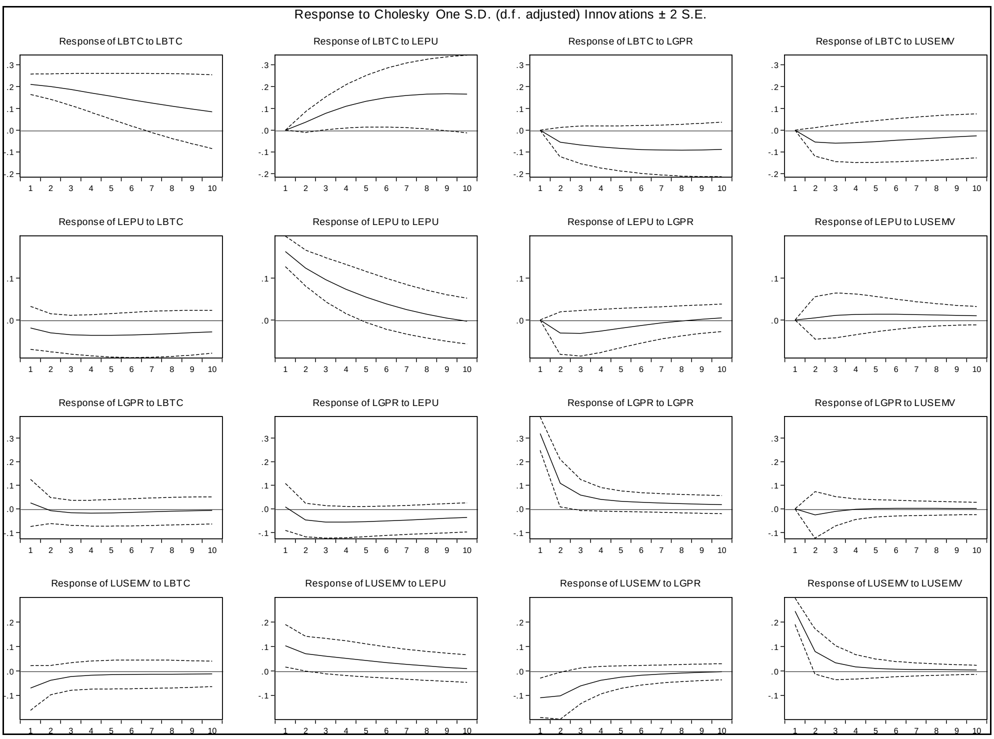

Figure 1: Impulse function for Model 1 (BTC)

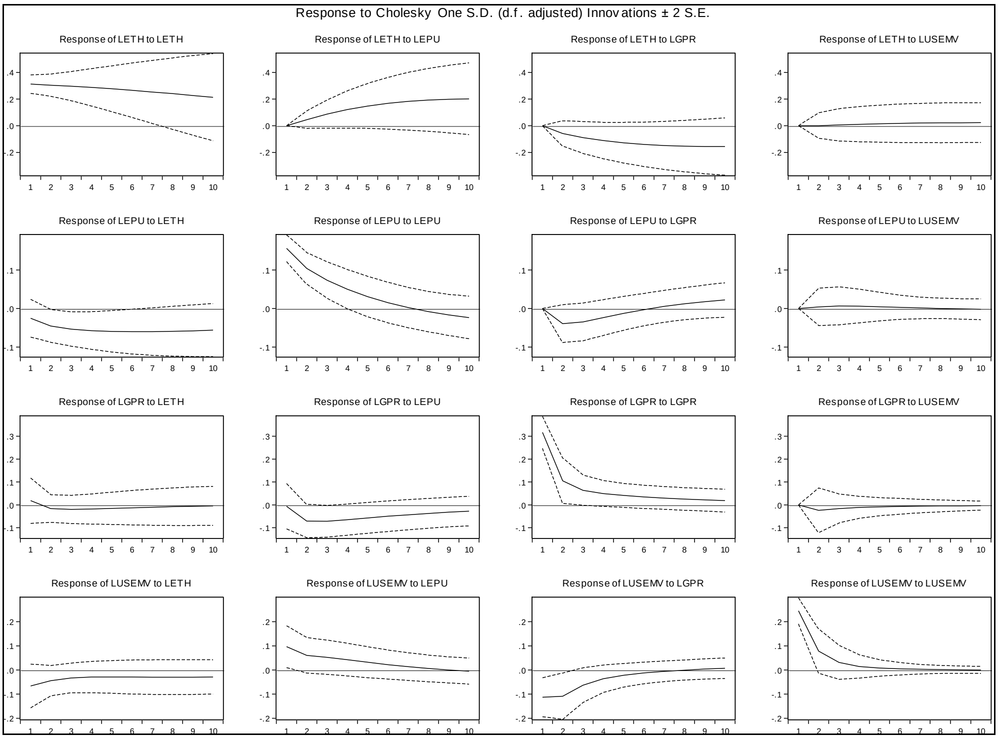

Figure 2: Impulse function for Model 2 (ETH)

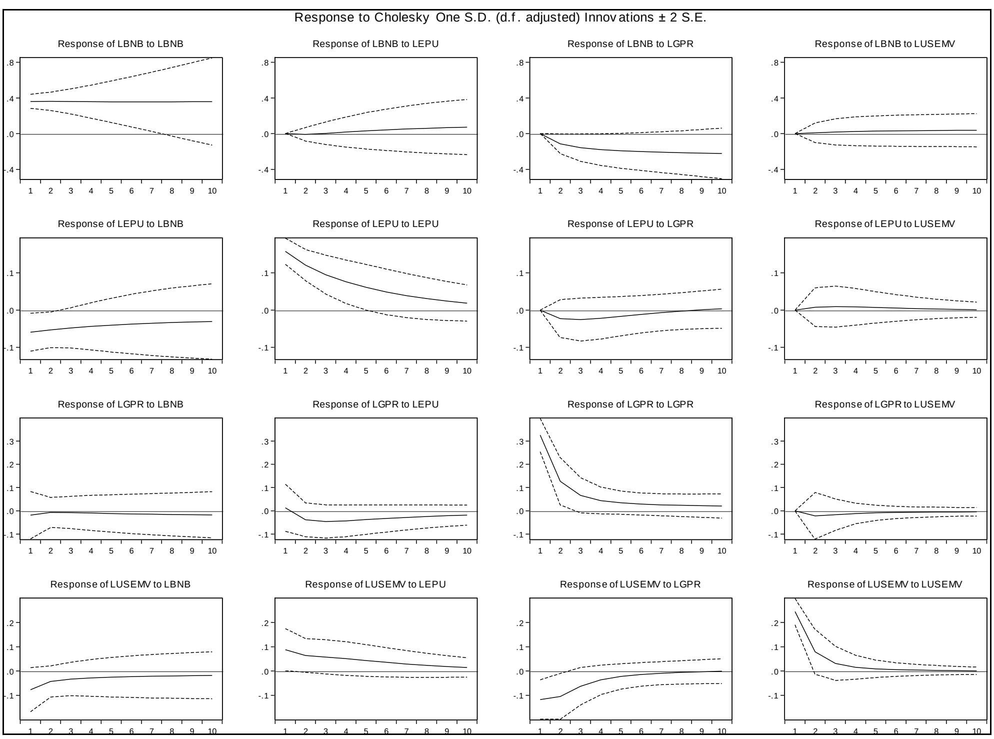

Figure 3: Impulse function for Model 3 (BNB)

5. Conclusion

This paper examines the impact of geopolitical risk (GPR), economic policy uncertainty (EPU) and US equity market uncertainty (USEMV) on the Bitcoin (BTC), Ethereum (ETH) and Binance Coin (BNB) by monthly data from December 2017 until May 2021 using cointegration and causality testing. This study extended the analysis by adopted the variance decomposition and impulse response function to examine the variable's exogeneity. The results shown EPU, GPR and USEMV are cointegrated when BTC is the dependent variable, but not cointegrated when ETH act as the dependent variable. However, BNB only cointegrated with GPR. Model 1 (BTC) exhibits EPU, GPR and USEMV Granger cause BTC, while in Model 3 (BNB) only GPR Granger cause the BNB. Our results suggested the investor and policymaker can keep an eye on the EPU, GPR and USEMV to forecast the BTC and pay close attention to GPR while forecast the BNB price. For further implication, we suggested employ other cryptocurrency and adopt other uncertainty measure to further explore the relation between cryptocurrency and uncertainty risk as well as consider utilize other methodology.

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CALL FOR PAPERS

26TH MALAYSIAN FINANCE ASSOCIATION INTERNATIONAL CONFERENCE (MFAIC 2024) & 1ST INTERNATIONAL CONFERENCE OF GLOBAL BUSINESS AND DIGITAL ECONOMY (ICGLOBDE 2024)

11-12 September 2024 | Bangi Resort Hotel, Selangor

"The Future of Finance in the Digital Age"

The forthcoming 26th Malaysian Finance Association International Conference (MFAIC 2024) and inaugural 1st International Conference of Global Business and Digital Economy (ICGLOBDE 2024) strive to facilitate thoughtful, interdisciplinary discussions surrounding the monumental digital transformation reshaping finance. With the theme "The Future of Finance in the Digital Age," the conferences actively welcome leading scholars across academic fields, industry experts, and policymakers to chart an informed, ethical path forward.

Sessions synthesize diverse insights on how emerging technologies can enhance financial access, efficiency, and stability while managing risks. All participants should feel encouraged to share findings, identify issues warranting further inspection, and forge networks to tackle forthcoming challenges at the intersection of technology, finance, business, and policy domestically and globally.

Sub-themes highlight how innovations in artificial intelligence, digital finance, financial technology, blockchain, predictive analytics, and more are widening financial inclusion worldwide and transforming investment markets. Related sessions also address resultant shifts in corporate finance, governance, accounting, financial economics, Islamic finance, and education.

With rapidly expanding research on sustainable finance, additional sub-themes and sessions specifically examine environmental, social, and governance (ESG) matters alongside economic growth. Mirroring digital advancements, further topics include how technologies shape global business models, cross-border services, intangible assets, data utilization, and maintaining competitiveness.

By gathering diversity amongst academics, practitioners, and policymakers, these conferences offer an invaluable forum for collegially debating the multifaceted implications of financial innovation. Scholars across all disciplines are highly encouraged to participate by submitting research and synthesizing perspectives during the conferences to chart an informed path forward.

We strongly believe that the immense knowledge and experience contemporary pioneers in finance, business, technology, policy, and academia can bring to these discussions is key to shaping an ethical digital future for the finance industry, domestically and globally. We very much look forward to welcoming this collective expertise and benefiting from these opportune, multidisciplinary exchanges of ideas.

Sub Themes

- AI, Digital Finance, and Fintech
- Corporate Finance
- Corporate Governance & Accounting
- Environmental, Social and Governance (ESG) and Climate Finance
- Financial Economics
- Financial Inclusion and Well-being
- Financial Markets and Investments
- Global Business & Financial Management
- Islamic Finance

Conference Objectives

- To facilitate thoughtful academic and professional discussion on emerging technologies shaping the future of key industries.
- To debate innovation's social impacts and role in supporting equitable, sustainable economic growth benefiting all communities.
- To forge connections between scholars, practitioners, and policymakers across disciplines to enable impactful research collaboration.
- To examine the ethics of technological progress and alignment with regulations that best serve societal needs.
- To identify insights from diverse fields that can responsibly guide industries adopting transformative technologies.

Best Paper Awards

- Three MFA Best Papers with an award of RM1,000 each.
- YTI-UKM Best Paper with an award of RM1,000 [Financial Markets and Investments theme].
- Three International Journal of Banking and Finance Best Papers with an award of RM400 each.
- Jurnal Pengurusan Best Management Paper
- Asian Journal of Accounting and Governance Best Paper
- 'Jurnal Ekonomi Malaysia Breakthrough in Economic Sciences Award' with an award of RM500.
- Three 'Emerald Most Provocative Research Awards'. The winning papers will receive a Certificate of Excellence and a token of appreciation.

Publication Opportunities

- Finance Research Letters (WoS-SSCI)
- Jurnal Ekonomi Malaysia (Scopus) *(see note 1)*
- Jurnal Pengurusan (Scopus) *(see note 2)*
- Malaysian Journal of Economic Studies (WoS-ESCI, Scopus) *(see note 3)*
- Asian Journal of Accounting and Governance (WoS-ESCI) *(see note 4)*
- International Journal of Islamic and Middle Eastern Finance and Management (WoS-SSCI, Scopus) *(see note 5)*
- Asian Academy of Management Journal of Accounting and Finance (WoS-ESCI, Scopus)
- International Journal of Banking and Finance (ERA, MyCite)
- Capital Markets Review (MyCite)
- Labuan Bulletin of International Business and Finance (MyCite)

***Notes:*

1. *The manuscript will be subject to normal refereeing process without any guarantee for publication. The journal also imposes Article Publication Charge of RM600 or USD150 for each accepted article.*
2. *The manuscript shall undergo a double-blind review process. If the manuscript is accepted for publication, the publication fee of RM700 will be waived for the JP Best Paper Award Recipient and the manuscript will be published in 2025.*
3. *MJES can consider up to 3 papers for publication. Publication is not guaranteed, and the articles will be subject to the normal refereeing process. The journal also imposes a page charge of USD100 for each accepted article.*
4. *The manuscript shall undergo a double-blind review process. If the manuscript is accepted for publication, the publication fee of RM500 will be waived for the AJAG Best Paper Award Recipient and the manuscript will be published in 2025.*
5. *The manuscript will go through the review process without any guarantee for publication.*

Registration and Submission Notes

a) Registration and submission of Full Paper must be done electronically through this online submission system: https://submit.confbay.com/conf/mfac2024
   - Click on the "Registration" menu to create ConfBay Account and proceed for conference registration by logging in the system.
   - Click on "Online Submission" menu to submit your full paper.

b) Abstract and Full Paper Format - Strictly follow the template which can be downloaded at the conference website: https://www.ukm.my/icglobde/

Important Dates

Item	Date
Full paper submission begins	1 March 2024
Full paper submission deadline	1 June 2024
Notification of acceptance	1 July 2024
Early bird payment deadline	21 July 2024
Payment deadline	21 August 2024
Submission of camera-ready deadline	21 August 2024
Conference dates	11-12 September 2024

Registration Fees

Category	Early Bird Registration Fee (by 21 July 2024)	Regular Registration Fee (by 21 August 2024)
Local:		
Presenter MFA member	RM950	RM1050
Presenter non-MFA member	RM1100	RM1200
Student/participant/PhD colloquium	RM700	RM750
International:		
Normal fee	USD400	USD450
Student/participant/PhD colloquium	USD250	USD350

***Notes:*
1. *A 70% discount will be given to the second paper submission from the same presenter.*
2. *International students studying in Malaysian universities are eligible for the local student registration fees.*

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Faculty Of Economics and Management
Universiti Kebangsaan Malaysia
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MALAYSIA.

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REGISTRATION FEES

CATEGORY	EARLY BIRD REGISTRATION	NORMAL REGISTRATION
LOCAL		
Presenter MFA member	RM 950	RM 1,050
Presenter non-MFA member	RM 1,100	RM 1,200
Student/ Participant/ PhD Colloquium	RM 700	RM 750
INTERNATIONAL		
Normal Fee	USD 400	USD 450
Student/ Participant/ PhD Colloquium	USD 250	USD 350

BEST PAPER AWARDS

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- AJAG Best Paper
- JEM Breakthrough in Economic Sciences Award
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3. Jurnal Pengurusan (Scopus)
4. Asian Journal of Accounting and Governance (WoS-ESCI)
5. Asian Academy of Management Journal of Accounting and Finance (Scopus)
6. Malaysian Journal of Economic Studies (Scopus)
7. International Journal of Banking and Finance (ERA)
8. Capital Markets Review (ABDC)
9. Labuan Bulletin of International Business and Finance (MyCite)

THEME

The Future of Finance in the Digital Age

SUB - THEMES

1. AI, Digital Finance, and Fintech
2. Corporate Finance
3. Corporate Governance & Accounting
4. ESG and Climate Finance
5. Financial Economics
6. Financial Inclusion and Well-being
7. Financial Markets and Investments
8. Global Business & Financial Management
9. Islamic Finance

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PAST MFA CONFERENCE

The MFA is proud to be the pioneer in organizing a national-level conference that specializes in finance. Since its inaugural workshop in 1999, the meeting of finance academicians and practitioners has developed to become an annual symposium and today, owing to the overwhelming response, the meeting is now known as an annual conference. The conference is hosted by local institutions of higher learning, both public and private, on rotational basis.

The conference is a great platform for academicians and practitioners to discuss and exchange ideas pertaining to issues related to finance. It also provides an avenue for researchers to share their findings on financial issues relevant to Malaysia. Selected papers from the conference are published in the Capital Market Review which is an official publication of Bursa Malaysia and Research Institute of Investment Analysts Malaysia (RIIAM).

Previous MFA Annual Conference:

1999: THE MALAYSIAN FINANCE ASSOCIATION 1ST ANNUAL WORKSHOP
Theme: The Inaugural MFA Workshop
Host: Universiti Kebangsaan Malaysia (UKM)

2000: THE MALAYSIAN FINANCE ASSOCIATION 2ND ANNUAL SYMPOSIUM
Theme: The Malaysian Financial Crisis and its Recovery
Host: Universiti Malaya (UM)

2001: THE MALAYSIAN FINANCE ASSOCIATION 3RD ANNUAL SYMPOSIUM
Theme: Malaysian Capital Markets: Challenges for the New Millennium
Host: Universiti Islam Antarabangsa Malaysia (UIAM)

2002: THE 4TH ANNUAL MALAYSIAN FINANCE ASSOCIATION SYMPOSIUM
Theme: Globalization and Malaysian Financial Market: Strategies for Sustainable Growth
Host: Universiti Sains Malaysia (USM)

2003: MALAYSIAN FINANCE ASSOCIATION'S (MFA'S) 5TH ANNUAL SYMPOSIUM
Theme: Competitiveness and Stability Financial Strategies in Malaysia
Host: Multimedia University (MMU)

2004: THE MALAYSIAN FINANCE ASSOCIATION 6TH ANNUAL SYMPOSIUM
Theme: Revitalising the Financial Market: The Tasks Ahead
Host: Universiti Utara Malaysia (UUM)

2005: THE MALAYSIAN FINANCE ASSOCIATION 7TH ANNUAL CONFERENCE
Theme: Consolidation and Prudent Financial Management: Roads to Malaysian Economic Prosperity
Host: Universiti Teknologi MARA (UiTM), Terengganu

2006: THE MALAYSIAN FINANCE ASSOCIATION 8TH ANNUAL CONFERENCE
Theme: Managing Finance for Global Business Growth
Host: Universiti Malaysia Sabah (UMS)

2007: THE MALAYSIAN FINANCE ASSOCIATION 9TH ANNUAL CONFERENCE
Theme: Positioning Malaysia as A Premier Financial Market
Host: Universiti Teknologi MARA (UiTM)

2008: THE MALAYSIAN FINANCE ASSOCIATION 10TH ANNUAL CONFERENCE
Theme: Strengthening Malaysia's Position as a Vibrant, Innovative and Competitive Financial Hub
Host: Faculty of Economics and Business, Universiti Malaysia Sarawak (UNIMAS)

2009: THE MALAYSIAN FINANCE ASSOCIATION 11TH ANNUAL CONFERENCE
Theme: Financial Markets, Governance and Growth: Issues & Challenges
Host: Faculty of Economics and Management and the Graduate School of Management, Universiti Putra Malaysia (UPM)

2010: THE MALAYSIAN FINANCE ASSOCIATION 12TH ANNUAL CONFERENCE
Theme: Re-Engineering the Financial System towards a Global Innovation Economy
Host: Taylor's University College

2011: THE MALAYSIAN FINANCE ASSOCIATION 13TH ANNUAL CONFERENCE
Theme: Financial Innovation & Transformation in the 21st Century World Conference
Host: UKM-Graduate School of Business, Universiti Kebangsaan Malaysia (UKM)

2012: THE 14TH MALAYSIAN FINANCE ASSOCIATION CONFERENCE
Theme: Emerging Markets and Financial Resilience: Decoupling Growth from Turbulence
Host: Graduate School of Business (GSB), Universiti Sains Malaysia (USM)

2013: THE 15TH MALAYSIAN FINANCE ASSOCIATION CONFERENCE
Theme: Financial Challenges and Economic Growth – The Way Forward
Host: Graduate Studies Department, INCEIF

2014: THE 16TH MALAYSIAN FINANCE ASSOCIATION CONFERENCE
Theme: Financial Systems Re-Generation: MAPS, GAPS and TRAPS
Host: Universiti Malaya (UM)

2015: THE 17TH MALAYSIAN FINANCE ASSOCIATION CONFERENCE
Theme: Financial Inclusion as A Means to Minimize Fragility
Host: Universiti Teknologi MARA (UiTM), Sabah

2016: THE 18TH MALAYSIAN FINANCE ASSOCIATION CONFERENCE
Theme: Towards a Vibrant Social Finance for A Sustainable Banking and Financial System
Host: Universiti Sains Islam Malaysia (USIM)

2017: THE 19TH MALAYSIAN FINANCE ASSOCIATION CONFERENCE
Theme: Challenges and New Directions amidst Global Financial Uncertainty
Host: Universiti Tunku Abdul Rahman (UTAR)

2018: THE 20TH MALAYSIAN FINANCE ASSOCIATION CONFERENCE
Theme: Innovative Ecosystem for Financial Revolution
Host: Universiti Utara Malaysia (UUM)

2019: THE 21ST MALAYSIAN FINANCE ASSOCIATION CONFERENCE
Theme: Charting A New Course in Financial Innovation and Education
Host: Sunway University

2020: THE 22ND MALAYSIAN FINANCE ASSOCIATION CONFERENCE [VIRTUAL CONFERENCE]
Theme: Financial Sustainability During the Era of Covid-19 Pandemic
Host: Malaysian Finance Association (MFA)

2021: THE 23RD MALAYSIAN FINANCE ASSOCIATION INTERNATIONAL CONFERENCE [VIRTUAL CONFERENCE]
Theme: Sustainability of Business and Finance: Embracing the New Norms Amidst Covid-19
Host: Universiti Sains Malaysia (USM)

2022: THE 24TH MALAYSIAN FINANCE ASSOCIATION INTERNATIONAL CONFERENCE
Theme: Global Finance: Evolving and Impacting the Post Pandemic World
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2023: THE 25TH MALAYSIAN FINANCE ASSOCIATION INTERNATIONAL CONFERENCE
Theme: Positioning the Financial System Towards a Sustainable Economy and Green Finance
Host: Taylor's University

MFA
Malaysian Finance Association

OBJECTIVES

The objectives of MFA are to stimulate public interest in finance related studies, to encourage the research and discussion of finance related issues with special reference to Malaysia, to issue Malaysian finance Journals and other publications with the prior approval of the relevant authorities, to promote and organize conferences, forums, dialogues and activities between private and public sectors on current finance issues of national and international concerns; and to undertake such management, economic, and other activities as the Association deems appropriate for the furtherance, promotion and execution of its aforesaid objectives.

MEMBERSHIP

Membership is open to academicians, professionals and students in the area of Finance, Banking, Economics, Insurance, Real Estate, Accounting and other finance related area.

There are three types of membership: Ordinary Membership, Associate Membership and Life Membership.

Ordinary Membership

The Ordinary Membership is open to all academicians and working person in the field of Accounting, Banking, Business Administration, Economics, Finance, Financial Engineering, Actuarial Science, Data Science, Insurance and other finance related area. Ordinary member is eligible to attend and vote at all general meetings of the Association.

Associate Membership

The Associate Membership is open to foreign professionals / scholars / postgraduates in the field of Finance, Banking, Economics, Insurance, Real Estate, Accounting and other finance related area. The associate members are entitle to all general meetings, but are not eligible to hold an office and to vote.

Life Membership

The Life Membership is open to Malaysian academicians, an extension of ordinary membership and entitles to all the rights and privileges of ordinary members.

Membership Fee

Ordinary member	RM 100 per year
Associate member	RM 100 per year
Life member	RM 600

Payment can be remitted via bank draft, cheque, money order made payable to "PERSATUAN KEWANGAN MALAYSIA (BARU)" or direct payment to BANK MUAMALAT MALAYSIA BERHAD: **1205-0003606-71-1**.

Please notify us your application by sending the application form and proof of payment to mgt@mfa.com.my.
Note: Ordinary and Associate Membership expires every 31 December each year.

Inquiries should be forwarded to:

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Malaysian Finance Association (MFA)
c/o: Faculty of Business and Management (FBM)
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Membership

Type of membership (Annual membership runs from Jan to Dec)

☐	Ordinary Membership	RM100 per year
☐	Associate Membership	RM100 per year
☐	Life Membership	RM600

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INSTRUCTION FOR AUTHORS

1. The cover page should contain the title of the manuscript, the author(s) and their affiliation(s). Title should be typewritten in bold and in 14pt fonts. Author's name and affiliation should be typewritten in single spacing using 8pt fonts with affiliations typed in italics. All text on this page should be centre aligned. Contact of corresponding author and acknowledgement should be mentioned in the footnote in 8pt fonts with a symbol *. Author must provide complete correspondence information – Author's name, telephone number and email address.
2. Manuscripts may be written in either Bahasa Melayu or English. Only original and unpublished works will be considered. The first page of text shows the title of the manuscript with an abstract of about 300-350 words and a maximum of 6 keywords identifying the main topics of the manuscript. JEL classification numbers should be included after the keywords.
3. Structured Abstract (300-350 words)
   Research Question: In one sentence, define the key features of the research question or problem statement. **Motivation:** In a few sentences, capture the core scholarly motivation for the study. If relevant, identify a 'puzzle' that this research aims to resolve. Identify up to 3 key papers upon which the research builds. What's new? Highlight where novelty exists in the study; how does it improve or build on existing literature? So what? Outline the primary reason why it is important to know the answer to your research question. **Idea:** Articulate the core idea behind the research – what specifically does the study do? If relevant: articulate the central hypothesis; highlight key independent variables and dependent variable(s). **Data:** Provide an overview of what data were collected/analysed/used in the study; including data source(s), time period, sample size and measurement tool(s). **Method/Tools:** Provide a brief summary of the empirical framework, research design and approach. **Findings:** Highlight the key takeaway points. Highlight any novel result – how do the findings agree/disagree with existing literature? What do the findings add? Highlight any important implications this research has for influence in real-world decisions/behaviour/activity. **Contributions:** Outline the primary contribution of this paper to the relevant research literature.
4. The paper starts after the JEL classification, with all pages numbered consecutively at the bottom right. Heading of main section (e.g. **1. Introduction**) and headings of subsections (e.g. **3.1 Data Sample**) should be typed in bold. Headings of subsequent subsections (e.g. *3.1.1 Data Source*) should be typed in italics.
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