Cross-Market Linkages and Dynamic Spillovers Between Energy Commodities and Financial Markets: Evidence From the USA and Asian Markets

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Abstract

This research examines the dynamic interactions among key energy commodities, macroeconomic indicators, and financial markets in both Asian and the USA contexts, applying the Autoregressive Distributed Lag (ARDL) and time-varying Granger causality test, including trend methodology (Baum et al., 2022). The primary objective is to explore how exogenous factors, such as the Economy Policy Uncertainty Index (EPUI) and Consumer Confidence Index (CCI), affect the dynamic spillovers between energy commodities and financial markets, as well as to assess the existence of short-term and long-term equilibrium relationships among the variables under investigation. The multivariate analysis is conducted using monthly data from January 2007 to June 2024. The energy commodities analysed are WTI crude oil, Brent crude oil, coal, and natural gas. The macroeconomic indicators considered are the Consumer Price Index (CPI), serving as a proxy for inflation, and the Industrial Production Index (IPI). Additionally, investor sentiment is assessed using the Economic Policy Uncertainty Index variable. The empirical findings, derived from the ARDL model and the time-varying Granger causality test, reveal significant and dynamic contagion effects between financial markets and key energy commodities. Evidence of Granger causality was identified across several temporal windows, indicating periods of heightened interdependence, particularly during times of economic turbulence. Notably, bidirectional causality between regional Sharpe indices, especially between the USA and Japanese markets, suggests the mutual transmission of risk and return shocks over the long term. Furthermore, the results demonstrate that WTI crude oil and coal prices exert a significant influence on several equity indices, particularly the S&P 500 and China Securities Index, confirming the sensitivity of these markets to global energy price fluctuations. The dynamic causality analysis also shows that the intensity of contagion evolved, strengthening during the Global Financial Crisis (2007–2008), the COVID-19 pandemic, and the Russia–Ukraine war, periods marked by high volatility and uncertainty. This study is relevant as it provides valuable insights for policymakers and market participants on the effects of volatility shocks on commodity prices and financial assets. Understanding the relationships between markets is essential to grasping the risk transmission between commodities and assets, such as stocks and treasury bonds. Furthermore, the study aims to guide investors in adjusting their portfolios in response to the spillover effects, and it examines how financial and commodity markets react to these changes. This enables policymakers to take appropriate measures to achieve their goals, while investors can develop more effective diversification and risk management

strategies to efficiently manage potential losses during severe market shocks, such as endogenous and exogenous crises, making an efficient allocation of their investment portfolios and identifying new market opportunities.

Keywords

Financial Markets; Commodities; Investor Sentiment; Consumer Confidence Index; Industrial Production Index; Economic Policy Uncertainty; ARDL; Granger Causality; Spillover Effects

Resumo Alargado

As matérias-primas têm assumido um papel de crescente relevância na última década, observando-se uma intensificação dos investimentos nos mercados futuros de matérias-primas por parte dos fundos de índice e dos fundos *hedge*. Essa migração de investidores financeiros para o mercado de matérias-primas resultou numa maior interconexão entre este e outros mercados financeiros, como os de ações e obrigações (Charlot et al., 2016). Diante deste fenómeno, torna-se essencial analisar as correlações entre esses mercados, permitindo aos investidores tomarem decisões mais informadas e mais alinhadas com o *trade-off* retorno-risco.

Este estudo investiga as interações dinâmicas e a conectividade entre as matérias-primas energéticas, a incerteza da política económica, o índice de Sharpe, a confiança do consumidor e diversas variáveis macroeconómicas, ao longo de diferentes fases de mercado, no período compreendido entre 01/01/2007 e 01/06/2024.

Esta análise tem como objetivo explorar os efeitos de contágio dinâmicos entre os mercados financeiros e o mercado de matérias-primas, utilizando um conjunto de metodologias empíricas, tais como o modelo ARDL (*AutoRegressive Distributed Lag*) e o teste de causalidade de Granger variável no tempo. Portanto, serão analisadas as relações de curto e de longo prazo entre as variáveis, com foco na influência dos preços das principais matérias-primas energéticas, do índice de confiança do consumidor e do índice de Sharpe no desempenho dos mercados acionistas.

As evidências empíricas revelam diversas implicações importantes para os investidores. Especificamente, aqueles que investem no S&P 500 dos EUA e no índice STI de Singapura devem reconhecer que os índices de incerteza política dos respetivos países exercem efeitos adversos de curto prazo sobre o S&P 500. Da mesma forma, os investidores no índice HSI de Hong Kong devem estar cientes da significativa influência a longo prazo da incerteza política interna. No que respeita ao índice Nikkei do Japão, tanto o índice de incerteza política como o índice de confiança dos investidores japoneses demonstram efeitos negativos no desempenho do mercado. Além disso, os investidores no S&P 500 devem monitorizar a evolução dos preços do petróleo bruto WTI e do carvão, enquanto no mercado chinês, o índice CSI é igualmente sensível às flutuações do petróleo bruto WTI.

No curto prazo, os preços do carvão afetam negativamente os índices Nikkei (Japão) e CSI (China). O índice Kospi da Coreia do Sul é também influenciado negativamente, no curto prazo, pelas variações dos preços do gás. Além disso, o Nikkei apresenta uma correlação negativa com o índice Sharpe dos EUA, enquanto o índice CSI é influenciado pelo índice Sharpe de Singapura no curto prazo. A análise indica ainda que o índice Sharpe de Hong Kong exerce um efeito negativo sobre os índices Sharpe dos EUA e do Japão, enquanto o índice Sharpe de Singapura afeta negativamente o da China. No mercado dos EUA, o índice Sharpe do Japão exerce um efeito negativo sobre o índice Sharpe dos EUA e, a longo prazo, observa-se uma relação bilateral negativa entre ambos. Em conclusão, os resultados destacam que, para o S&P 500, os índices Sharpe do Japão e de Singapura merecem uma atenção cuidada por parte dos investidores, dado o seu impacto negativo a longo prazo no mercado dos EUA.

Os resultados obtidos através da análise de causalidade de Granger com variação temporal revelam a presença de relações causais dinâmicas e heterogéneas entre os índices do mercado financeiro e as principais matérias-primas energéticas no período de janeiro de 2007 a junho de 2024. As evidências empíricas demonstram que a causalidade não é estável ao longo do tempo, mas evolui de acordo com diferentes contextos económicos e geopolíticos, refletindo períodos de maior interdependência entre os mercados financeiros e energéticos. De um modo geral, observou-se que os efeitos causais se intensificam durante períodos de maior incerteza global, nomeadamente durante a crise financeira de 2007-2008, a pandemia de COVID-19 e a guerra entre a Rússia e a Ucrânia. Estes períodos coincidem com uma maior frequência de estatísticas de Wald significativas, indicando que os efeitos de contágio tendem a amplificar-se em contextos de elevada volatilidade e instabilidade económica. Especificamente, os resultados indicam a existência de relações causais bidirecionais entre determinados mercados financeiros, como a relação entre os rácios de Sharpe dos Estados Unidos e do Japão, o que demonstra a transmissão mútua de choques nos retornos ajustados ao risco. Foram também identificadas relações causais unidirecionais dos mercados asiáticos para outros mercados, incluindo o índice de Sharpe de Hong Kong em relação aos índices de Sharpe dos Estados Unidos e do Japão, bem como o índice de Sharpe de Singapura em relação ao da China. Estas descobertas apontam para a presença de contágio inter-regional e para a transmissão de choques entre os mercados asiáticos e ocidentais.

Em relação às matérias-primas energéticas, o teste demonstra causalidade unidirecional, particularmente entre o petróleo bruto WTI e o carvão, para diversos índices de ações. O petróleo bruto WTI apresenta causalidade significativa para os índices S&P 500, Nikkei e CSI, enquanto o carvão demonstra causalidade para os mercados japonês e chinês. O gás natural apresenta causalidade em mercados específicos, nomeadamente o CSI, e o índice Nikkei demonstra causalidade em resposta a choques tanto do petróleo bruto WTI como do carvão. Estes resultados indicam que as matérias-primas energéticas funcionam como canais de transmissão de choques financeiros entre mercados e regiões. Além disso, observam-se relações causais entre os próprios índices de Sharpe, revelando contágio entre os mercados americano, japonês, chinês e singapurense. A identificação de relações significativas, como o S&P 500 → Nikkei e o CSI → S&P 500, reforça a noção de que certas economias desempenham um papel central na propagação global dos choques financeiros.

Em síntese, o presente estudo procura aprofundar o corpo de literatura existente com o objetivo de apoiar os investidores na formulação de estratégias de investimento geograficamente mais eficientes, dado que os resultados confirmam a existência de efeitos de contágio inter-regionais e intersectoriais, com implicações diretas para a diversificação internacional de portfólios e para a formulação de políticas de mitigação de risco em ambientes de elevada incerteza económica.

Palavras-chave

Mercados Financeiros; Matérias-Primas; Sentimento do Investidor; Índice de Confiança do Consumidor; Índice de Produção Industrial; Incerteza da Política Económica; ARDL; Causalidade de Granger; Efeitos de Contágio

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List of Acronyms

AIC	Akaike Information Criterion
APEC	Asia-Pacific Economic Cooperation
ARDL	Autoregressive Distributed Lag
BIC	Bayesian Information Criterion
BRICS	Brazil, Russia, India, China and South Africa
CAPM	Capital Asset Pricing Model
CCI	Consumer Confidence Index
COVID	Corona Virus Disease
CPI	Consumer Price Index
CSI	China Securities Index
EMH	Efficient Market Hypothesis
EPUI	Economic Policy Uncertainty Index
FSI	Financial Stress Index
HSI	Hang Seng Index
IEA	Internacional Energy Agency
IPI	Industrial Production Index
KOSPI	Korea Composite Stock Price Index
KPSS	Kwiatkowski-Philipps-Schmidt-Shin
OPEC	Organization of the Petroleum Exporting Countries
SET	Stock Exchange of Thailand
SP	Standard & Poor's
SSE	Shanghai Stock Exchange
STI	Straits Times Index
TWII	Taiwan Weighted Index
USA	United States of America
VAR	Vector Autoregressive
WTI	West Texas Intermediate

1. Introduction

Energy commodities and economic variables play a crucial role in the performance of financial markets, including market index returns. According to the International Energy Agency (IEA), in 2024, there has been an increase in demand across the various existing energy sources (see Figure 1), namely renewables (38%), nuclear energy (8%), oil (11%), coal (15%), and natural gas (28%). About fossil fuels, there was a sharp rise in demand for natural gas (2.7%), while crude oil and coal experienced slower growth compared with 2023. This new historical peak in gas demand is primarily attributable to its increased use for industrial purposes and power generation. A decline in inflation was observed in 2024, following the post COVID-19 and Russia–Ukraine conflict periods, during which price levels had been significantly higher.[1]

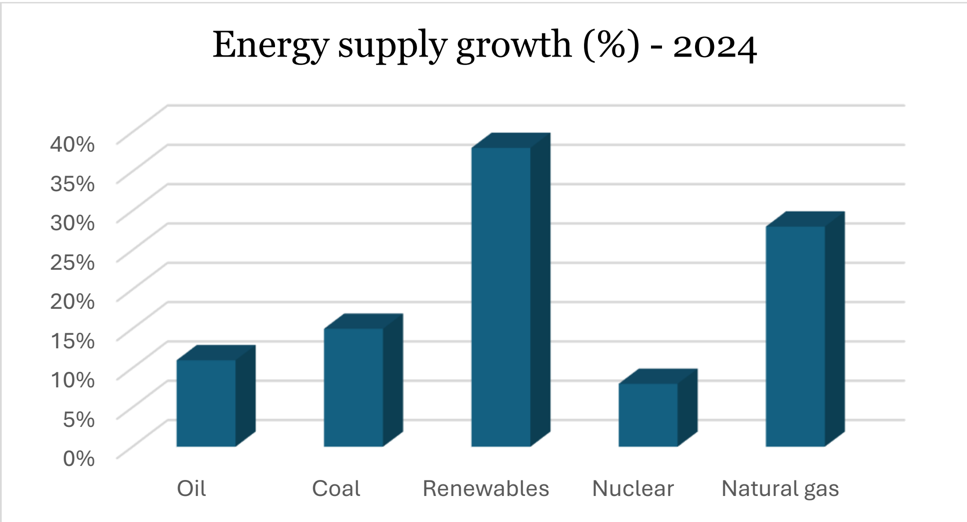

Figure 1 – Energy supply growth (%) - 2024

Source: own authorship based on https://www.iea.org/reports/global-energy-review-2025/global-trends#abstract

During periods such as the Asian financial crisis, the global financial crisis, the COVID-19 pandemic, and the Russia-Ukraine war, among other crises and events, it became evident that uncertainty and financial risk indicate the existence of temporal persistence, which in turn caused a loss of value in both capital markets and commodity markets. According to

[1] AIE (2025), *Global Energy* Review *2025* , AIE, Paris
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Sheth et al. (2022), the commodities market was among the most negatively affected sectors within the financial system.

The COVID-19 pandemic, an exogenous crisis that originated in Wuhan, China, in late 2019, has had a profound impact on the global economy, leading to several significant consequences, including a public health emergency, rising unemployment rates, high levels of business bankruptcies, and restrictions on international trade and commercial activities in general, aimed at containing the spread of the COVID-19 virus. As a result, numerous studies have emerged that analyse both the effects of the pandemic on the returns of stock and commodity markets and the volatility of these markets. Additionally, these studies investigate the impact of announcements regarding new COVID-19 infections and deaths on market volatility. These negative announcements significantly influenced investor sentiment, increasing market volatility (Albulescu, 2021; Bouteska et al., 2023; Yin et al., 2023; W. Zhang & Hamori, 2021). This health crisis necessitated a fiscal stimulus by the monetary and fiscal authorities greater than that implemented during the global financial crisis of 2007-08. This deficit situation was further exacerbated by the rise in energy prices resulting from the Russia–Ukraine conflict (Saeed et al., 2023).

During crises of an exogenous nature, such as the pandemic, high volatility prevailed, particularly in oil prices during the first half of 2020, which surprised all market participants. After beginning 2020 at US$61 per barrel, WTI crude oil (traded in the United States) fell below the ‘minimum positive threshold’ on 20 April and was traded at negative prices of –US$37.63. The combination of these two major facts justifies, from the outset, the study of volatility and the relationship between commodity prices and stock market indices during the COVID-19 period. These same observations also explain the need to identify the presence of volatility spillovers in both financial and commodity markets. Understanding the existence of price volatility spillovers and the consequent transmission of risk is essential for competent authorities across different economies and regions to adopt objective measures aimed at mitigating or preventing cross-hedging related to financial crises, particularly in the regulation of financial institutions.

In this research, considering that the correlation between the returns of financial assets in international markets increased following a price shock in a given commodity market, such a phenomenon may spread and reduce the diversification benefits of investments, including assets traditionally regarded as “safe havens”, such as gold. This therefore justifies the analysis of the relationships between commodity prices and stock market indices, following the studies of Cui et al. (2021), Hung (2023), Wang & Li (2021), among others. In recent years, the Asian markets selected for this study have experienced rapid economic growth and financial market development. However, they have simultaneously revealed the problem of systemic risk transmission to other markets, notably China, Japan, and the United States. For example, the Asian financial crisis, the global financial crisis, the COVID-19 pandemic, the Russia–Ukraine war, and other incidents have severely affected all these financial and energy commodity markets, particularly due to price variability. Therefore, studying the interaction mechanism between stock markets within our sample and systemic risks, both in these markets and in energy commodity markets, is of great theoretical and empirical importance. It contributes to a better understanding of the mechanism of risk propagation in financial and energy markets, to identifying the causality and direction associated with financial risks, and to informing macroeconomic and energy policy formulation.

In line with recent studies discussed in the literature review section, empirical evidence highlights the contagion effects of risk transmission between stock markets and energy commodity markets. However, most of the literature focuses on unidirectional versus bidirectional contagion effects between Asian and Chinese stock markets. Moreover, existing studies mainly examine the impact of financial crises of endogenous or exogenous (pandemic or military conflict) nature on contagion effects, rarely incorporating multiple crises simultaneously, or analysing the risk–return relationship across the same financial markets, as well as the corresponding risk–return dynamics in commodity markets. Furthermore, to the best of our knowledge, most of the existing literature does not employ a combined analysis of risk–return transmission effects using both the ARDL approach and the time-varying analysis technique.

Therefore, the main objective of this study is to analyse the cointegration relationship and dynamic spillover effects between energy commodities, macroeconomic variables, and financial markets. The chosen period aims to understand the cross-market linkages and spillover effects in different periods of crises, both endogenous and exogenous. Furthermore, the aim is to analyse the results in light of the main existing financial theories, ranging from traditional to behavioural finance.

Some of the research questions intended to be analysed in this study are:

- How do exogenous factors, such as the Economy Policy Uncertainty Index (EPUI), and Consumer Confidence Index (CCI), drive the existing spillovers between energy commodities and financial markets?

- How does the Consumer Confidence Index (CCI) affect stock returns?
- Do the selected macroeconomic indicators have a connection with the Asian and the USA stock markets?
- Is there any short-term or long-term equilibrium among the variables under analysis?
- How do risk-adjusted performances (measured by the Sharpe ratio) in Asian and North American markets interact over time, and what is the direction of influence?

To address these questions, the current study employs recent econometric techniques, such as the ARDL model and the time-varying Granger causality test, including trend.

This study is relevant as it provides valuable insights for policymakers and market participants on the effects of volatility shocks on commodity prices and financial assets. Understanding the relationships between markets is essential to grasping the risk transmission between commodities and assets, such as stocks and treasury bonds. This enables policymakers to take appropriate measures to achieve their goals. At the same time, investors can develop more effective diversification and risk management strategies to efficiently manage potential losses during severe market shocks, such as endogenous and exogenous crises, efficiently allocating their investment portfolios and identifying new market opportunities.

The remainder of this work is organised as follows. Firstly, reviews the existing state of the art on the subject. Then we present the adopted methodology and the collected data. After discussing this topic, we will show the results and the corresponding discussion. Finally, we analyse the results and discuss the conclusions and policy implications.

2. Literature Review

Financial decisions play a fundamental role in corporate performance and economic stability (Linnenluecke et al., 2016). The financial market is an environment where two central intermediaries operate: the buyer and the seller. The buyer possesses capital to invest and thus acquires financial instruments such as stocks, bonds, derivatives, commodities, and currencies, expecting future economic returns. On the other hand, the seller needs capital and, to achieve this, sells these financial instruments, generating future cash flows from the capital obtained. Therefore, the capital market functions as an intermediary by channelling funds from savers and efficiently directing them to industries that require financing for expansion, thus promoting economic growth (Schrank, 2024; Singh, Gaurav, 2015).

2.1. From Traditional Finance to Behavioural Finance

The idea that stock and commodity prices in competitive markets follow a 'random walk' emerged from Maurice Kendall's discovery in 1953. This means that successive price changes in financial assets are independent, with no correlation between them (Brealey et al., 2010).

According to traditional finance, economic agents are rational and make their decisions to maximise the expected utility ("happiness") of the money gained or lost (Altuntaş & Ersoy, 2021). Since the 1970s, following the formalisation of the Efficient Market Hypothesis (EMH) by Eugene Fama, numerous attempts have been made to test it. However, there is no consensus regarding the results obtained, as they vary depending on the periods analysed, the estimation methods employed, and even the financial markets considered (Liu & Chen, 2020). According to efficient market theory, there are three levels of market efficiency: weak, semi-strong, and strong. Weak market efficiency occurs when financial asset prices already incorporate all information from past prices. Semi-strong efficiency arises when, in addition to past information, asset prices also reflect public information, such as news. Strong market efficiency, however, is reached when all information, including that obtained through fundamental analysis, is already reflected in asset prices. Financial asset prices are fair in this case, fully representing their intrinsic value. Therefore, the best strategy for investors would be to invest in a market index, as they can only expect returns that are compatible with the level of risk taken (Brealey et al., 2010; Fama, 1969). However, when Fama formulated the strong market efficiency hypothesis, he did not account for the inherent costs of information and trading (Fama, 1991).

The Capital Asset Price Model (CAPM) is one of the principal developments of modern capital market theory, which assumes that investors build their investment portfolios based on Markowitz's mean-variance model (Merton, 1973). According to this model, an asset's expected abnormal return is proportional to the covariance of the asset's return with the market portfolio. However, Black et al. (1972) found that contrary to expectations, assets with a "low beta" generally yielded higher returns than those predicted by the model, and vice versa. In the intertemporal model, unlike a single-period model, current asset demands are influenced by uncertainty regarding future investment opportunities (Fama & French, 2004; Merton, 1973).

According to behavioural finance, investors are not rational. They are subject to cognitive biases, such as prejudices and errors, which influence investment behaviour and challenge efficient market theory, often resulting in satisfactory but suboptimal decisions. These cognitive biases are particularly significant in situations of high complexity and uncertainty (Altuntaş & Ersoy, 2021; Shu & Chang, 2015). Behavioural finance focuses on identifying and categorising these behavioural patterns among economic agents, which interfere with the pricing of financial assets and conflict with the rational choice model advocated by traditional finance (Altuntaş & Ersoy, 2021; Grežo, 2020; Shu & Chang, 2015). For instance, overconfidence among investors may lead them to process available information less systematically and with reduced attention to detail, resulting in an overvaluation of financial assets and driving prices above their intrinsic values, thereby creating an unrealistic wave of optimism in financial markets. Conversely, widespread pessimism in financial markets can cause asset prices to fall below their intrinsic values, triggering panic and potentially leading to recessions (Shu & Chang, 2015).

There are two types of traders: noise traders and fundamental traders. The behaviour of noise traders causes the prices of financial assets to deviate from their equilibrium price. Conversely, the behaviour of fundamental traders, or arbitrage, drives financial asset prices towards their equilibrium price (McMillan & Speight, 2006). According to behavioural finance models focusing on noise traders, these individuals are influenced by emotions and cognitive biases from using heuristics in their investment decision-making process. Heuristics include representativeness, overconfidence, familiarity, anchoring to past representative values, herding, ambiguity aversion, and mental accounting. These factors lead to biased judgments or systematic errors by economic agents when assessing uncertain events, resulting, in turn, in market anomalies and, consequently, an inefficient market (Corzo et al., 2024; Stracca, 2004). Therefore, noise traders do not base their decisions on objective and rational factors. Instead, they follow trends and the behaviour of other traders in the market. This, in turn, leads to overreactions in the short term and reversals in the long term, as the market adjusts financial asset prices to their fundamentals. Furthermore, noise traders adapt their behaviour as the market evolves. In a bull market, they tend to exhibit overconfidence and overreaction, often driven by the "fear of missing out." In contrast, during a bear market, they adopt a more conservative and anchored approach, paying greater attention to fundamental news (McMillan & Speight, 2006).

The overconfidence effect, framed within the context of "positive illusions", meaning systematic tendencies towards overly optimistic beliefs, is a concept used in financial markets since the 1990s to describe the exaggerated self-confidence of economic agents when making their judgments. This overconfidence leads to a greater propensity for investments and excessive trading. The overconfidence effect results in overinvestment, as overconfident investors underestimate risks, causing them to trade more than rational investors. This overconfidence leads to an increase in trading volume and, consequently, to excessive trading (Grežo, 2020).

As suggested by the Allais paradox, developed by Maurice Allais in 1953, economic agents are not always rational in risky situations. They often make decisions that disregard the expected value and the probabilities of outcomes, thereby violating utility theory (Aguado-Franco, 2023).

According to Prospect Theory, developed in 1979 by Daniel Kahneman and Amos Tversky, economic agents do not evaluate outcomes based on overall utility but on their perceived gains and losses. In risky situations, economic agents exhibit a strong aversion to losses. Considering some limitations of Prospect Theory, the Cumulative Prospect Theory was subsequently formulated (Ao et al., 2023).

2.2. The Commodities' Role in Stock Markets

Energy commodities, particularly crude oil, natural gas, and coal, play an essential role in economic and technological development, as well as in employment levels (Feng et al., 2023; Huseynli, 2022).

Until the 2000s, the commodities market was dominated by two types of participants: commercial traders and non-commercial traders. The former were producers or industrial firms that traded commodity futures to hedge against the risks arising from price fluctuations of the goods produced. On the other hand, the latter were investors, such as hedge funds and asset managers, who took positions in commodity derivatives, like futures and options, on behalf of their clients. In 2004, commodity index traders emerged, making significant investments in commodity futures, leading to the financialization of the commodities market, characterised by increased institutional investment flows into the commodities market (Bonnier, 2021). Joint advances in technological and financial engineering later intensified this trend. As the 2007-2008 financial crisis unfolded, investors who were already engaged in trading commodity derivatives and financial instruments used for risk management further expanded these operations, shifting their investments from real estate derivatives to commodity derivatives (Shamsher, 2021). This increased exposure to the commodities market resulted in heightened speculation and, consequently, increased market volatility, with the commodities market acting as a transmitter of volatility (Bonnier, 2021; Cheng & Xiong, 2014).

Since the 2008 financial crisis, the intensification of commodity financialisation and the promotion of financial market integration have attracted the attention of policymakers, investors, and market professionals such as investment bankers, as these developments have altered price discovery, calling into question market efficiency and, consequently, the motivations and strategies adopted by investors. On the other hand, the increased market integration, combined with the global financialisation of commodities, has resulted in greater liquidity and, consequently, increased efficiency in commodity trading (Bonnier, 2021; Chan et al., 2011; Cheng & Xiong, 2014; Domanski & Heath, 2007; Huang et al., 2023).

2.3. Spillover Effects on Financial Markets

The growing financialisation of commodities, combined with factors such as financial liberalisation, an increase in the international flow of capital, technology, and information, and the globalisation of economies and international financial markets, has resulted in greater interconnectedness between these markets, making them increasingly correlated. This interconnectedness enhances market efficiency and societal development but also increases the exposure of emerging financial markets to external events and shocks, amplifying the risks of global spillovers. This phenomenon leads to a rise in contagion risk, also known as systemic risk, through various interconnected channels, contributing to greater vulnerability in economies. These risks can arise both between geographically distinct markets and across different segments of the financial market, such as equities, bonds, and foreign exchange (Rui-fengi et al., 2007). Moreover, contagion effects reduce the effectiveness of international portfolio diversification as a risk management tool (Mensi et al., 2021). Historically and in the current context, the concept of contagion (or spillover) has been used by economists to describe uncertain and volatile events that seem to lack a rational economic explanation (Afonso et al., 2022; Hansen, 2021; H. Wang & Li, 2021).

According to Hansen (2021) and Pasquariello (2007), researchers and investors use the term financial contagion to define the transmission of a shock from one financial asset or market to other financial assets and markets with little or no economic connection.

Hu et al. (2023) analyse the dynamic connectivity between global energy and carbon credit markets, concluding that there is a significant risk of spillover effects in international energy markets. According to the authors, unexpected, rare, and extreme fluctuations in WTI and Brent crude oil prices, driven by uncertainty shocks, impact other energy markets, such as Shanghai crude oil. Thus, WTI and Brent act as tail risk transmitters, while Shanghai crude oil and carbon credits are buffers.

Unpredictable events, known as 'black swan' events, amplify spillover effects (Zhou et al., 2022). According to Adams and Glück (2015), the spillover effects between equity and commodity markets have increased significantly following the 2008 financial crisis, influenced by dynamic geopolitical risks, economic policy uncertainties, and stock market volatility (Feng et al., 2023). Therefore, the global financial crisis of 2008, which was endogenous, led policymakers, investors, and regulators to pay increased attention to the correlation between financial markets, seeking to mitigate the risks associated with the contagion effect (Afonso et al., 2022). Zhang and Hamori (2021) found that the COVID-19 pandemic generated even greater volatility than the 2008 financial crisis, affecting both the stock and oil markets.

Numerous studies focus on analysing the contagion effects between global crude oil markets and stock markets, which are intensified by endogenous and exogenous crises. Most crude oil imports from OPEC are directed to the Asia-Pacific region, with China being the primary destination (Lin et al., 2021).

According to Cai and Wu (2021), based on the time-varying Granger causality test, there is unidirectional causality from oil market prices to the natural gas market in Europe and Asia, contrary to what is observed in the USA. These findings can be explained by the fact that the American natural gas market is currently deregulated. Gas prices are determined by supply and demand dynamics in trading hubs, leading to greater resource efficiency. Conversely, the Asian market, being the leading importer of natural gas, has its prices indexed to oil prices, resulting in lower efficiency in the natural gas market. Given this causal relationship, the Asian and European markets need to adopt alternative natural gas pricing mechanisms, such as trading hubs, to minimise contagion risks.

The study by Rui-fengi et al. (2007) aimed to measure volatility spillovers among Asian financial markets over the period from 4 January 2000 to 20 June 2005, using data from major regional indices such as the Shanghai Composite Index, Shenzhen Component Index, Hong Kong Hang Seng Index, Korea Composite Index, Nikkei 225 Index, and Singapore Straits Index, obtained from the Webstock Market Information system. Stochastic Volatility (SV) models were applied to describe the marginal distribution of returns, followed by identifying a structural break in volatility. From this point, the Frank copula function was employed to estimate dependence relationships between markets and to assess whether significant changes occurred in the correlation coefficient. The results reveal long-term volatility spillovers between the Shenzhen and Shanghai stock markets, indicating a strong interdependence between these Chinese financial centres.

In a recent study, Fang (2025) uses data from 2000 to 2024 to empirically analyse and validate the asymmetric transmission of systemic risk between China and emerging Asian markets. The main findings reveal significant contagion patterns, with the Korean Stock Index (KOSPI) showing high sensitivity to risks from the Shanghai Stock Exchange (SSE). Additionally, the Malaysian Stock Index (KLCI) demonstrates a strong influence in the transmission of risk, while the Thai Index (SET) and the Taiwanese Index (TWII) stand out as both key contributors to and recipients of systemic risk. Under extreme market conditions, spillover effects become more pronounced, positioning the SSE as a critical hub in regional risk dynamics (see Fang, 2025).

In a related study, Zhao & Park (2024) investigate the bidirectional contagion effects of risk between the Chinese stock market and other Asian markets. Their analysis considers eleven

Asian stock indices covering the period from 1 January 2007 to 31 December 2021. The results indicate that during the global financial crisis of 2007 to 2009, the European sovereign debt crisis, the Chinese stock market crash of 2015 to 2016, and the trade tensions between China and the United States, the Chinese equity market generated substantial extreme risk contagion effects across other Asian markets. However, during the COVID-19 pandemic crisis, the contagion effect from the Chinese stock market towards other Asian indices weakened, and the Chinese market acted primarily as a recipient of risk from other Asian equity markets. B. Wang and Xiao (2023) present evidence of significant contagion effects from the Chinese stock index to East Asian equity markets. Nevertheless, they highlight that this contagion effect tends to weaken during periods of high volatility in stock markets. Similarly, Jiang et al. (2021) argue that several developed economies, including the United States, the United Kingdom, and Japan, exert significant contagion effects on the Chinese stock market.

In another contribution, Sun et al. (2023) identify a risk linkage between China and the stock markets of APEC countries. They emphasise that the liberalisation reforms in China's capital markets have played a significant role in strengthening the connection between these markets. Furthermore, X. Zhang et al. (2022) evaluate the contagion pathways among European, American, and East Asian stock markets. Their findings confirm that risks originating in European and American markets are transmitted to China via the Japanese and Hong Kong equity markets. Du et al. (2023) highlight evidence showing that contagion effects from the Hong Kong market to the Chinese stock market have been increasing. On the other hand, there is no substantial evidence supporting the existence of direct contagion effects between the Chinese and American stock markets.

Several empirical studies focus on analysing the effects of the commodities markets, particularly the crude oil market, on financial markets. The methodology adopted by these studies is based on the VAR model, its derivatives, and the GARCH family of models. These models have a limitation in measuring spillover risk, as they cannot determine its direction or quantify the intensity of the effect (H. Wang & Li, 2021). Therefore, a gap in the analysis of spillovers is that studies typically focus only on verifying the existence of spillovers between markets, without examining the direction and intensity of these effects. Such an analysis is crucial for investors to manage risk better and forecast the performance of their portfolios, enabling them to allocate resources in a manner that aligns with different market regimes, such as periods of expansion and recession (Mensi et al., 2021).

2.4. The Influence of Analysed Variables on Financial Markets

2.4.1. The Influence of Energy Commodities on Financial Markets

Energy commodity prices indirectly influence stock prices, as they are inputs in companies' production processes and, therefore, affect their production costs. These increases in costs lead to a decrease in the expected cash flows of the company, which in turn results in a decline in stock prices (Huseynli, 2022; Mensi et al., 2021). On the other hand, in the specific case of energy companies, commodity prices directly impact their profitability (Huseynli, 2022).

An increase in international oil prices leads to a slight rise in inflation, which the country's central bank can easily control by implementing monetary policies. However, the higher the economic and monetary policy uncertainty index, the greater the volatility of oil prices and, consequently, the greater the volatility of inflation. The reverse also applies, that is, an increase in the volatility of energy prices, especially oil prices, raises the economic and monetary policy uncertainty index (Kyriazis et al., 2024). In another recent study, Antonakakis et al. (2023) found that the connectivity between different asset classes and implied volatilities in oil prices varies over time, fluctuating at high levels, indicating significant risk links between these markets. They asserted that the oil market is integrated with financial markets and is significantly affected by sudden fluctuations in financial market volatilities due to globalisation. Hung (2023) examined the dynamic causality between crude oil and exchange rate markets in G7 countries throughout the COVID-19 pandemic and the Russia–Ukraine conflict, employing time-varying Granger causality tests and pass-through index models with data spanning from December 31, 2019, to October 31, 2022. Similarly, Cui et al. (2021) and Li et al. (2023) investigated the interdependence between oil prices and the Chinese stock market, highlighting the transmission of crude oil price risk to the equity market. Xie & Tang (2022), using a modified quantile-on-quantile approach to overcome limitations in existing methodologies, demonstrated that uncertainty in the oil market exerts a positive and asymmetric influence on stock market uncertainty across BRICS nations. The pandemic substantially disrupted commodity indices, resulting in fluctuations in prices and volatility, increased uncertainty, and shifts in the relationships among raw materials.

Hung and Vo (2021) analysed spillover effects and interdependencies among the S&P 500, oil, and gold using the Diebold and Yilmaz spillover index alongside the wavelet coherence method, comparing pre-COVID-19 and COVID-19 periods. Their findings indicated stronger spillovers during the pandemic, with the S&P 500 and oil serving as net risk receivers, while gold shifted from being a net issuer before COVID-19 to a net transmitter during the crisis. Likewise, Balcilar et al. (2021) applied the Diebold & Yilmaz (2012) spillover index to assess the interconnectedness of returns and volatility among the S&P 500, oil, and gold, showing that the S&P 500 and oil acted as net emitters of return spillovers, whereas gold functioned as a net receiver. Regarding volatility spillovers, the S&P 500 and gold were identified as net issuers, while oil played the role of a net receiver.

2.4.2. The Influence of the Consumer Price Index (CPI) on Commodities and Financial Markets

The increase in energy commodity prices leads to higher production costs for companies, which, in turn, causes the prices of goods and services to rise as well (Gubareva et al., 2023). Saeed et al. (2023) analysed the relationship between energy commodities and the Consumer Price Index (CPI) in G7 economies and China using the Continuous Wavelet Transform (CWT) methodology. They divided the sample into pre- and post-COVID-19 periods to assess the impact of COVID-19. According to the Wavelet Transform Coherence (WTC) analysis, a significant positive relationship exists between the CPI variable, used as a proxy for inflation, and crude oil in France and the United States. Conversely, a significant negative relationship exists between the CPI and natural gas in several G7 economies. The USA and Japan are the primary transmitters of inflation, while Poland and other smaller European economies are net recipients of inflation from the Eurozone.

According to Kyriazis et al. (2024), there is a significant relationship between inflation and the money supply, oil, and gold, particularly during times of crisis. Oil and gold have acted as hedge assets during uncertain economic and monetary policy periods.

2.4.3. The Influence of the Economic Policy Uncertainty Index (EPUI), Industrial Production Index, Investor's Sentiment, Consumer's Sentiment Index on Commodities and Financial Markets

In his book “Risk, Uncertainty and Profit”, published in 1921, Frank Knight emphasises distinguishing between risk and uncertainty. Risk, unlike uncertainty, refers to situations with a set of events with a known probability distribution. Uncertainty, on the other hand, is measured through a range of indirect indicators, such as the occurrence of the word “uncertainty” in news reports (Bloom, 2014; Knight, 1921).

Economic policy uncertainty arises from government intervention, which influences a country's economic development. In this context, the Economic Policy Uncertainty (EPU) index serves as a measure of uncertainty that seeks to capture the perceptions of economic agents, such as consumers, managers, and investors, regarding potential future outcomes. This uncertainty stems from their inability to accurately predict the future due to policy changes, including their direction, timing, and the content of adjustments. Economic policy uncertainty can be used to forecast the volatility of financial and commodity markets, particularly the stock market. Economic uncertainty tends to rise significantly during periods of recession and decline during times of economic expansion. Furthermore, exogenous shocks to the economy, such as financial crises, wars, and surges in energy commodity prices, often lead to heightened economic uncertainty (Bloom, 2014; Yin et al., 2023). Global uncertainty's growing economic and social instability has increasingly attracted decision-makers' attention. Uncertainty related to economic policy is a significant concern, especially in the context of increasing openness to international trade and the integration of global financial markets (Zhou et al., 2022).

Economic policy uncertainty holds significant implications for both commodity and financial markets, as well as economic and financial activity, as it influences future investment and consumption decisions made by economic agents (Lee et al., 2021). An increase in economic policy uncertainty, often arising from either endogenous or exogenous crises, tends to negatively affect financial market performance, resulting in a decline in the prices of financial assets. This occurs because companies tend to scale back investment in new projects, and investors adopt a more conservative approach. This scenario, in turn, also impacts the cost of financing, as heightened uncertainty leads creditors to become more cautious, resulting in higher interest rates (Fasanya et al., 2021; Henríquez & Gálvez-Gamboa, 2022; Wu et al., 2023). As a result of increased political uncertainty indices in both the USA and China, USA companies reduce their investments (Lee et al., 2021).

An increase in consumption volatility, driven by news related to economic uncertainty, leads to a decline in the prices of financial assets, as economic agents find it harder to forecast future growth rates and the level of economic uncertainty. Therefore, policymakers, shareholders, consumers, investors, portfolio managers, risk managers, and others should pay close attention to changes in the Economic Policy Uncertainty (EPU) Index to develop investment strategies to protect themselves against significant fluctuations in financial asset prices (Bansal et al., 2004).

According to Prokopczuk et al. (2019), there is a strong correlation between the commodity market and economic and financial uncertainty, especially during periods of recession. Xie and Tang (2022) using a modified quantile-on-quantile approach, concluded that oil market uncertainty positively and asymmetrically impacts the stock volatility of BRICS countries (Brazil, Russia, India, China, and South Africa). This impact is more pronounced under bearish market conditions (higher quantiles).

Studies examining the relationship between economic policy uncertainty and financial and commodity markets predominantly utilise linear models, such as the VAR model, whose parameters are invariant. As a result, these models fail to capture the dynamic behaviour of economic policy uncertainty within the markets (Yin et al., 2023).

According to Chevallier and Ielpo (2014), the influence of the growth rate of the industrial production index on commodity markets, as well as on equity and bond markets, in other words, the relationships between these markets in both the short and long-term, will be influenced by a variety of factors. These include the type of commodities under study, the country, the period under analysis, and whether structural breaks are included. A decrease in commodity prices results in reduced production costs, which, in turn, leads to an increase in demand for goods and services, indirectly raising the industrial production index (Chevallier & Ielpo, 2014).

According to Yao and Li (2020), investor sentiment does not impact stock prices as traditionally accepted. Instead, stock market information, such as fluctuations in stock price returns, affects investor sentiment. Additionally, beyond stock market information, investor sentiment is influenced by the economic policies adopted by policymakers. On the other hand, Shu and Chang (2015) analysed how investor sentiment affects the traditional asset pricing model, using time preference and risk attitude as sentiment factors linked to the postponement of consumption and risk tolerance. They concluded that changes in sentiment factors result in high volatility in financial markets, with the stock market being more sensitive than the bond market. Thus, according to their findings, investor sentiment has a positive impact on both the returns and volatility of stock markets, with this impact being more significant during market expansion periods, characterised by optimistic sentiment. Therefore, the more optimistic the consumer sentiment is, the higher the stock prices are, and vice versa.

B. Zhang (2019) empirically investigates the causal relationship between economic policy uncertainty and investor sentiment in the United States, using monthly data from January

1985 to December 2016, to understand whether changes in the level of economic uncertainty can predict variations in financial market mood. The Economic Policy Uncertainty (EPU) index is obtained from S. R. Baker et al. (2016), while investor sentiment is measured using the M. Baker and Wurgler (2007) index, which is widely employed in the behavioural finance literature. The results show a significant unidirectional causality running from EPU to investor sentiment in the linear context, indicating that changes in economic policy uncertainty precede shifts in investor mood. When the author applies a non-linear test, this relationship remains robust and even stronger, suggesting that the effect of uncertainty is not constant but asymmetrical. In other words, during periods of political shocks, financial crises, or high macroeconomic volatility, the impact of uncertainty on sentiment becomes more pronounced. Conversely, the opposite direction, from sentiment to EPU, shows no statistically significant evidence. In turn, Boungou & Yatié, (2024) examine the effects of the war between Ukraine and Russia on economic uncertainty, global stock index returns, and commodity prices, using data from January 2022 to April 2023 covering a sample of 96 stock indices and 67 commodities. They find that the conflict significantly increased levels of uncertainty (measured by the Economic Policy Uncertainty index), which in turn exerted a negative effect on global stock market performance, particularly in Europe and the Americas. At the same time, they observe that the war led to higher commodity prices, with the negative shocks tending to subside as the conflict persisted. This study contributes to the literature by demonstrating not only the existence of this adverse relationship between uncertainty and financial markets in a wartime context, but also its regional and temporal heterogeneity.

The EPU Index is linked to investor sentiment, as higher levels of uncertainty stemming from changes in government policies and regulations increase the concerns of economic agents. In response, investors adjust their investment portfolios, guided by their perception of risk or opportunity (Chowdhury & Humaira, 2023).

Engeloğlu & Yurdakul (2025) empirically examine the determinants of consumer behaviour in European Union countries, using monthly data from January 2012 to December 2019, and employing the Consumer Confidence Index (CCI) as a proxy for consumer sentiment and behaviour. The study applies to the nonlinear quantile causality test, which captures differing relationships between positive and negative shocks in macroeconomic variables and the CCI, thereby overcoming the limitations of traditional linear models. Additionally, the authors perform a hierarchical cluster analysis (Ward's method) to identify regional patterns among the 27 EU countries based on the similarity of the estimated coefficients. The empirical results indicate that the stock market index, representing financial market performance, exerts the most significant influence on the CCI, demonstrating that European consumer optimism is strongly associated with capital market performance, particularly in more open and financially developed economies such as Germany, France, and the Netherlands. The consumer price index (CPI) is also significant, though its impact is more moderate, suggesting that inflation affects consumer sentiment indirectly, especially when combined with labour market shocks. Furthermore, the authors identify statistically significant effects around election periods, indicating that short-term political uncertainty contributes to temporary fluctuations in consumer confidence.

Ghosh (2022) examines the impact of economic uncertainty and financial stress on consumer confidence in Japan, using quarterly data from 1990 to 2020 and applying the NARDL (Nonlinear Autoregressive Distributed Lag) model to capture asymmetric effects. The empirical results show that positive shocks to economic uncertainty significantly reduce consumer confidence, with an estimated elasticity of approximately -0.45, whereas negative shocks have a smaller effect (-0.18), confirming the presence of an asymmetric response. Furthermore, increases in the Financial Stress Index (FSI) trigger immediate declines in consumer confidence, particularly during global financial crises (2008–2009 and 2020), with short-term effects being more pronounced than long-term ones. The study also finds that declines in the Japanese stock market are associated with substantial losses in confidence, with a 10% reduction in the Nikkei 225 index corresponding, on average, to a 3.2-point drop in the Consumer Confidence Index.

3. Methodology and Data

3.1. Methodology

Since the period under analysis spans from January 1, 2007, to June 1, 2024, encompassing 210 months, it becomes crucial to identify structural changes over time, as model parameters may undergo alterations due to significant events, such as economic and financial crises. This approach allows for obtaining estimates and inferences that are as unbiased as possible, while also identifying the events that triggered specific disruptions and their corresponding effects (Ditzen et al., 2021).

Therefore, in line with the previously stated rationale, unit root tests with structural breaks will be applied to determine whether the selected time series is stationary, i.e., whether the time series has unit roots and exhibits structural breaks. Therefore, two different unit root tests will be used, one that can detect up to 2 breakpoints and the other that detects multiple unknown breakpoints. These results aim to confirm that the time series are integrated with order 1, which is a prerequisite for cointegration.

3.1.1. ARDL Method

To confirm the results obtained from the unit root tests, the ARDL bounds test will be applied to investigate cointegration relationships. Next, considering the requirement that the variables be integrated of order 0 and 1, we will apply the Autoregressive Distributed Lag (ARDL) econometric model, distinguishing short and long-term effects.

To examine the short- and long-run relationships between the dependent variable and the independent variables, the ARDL (Autoregressive Distributed Lag) model was applied. The bounds testing procedure associated with this methodology allows the estimation of a relationship between the variables under analysis without the need for prior verification of their order of integration, in other words, whether the independent variables are stationary in levels or first differences. The tests are based on F- and t-statistics applied to the coefficients of the lagged terms of the variables (Pesaran et al., 2001a).

The ARDL equation, in its condensed form, can be expressed as follows:

$$\Omega\,(\mathrm{L}, \mathrm{p})y_t \;=\; a_0 \;+\; \sum_{i=1}^{k} \beta_i\,(\mathrm{L}, q_i)x_{it} \;+\; \delta'^{w_t} \;+\; \mu_t \tag{1}$$

In which:

$$\Omega\,(\mathrm{L,p}) = 1 - \Omega_1\delta_1 L^1 - \Omega_2\delta_2 L^2 - \cdots \Omega_p L^p \tag{2}$$

$$\beta_i(L, q_i) = \beta_{i0} + \beta_{i1}\mathrm{L} + \beta_{i2}L^2 + \beta_{iqi}L^{iqi}, \qquad \mathrm{i} = 1, 2, \ldots, \mathrm{k}, \tag{3}$$

y_t is the dependent variable; α is the intercept; L is a lag operator such that Ly_t= y_{t-1}, and w_t is an s x 1 vector of deterministic variables.

In the ARDL model, the values at time t-1 appear in levels until the lag of the first difference of the explained variable (p) and the regressors (q_k), as outlined by Jordan & Philips (2018).

The speed of adjustment ($\sigma_i = 1 - \sum_{j=1}^{p} \emptyset_{i,k}$) measures how quickly a deviation is corrected, with long-run coefficients ($\theta = \frac{\sum_{j=0}^{q} \beta_{i,k}}{\alpha_i}$) indicating the equilibrium ratio of the independent variables to the dependent variable. For more details, see Moutinho and Madaleno (2020). Standard co-integration tests may fail to establish co-integration when structural breaks are present. To address this issue, researchers like Gregory & Hansen (1996b, 1996a) and Maki (2012) developed co-integration approaches that account for structural breaks in the co-integrating vectors (Moutinho et al., 2023). This alternative methodology makes it possible to identify co-integrating relationships with high precision, even in the presence of structural breaks (Moutinho et al., 2023).

The use of the ARDL methodology allows us to differentiate between short- and long-term effects, offering insights into the behaviour investors should be adopting to optimise their portfolios, as well as the decisions policymakers should be making to achieve their objectives. One of the main advantages of the ARDL model is that it automatically selects the optimal lag order by means of the Akaike Information Criterion (AIC) and the Bayesian (Schwarz) Information Criterion (BIC).

3.1.2. Time-Varying Granger Causality

Since the use of time-invariant Granger causality tests can yield biased results (Cai & Wu, 2021), to examine the spillover effects among the variables under analysis, the methodology will incorporate a time-varying Granger causality test, including the consideration of underlying trends. Therefore, to evaluate causality between time series, the time-varying Granger causality test, including a trend, was performed, based on Baum et al. (2022). The time-varying Granger causality test allows for the identification of intervals where Granger causal relationships between variables exist, which can change considerably throughout the analysed period (Baum et al., 2022).

The time-varying Granger causality approach offers several significant advantages. First, it enables the analysis of bidirectional causality between variables, identifying causal relationships in both directions. Additionally, this approach can accommodate unexpected or extreme events, or "black swan" events, ensuring robust analysis in highly volatile contexts. It also allows for the detection of potential heteroskedasticity, making it possible to adjust models for variations in error variance over time. Another notable aspect is its ability to delineate Granger causality over time, facilitating the identification of whether causal relationships are persistent or transient. The approach is also flexible concerning the stationarity of variables, making it applicable to stationary and non-stationary time series. Lastly, it enables the analysis of both the intensity and direction of causal relationships, allowing for the examination of variations in the strength and direction of impact between variables over the analysed period (Fromentin et al., 2022).

The bivariate VAR model is specified as follows:

$$y_{1t} = \emptyset_0^{(1)} + \sum_{k=1}^{m} \emptyset_{1k}^{(1)} y1_{t-k} + \sum_{k=1}^{m} \emptyset_{2k}^{(1)} y2_{t-k} + \varepsilon_{1t} \tag{4}$$

$$y_{2t} = \emptyset_0^{(2)} + \sum_{k=1}^{m} \emptyset_{1k}^{(2)} y1_{t-k} + \sum_{k=1}^{m} \emptyset_{2}^{(2)} y2_{t-k} + \varepsilon_{2t} \tag{5}$$

Where y_{1t} and y_{2t} represent the economic time series under analysis. The error terms ε_{1t} and ε_{2t} are assumed to be uncorrelated over time, implying the absence of serial correlation. However, these error terms may be heteroskedastic, meaning that their variances can change over time, affecting the efficiency of the model's estimators. The null hypothesis of no Granger causality from y1 to y2 is tested by examining the joint significance of the $\emptyset_{1k}^{(2)}(k = 1, \dots, m)$ through a Wald test.

A sequence of steps was undertaken to implement the time-varying causality methodology. Firstly, the order of the integration of the variables was ascertained. Subsequently, the specification of the VAR model to be estimated was defined. The causality tests were conducted for the full sample, and the time-varying causality tests were estimated.

The results of the unit root tests are presented in Table 1 and Table 2. Although it is not a strict requirement for the time series to be stationary for this methodology to be applied, it nonetheless remains necessary to establish the order of integration of the time series.

The null hypothesis (H0) to be tested in the time-varying Granger causality test is the absence of Granger causality among all the variables in the system. A variable X Granger causes a variable Y if and only if there is an improvement in the prediction of Y when the past values of X are considered, ceteris paribus (Baum et al., 2022).

Building on a stationary VAR model, it is possible to analyse causal relationships between variables, assuming these relationships remain stable over time. In cases where non-stationary variables are present, a Lag-Augmented VAR (LA-VAR) model is employed, which allows for the inclusion of integrated variables without compromising the validity of causal inferences.

To capture temporal dynamics and to identify potential periods of instability in causal linkages, three time-varying parameter causality algorithms are utilised: the forward expanding (FE) window, the rolling (RO) window, and the recursive evolving (RE) window. In the forward expanding (FE) window approach, the causal relationship between the variables is tested recursively, with a progressively expanding sample. An additional observation is incorporated into the dataset at each iteration, and the causality test is re-estimated. By contrast, the rolling (RO) window applies a fixed size moving window across the entire time series, conducting the causality test within each sub-sample separately. Lastly, the recursive evolving (RE) window algorithm combines features of the forward expanding and rolling window methods. This approach carries out causality tests recursively, gradually expanding the sample size over time. A new observation is added at each step, and the test is re-estimated, allowing for a dynamic update of the model's structure and parameters.

3.2. Data

This study covers the period from January 1, 2007, to June 1, 2024, and uses monthly time series data (210 months). Considering the period under analysis, the study aims to cover crucial events, such as endogenous and exogenous crises, including the 2007-2008 subprime crisis, the 2008-2009 global financial crisis, the sovereign debt crisis (2010-2012), the COVID-19 pandemic recession, and the Russia-Ukraine war (2022).

To achieve the proposed objectives, monthly price data of representative proxies for each market were collected to analyse the cross-market linkages and dynamic spillover effects between the energy commodity and financial markets (see Table A. 2 in the Appendix A). For representative financial markets, the historical data were collected from the stock indices of the USA and five Asian countries analysed: S&P 500, Nikkei 225, CSI 300 Index, Hang Seng Index, STI Index and Kospi Composite Index (see Table A. 2 in the Appendix A). Therefore, the six countries analysed are the USA, Japan, China, Hong Kong, Singapore, and Korea.

Together with the Asian markets, the USA market was also analysed for several reasons, among which the following stand out: the dominant position the United States holds in the global financial system, the strong interdependence between its economy and the Asian markets, the fact that it is the world's largest consumer and importer of crude oil, and its ability to generate economic shocks with global repercussions, as occurred during the 2007-2008 financial crisis. These characteristics make the USA market a crucial player in international economic analysis (Bouteska et al., 2023; Tiwari et al., 2021).

The following indexes and rates were chosen: Economic Policy Uncertainty Index, Consumer Confidence Index (amplitude adjusted), Consumer Price Index (national index), Industrial Production Index (2015 index, calendar and seasonally adjusted), Sharpe ratio and key fossil energy commodities (price of West Texas Intermediate crude oil, Brent crude oil, coal, and Henry Hub natural gas).

Each economy's Economic Policy Uncertainty Index will quantify this uncertainty. The Economic Policy Uncertainty Index (EPUI) measures the level of uncertainty in an economy resulting from government regulations and policies. The index is constructed based on the frequency of economic and political uncertainty terms mentioned in major newspapers (Chowdhury & Humaira, 2023) (see Table A. 1 in the Appendix A).

The analysis of investor sentiment will be conducted indirectly, given that investor sentiment and the political uncertainty index exhibit an inverse relationship (Boungou & Yatié, 2024; B. Zhang, 2019).

The Sharpe ratio is used to analyse the risk-return trade-off. It is formulated as:

$$Sharpe\ index = \frac{R_p - R_f}{\sigma_p} \quad (6)$$

where

R_p	Return of portfolio;
R_f	Risk-free rate of return;
σ_p	Standard deviation of portfolio return/volatility.

Therefore, the Sharpe ratio can be defined as the difference between a portfolio's return and the risk-free rate, divided by its volatility. As proxies for risk-free rates, the yields of 10-year bonds from each analysed economy will be used. It provides the return by unit of risk.

The variables were initially collected in their base currency and converted to US dollars.

The main descriptive statistics of the variables results presented in Table A. 3 in the Appendix A.

4. Empirical Results and Discussion

4.1. Results of Unit Root Tests – Stationarity Analysis

Unit root tests were conducted to confirm the stationarity of all the variables analysed (see Table 1 and Table 2). According to Table 1, some variables are stationary in levels (I(0)), including the economic policy uncertainty indices for Hong Kong and Korea (epu.hk, epu.kor), the equity indices S&P500 (sp), HSI (hsi), STI (sti), and KOSPI (kospi), the consumer confidence indices (cci.kor, cci.us, cci.jap), the USA industrial production index (ipi.us), and the Sharpe ratios (sr.us, sr.jap, sr.chi, sr.hk, sr.sing, sr.kor), with significance primarily at the 1% level. Other variables, such as gas prices (gas), the economic policy uncertainty indices of the USA and Japan (epu.us, epu.jap), the CSI index (csi), and USA inflation (cpi.us), are stationary in levels at the 5% significance level, while the HSI is significant at the 10% level. Conversely, some series exhibit stationarity only after first difference (I(1)), including 10-year yields (10yb.us, 10yb.jap, 10yb.chi, 10yb.hk, 10yb.sing, 10yb.kor) and coal prices (coal). These results indicate the presence of long-term trends and persistent shocks in these variables.

Considering Table 2, the energy commodities analysed (WTI, Brent, coal, and natural gas) exhibit high and statistically significant F-values at the 1% significance level. This evidence suggests that the energy sector has undergone recurrent structural changes, possibly associated with global supply and demand shocks, international financial crises, and major geopolitical events such as the oil price collapse of 2014–2016, the COVID-19 pandemic in 2020, and the war in Ukraine from 2022 onwards. The presence of multiple breaks, therefore, indicates that the dynamics of energy prices cannot be adequately described by stationary or simple linear models, requiring approaches that account for regime shifts over time.

The Economic Policy Uncertainty (EPU) indices for the United States, Japan, China, Hong Kong, Singapore, and South Korea also display extremely high F-values, particularly for China and Singapore. This evidence indicates that global economic uncertainty has experienced marked structural variations, reflecting the occurrence of crisis episodes and exogenous shocks such as the 2008 financial crisis, the turmoil in Asian markets, the US–China trade conflict, and the COVID-19 pandemic. These results reinforce the notion that the behaviour of economic uncertainty is highly non-stationary and subject to frequent regime changes.

The Consumer Confidence Indices (CCI) of all the economies analysed also exhibit multiple significant breaks, with five structural ruptures detected in every case. This suggests that consumer sentiment, a key indicator of the economic cycle, reacts sensitively to changes in macroeconomic and financial conditions, undergoing structural shifts during periods of recession, recovery, or external shocks. The results, therefore, imply that consumer confidence evolves across distinct economic regimes, in line with cyclical fluctuations.

Similarly, the Industrial Production Index (IPI) series for the United States, Japan, and South Korea reveals five significant breaks, reflecting successive phases of expansion and contraction in economic activity. These breaks may be linked both to global crises (for instance, those of 2008 and 2020) and to internal structural transformations, such as technological changes and the reconfiguration of international production chains. The findings highlight that the industrial dynamics of the major Asian and Western economies have been characterised by recurrent and persistent disruptions.

The results relating to stock market indices (S&P 500, Nikkei, CSI, HSI, STI, KOSPI) and Sharpe ratios reveal a mixed pattern. In general, multiple structural breaks are observed across nearly all indices, except the S&P 500 returns and the USA Sharpe ratio, which display non-significant F-values in the initial stages of testing. This suggests that the USA market maintained greater structural stability over the period, whereas Asian markets proved more volatile and prone to regime changes. The pronounced structural instability observed in indices such as the KOSPI and CSI may be linked to these markets' heightened sensitivity to external shocks, capital flows, and policy interventions.

The coexistence of I(0) and I(1) series justifies the adoption of the LA-VAR (Lag Augmented VAR) model with a lag of d = 1 to analyse time-varying causality, allowing the capture of both short-term effects and long-term dynamics.

Table 1 – Zivot and Andrews unit root test with structural break, considering the trend and intercept

Variables	Trend				Intercept			
	At level		At 1st difference		At level		At 1st difference	
	Minimum t-statistic	Time-Break	Minimum t-statistic	Time-Break	Minimum t-statistic	Time-Break	Minimum t-statistic	Time-Break
wti	-3.943	2020M03	-9.781***	2014M11	-5.139**	2014M10	-9.938***	2020M05
brent	-3.505	2020M03	-9.999***	2014M11	-4.912**	2014M07	-10.157***	2020M05
coal	-3.339	2015M11	-4.771**	2021M11	-4.347**	2021M06	-4.669*	2020M8
gas	-4.317**	2010M04	-11.370***	2021M10	-4.288**	2021M04	-11.406***	2009M10
epu.us	-4.227**	2020M11	-10.323***	2020M04	-4.364**	2018M10	-10.723***	2020M08
epu.jap	-4.665**	2020M05	-10.207	2009M12	-4.947**	2012M07	-10.238	2018M02
epu.chi	-3.425	2021M11	-12.706***	2019M06	-4.346	2017M01	-12.983***	2020M12
epu.hk	-5.717***	2011M12	-11.092***	2021M11	-5.957***	2017M03	-11.176***	2012M01
epu.sing	-3.189	2021M11	-11.729***	2019M07	-4.047	2018M05	-11.900***	2020M06
epu.kor	-6.902***	2014M09	-11.003***	2021M11	-7.312***	2013M02	-11.114***	2019M09
sp	-14.590***	2020M08	-12.204***	2020M08	-14.693***	2020M07	-12.635***	2020M09
nikkei	-2.938	2021M11	-13.980***	2021M11	-1.283	2021M08	-14.186***	2015M06
csi	-4.296**	2009M10	-6.223***	2015M03	-3.470	2010M1	-6.310***	2021M02
hsi	-4.170*	2020M12	-14.349***	2017M07	-4.220	2021M07	-14.491***	2018M02
sti	-3.922	2018M06	-8.879***	2009M10	-4.072	2019M12	-8.883***	2015M04
kospi	-4.070	2019M06	-16.214***	2012M07	-5.402***	2020M11	-16.447***	2020M04
cci.us	-4.282**	2017M11	-7.523***	2009M12	-4.921**	2020M2	-7.297***	2018M03
cci.jap	-4.246**	2015M11	-6.297***	2009M12	-5.179	2019M12	-6.136***	2017M10
cci.chi	-3.633	2020M10	-6.823***	2017M07	-4.425	2021M11	-7.027***	2021M10
cci.kor	-5.339***	2010M04	-6.163***	2020M02	-5.313**	2009M12	-6.268***	2020M04
cpi.us	-4.519**	2020M04	-8.466***	2015M10	-3.704	2021M03	-8.952***	2021M01
cpi.chi	-3.637	2012M11	-11.151***	2016M01	-3.602	2018M05	-11.370	2019M11

cpi.kor	-4.087	2020M12	-12.101***	2010M10	-4.032	2021M11	-12.183***	2021M01
ipi.us	-2.706***	2014M10	-11.295***	2010M10	-2.975	2019M09	-11.516***	2009M10
ipi.jap	-2.878	2020M06	-8.763***	2013M01	-3.036	2021M10	-8.972***	2015M08
ipi.kor	-3.757	2020M08	-10.992***	2012M11	-3.903	2021M07	-11.044***	2010M09
10yb.us	-3.535	2020M8	-13.539***	2020M02	-3.491	2021M11	-13.685***	2020M08
10yb.jap	-3.721	2019M07	-9.164***	2016M03	-1.082	2021M08	-9.144***	2011M05
10yb.chi	-3.508	2012M11	-10.848***	2009M09	-3.536	2010M10	-11.046***	2019M10
10yb.hk	-3.323	2012M08	-15.429***	2021M11	-3.951	2017M03	-15.570***	2018M05
10yb.sing	-3.678	2011M01	-15.061***	2014M12	-4.079	2010M06	-15.218***	2011M08
10yb.kor	-3.679	2019M06	-7.911***	2010M04	-3.678	2021M09	-7.971***	2016M08
sr.us	-14.206***	2013M06	-12.130***	2013M11	-14.481***	2014M01	-12.485***	2013M07
sr.jap	-14.275***	2017M06	-12.158***	2010M02	-14.475***	2017M05	-12.470***	2017M07
sr.chi	-13.846***	2009M10	-12.166***	2010M02	-13.505***	2009M12	-12.299***	2012M09
sr.hk	-14.219***	2017M04	-12.058***	2016M09	-14.381***	2016M08	-12.561***	2017M05
sr.sing	-8.403***	2020M03	-12.041***	2010M02	-8.489***	2020M11	-12.105***	2014M05
sr,kor	-13.327***	2013M12	-11.747***	2014M05	-13.376***	2012M05	-12.134***	2014M01

Note: the level of statistical significance of 1% is denoted by ***, 5% is denoted by **, and 10% by *. The critical value in a test with the trend at 1% is – 4.93, at 5% is - 4.42, and at 10% is - 4.11; while test estimation with an intercept at 1% is – 5.34, at 5% is – 4.93, and at 10% is - 4.58, respectively. The maximum lag order is 4 in both unit root tests.

Table 2 – Sequential test for multiple breaks at unknown breakpoints for the variables (Ditzen et al., 2021)

	wti	brent	coal	gas	epu.us	epu.jap	epu.chi	epu.hk
F(1|0)	98.64***	88.80***	245.45***	167.50***	57.37***	8.65**	356.39***	21.37***
F(2|1)	110.61***	82.63***	162.19***	49.23***	49.69***	33.52***	26.23***	5.20
F(3|2)	39.17***	111.25***	170.40***	68.12***	36.03***	21.78***	41.07***	20.67***
F(4|3)	32.74***	26.54***	175.64***	80.27***	36.85***	22.90***	23.45***	18.88***
F(5|4)	33.61***	27.88***	177.30***	80.64***	38.35***	24.14***	23.76***	19.03***
Detected number of breaks:	5***,5**,5*	5***,5**,5*	5***,5**,5*	5***,5**,5*	5***,5**,5*	5***,5**,5*	5***,5**,5*	5***,5**,5*

	epu.sing	epu.kor	cci.us	cci.jap	cci.chi	cci.kor	ipi.us	ipi.jap
F(1|0)	375.52***	92.45***	64.22***	103.66***	119.30***	27.56***	109.76***	77.26***
F(2|1)	39.83***	10.32**	238.74***	29.60***	360.00***	58.02***	116.20***	50.82***
F(3|2)	30.21***	27.27***	49.56***	55.59***	205.04***	46.91***	134.90***	109.04***
F(4|3)	22.02***	20.84***	103.17***	158.45***	240.74***	35.86***	151.97***	195.98***
F(5|4)	16.56***	14.73**	107.20***	162.92***	262.37***	37.27***	161.99***	224.51***
Detected number of breaks:	5***,5**,5*	5***,5**,5*	5***,5**,5*	5***,5**,5*	5***,5**,5*	5***,5**,5*	5***,5**,5*	5***,5**,5*

	ipi.kor	sp	nikkei	csi	hsi	sti	kospi	sr.us
F(1|0)	262.73***	5.93	340.57***	91.93***	35.62***	19.27***	511.68***	1.01
F(2|1)	219.55***	28.55***	167.09***	65.19***	157.37***	152.72***	273.17***	15.39***
F(3|2)	114.69***	7.08	116.86***	110.66***	16.31***	225.31***	124.60***	11.08*
F(4|3)	104.72***	7.05	133.75***	147.60***	35.35***	114.79***	23.15***	18.60***
F(5|4)	135.31***	7.01	159.55***	157.01***	87.27***	248.77***	23.79***	18.56***

Detected number of breaks:	$5^{***},5^{**},5^{*}$	$5^{***},5^{**},5^{*}$	$5^{***},5^{**},5^{*}$	$5^{***},5^{**},5^{*}$	$5^{***},5^{**},5^{*}$	$5^{***},5^{**},5^{*}$	$5^{***},5^{**},5^{*}$	$5^{***},5^{**},5^{*}$

	sr.jap	sr.chi	sr.hk	sr.sing	sr.kor
F(1|0)	1.13	5.78	1.47	1.73	3.44
F(2|1)	11.78^{**}	21.36^{***}	14.13^{***}	1.37	15.42^{***}
F(3|2)	29.83^{***}	22.34^{***}	7.71	5.53	14.38^{**}
F(4|3)	29.90^{***}	22.29^{***}	7.71	5.52	14.32^{**}
F(5|4)	29.77^{***}	22.26^{***}	7.68	5.56	14.26^{**}
Detected number of breaks:	$5^{***},5^{**},5^{*}$	$5^{***},5^{**},5^{*}$	$5^{***},5^{**},5^{*}$	$5^{***},5^{**},5^{*}$	$5^{***},5^{**},5^{*}$

Note: The ***, **, and * represent the number of breaks detected according to the critical values 1%, 5%, and 10%, respectively. The critical values for F(1|0): 12.29^{***}; 8.58^{**}; 7.04^{*}. F(2|1): 13.89^{***}; 10.13^{**}; 8.51^{*}. F(3|2): 14.8^{***}; 11.14^{**}; 9.41^{*}. F(4|3): 15.28^{***}; 11.83^{**}; 10.04^{*}; F(5|4): 15.76^{***}; 12.25^{**}; 10.58^{*}.

4.2. Results for the ARDL Model

To perform ARDL modelling, the data will be separated into 22 different equations:

$$sp = \beta_0 + \beta_1 sr.\mathrm{us} + \beta_2 epu.us + \beta_3 cci.us + \beta_4 cpi.us + \beta_5 \mathrm{ipi.us} \tag{7}$$
$$nikkei = \beta_0 + \beta_1 sr.\mathrm{jap} + \beta_2 epu.jap + \beta_3 cci.jap + \beta_4 ipi.jap \tag{8}$$
$$csi = \beta_0 + \beta_1 sr.\mathrm{chi} + \beta_2 epu.chi + \beta_3 cci.chi + \beta_4 cpi.chi \tag{9}$$
$$hsi = \beta_0 + \beta_1 sr.\mathrm{hk} + \beta_2 epu.hk \tag{10}$$
$$sti = \beta_0 + \beta_1 sr.\mathrm{sig} + \beta_2 epu.sing \tag{11}$$
$$kospi = \beta_0 + \beta_1 sr.\mathrm{kor} + \beta_2 epu.kor + \beta_3 cci.kor + \beta_4 cpi.kor + \beta_5 \mathrm{ipi.kor} \tag{12}$$
$$sp = \beta_0 + \beta_1 lwti + \beta_2 lbrent + \beta_3 lcoal + \beta_4 lgas \tag{13}$$
$$nikkei = \beta_0 + \beta_1 lwti + \beta_2 lbrent + \beta_3 lcoal + \beta_4 lgas \tag{14}$$
$$csi = \beta_0 + \beta_1 lwti + \beta_2 lbrent + \beta_3 lcoal + \beta_4 lgas \tag{15}$$
$$hsi = \beta_0 + \beta_1 lwti + \beta_2 lbrent + \beta_3 lcoal + \beta_4 lgas \tag{16}$$
$$sti = \beta_0 + \beta_1 lwti + \beta_2 lbrent + \beta_3 lcoal + \beta_4 lgas \tag{17}$$
$$kospi = \beta_0 + \beta_1 lwti + \beta_2 lbrent + \beta_3 lcoal + \beta_4 lgas \tag{18}$$
$$sp = \beta_0 + \beta_1 nikkei + \beta_2 csi + \beta_3 hsi + \beta_4 sti + \beta_5 kospi \tag{19}$$
$$nikkei = \beta_0 + \beta_1 sp + \beta_2 csi + \beta_3 hsi + \beta_4 sti + \beta_5 kospi \tag{20}$$
$$csi = \beta_0 + \beta_1 nikkei + \beta_2 sp + \beta_3 hsi + \beta_4 sti + \beta_5 kospi \tag{21}$$
$$hsi = \beta_0 + \beta_1 nikkei + \beta_2 csi + \beta_3 sp + \beta_4 sti + \beta_5 kospi \tag{22}$$
$$sti = \beta_0 + \beta_1 nikkei + \beta_2 csi + \beta_3 hsi + \beta_4 sp + \beta_5 kospi \tag{23}$$
$$kospi = \beta_0 + \beta_1 nikkei + \beta_2 csi + \beta_3 hsi + \beta_4 sti + \beta_5 sp \tag{24}$$
$$sr.\mathrm{us} = \beta_0 + \beta_1 sr.\mathrm{jap} + \beta_2 sr.chi + \beta_3 sr.\mathrm{hk} + \beta_4 sr.\mathrm{sing} + \beta_5 sr.\mathrm{kor} \tag{25}$$
$$sr.\mathrm{jap} = \beta_0 + \beta_1 sr.\mathrm{us} + \beta_2 sr.\mathrm{chi} + \beta_3 sr.\mathrm{hk} + \beta_4 sr.\mathrm{sing} + \beta_5 sr.\mathrm{kor} \tag{26}$$
$$sr.\mathrm{chi} = \beta_0 + \beta_1 sr.\mathrm{jap} + \beta_2 sr.\mathrm{us} + \beta_3 sr.\mathrm{hk} + \beta_4 sr.\mathrm{sing} + \beta_5 sr.\mathrm{kor} \tag{27}$$
$$sr.\mathrm{hk} = \beta_0 + \beta_1 sr.\mathrm{jap} + \beta_2 sr.\mathrm{chi} + \beta_3 sr.\mathrm{us} + \beta_4 sr.\mathrm{sing} + \beta_5 sr.\mathrm{kor} \tag{28}$$
$$sr.\mathrm{sing} = \beta_0 + \beta_1 sr.\mathrm{jap} + \beta_2 sr.\mathrm{chi} + \beta_3 sr.\mathrm{hk} + \beta_4 sr.\mathrm{us} + \beta_5 sr.\mathrm{kor} \tag{29}$$
$$sr.\mathrm{kor} = \beta_0 + \beta_1 sr.\mathrm{jap} + \beta_2 sr.\mathrm{chi} + \beta_3 sr.\mathrm{hk} + \beta_4 sr.\mathrm{sing} + \beta_5 sr.\mathrm{us} \tag{30}$$

It is expected that oil variables, such as WTI and Brent oil, will have a positive impact on the financial markets of oil-exporting economies and a negative impact on oil-importing economies (Prabheesh et al., 2020; Xie & Tang, 2022). Oil and gas are perfectly replaceable commodities that compete within the same market and share a cointegration relationship, meaning a stable long-term correlation between their prices. After the 2008 financial crisis, gas experienced downward pressure, which was mitigated by an increase in demand (Asadi et al., 2023; Asche et al., 2012).

According to Asadi et al. (2023), steel production is highly dependent on coal, which plays a predominant role, and relies significantly on iron ore. Like steel, titanium is a raw material sensitive to other financial assets and commodities, such as crude oil (Asadi et al., 2023; Schrank, 2024). Although a direct relationship between coal and the markets cannot be established, this raw material influences others, such as steel and titanium, which in turn directly affect the markets (Asadi et al., 2023). The coal and gas variables are expected to indirectly influence the financial markets through their effects on other variables. In summary, all the analysed energy commodities are expected to have a positive impact on the financial markets.

Ahmed & Sarkodie (2021), through ARDL estimation, identified the existence of a long-run positive relationship between energy commodities (Brent crude oil, WTI crude oil, coal, and gas) and the S&P500 stock index. Likewise, in the long run, a positive relationship was also observed between the industrial production index and the S&P500 stock index. In the short run, they found a positive relationship between energy commodities and the S&P500 stock index. Conversely, in the short run, the industrial production index and the S&P 500 stock index exhibit a negative relationship.

A positive relationship is expected between money supply levels, stock market indices, and treasury bond yields (Schrank, 2024). Economic policy uncertainty is expected to negatively impact financial markets, including the stock and bond markets (Albrecht et al., 2023).

Numerous empirical studies identify a negative relationship between economic policy uncertainty and stock market performance (Bloom, 2014; Yin et al., 2023). The higher the EPU Index, the greater the perceived uncertainty, which tends to result in increased volatility in financial markets (Chowdhury & Humaira, 2023).

An increase in the consumer confidence index leads to higher consumer spending. This, in turn, influences companies' revenues, boosting their profits and resulting in a rise in stock prices. This increase in consumer confidence is viewed as a positive economic signal and, consequently, as an optimistic phase for the economy (FİLİZ BAŞTÜRK, 2019; Huseynli, 2022).

The ARDL bounds test for investigating long-run equilibrium relationships results presented in Table 3.

Table 3 – ARDL bounds test for investigating long-run equilibrium relationships.

Equation	ARDL Regression	F-Statistic	K	Case	t-Statistic	Cointegration Decision
(7)	ARDL(3,0,2,4,0,4)	19.805***	5	3	-10.668***	YES***
(8)	ARDL(1,0,2,3,1)	64.965***	4	3	-17.753***	YES***
(9)	ARDL(1,0,0,1,1)	41.519***	4	3	-14.322***	YES***
(10)	ARDL(1,0,0)	68.450***	2	3	-14.307***	YES***
(11)	ARDL(2,0,1)	35.067***	2	3	-9.136***	YES***
(12)	ARDL(2,0,1,1,1,0)	28.806***	5	3	-12.889***	YES***
(13)	ARDL(1,4,0,3,0)	47.828***	4	3	-15.312***	YES***
(14)	ARDL(1,0,1,4,0)	36.238***	4	3	-13.353***	YES***
(15)	ARDL(4,4,0,0,1)	7.298***	4	3	-5.999***	YES***
(16)	ARDL(1,2,0,2,0)	43.925***	4	3	-14.676***	YES***
(17)	ARDL(2,1,0,0,0)	18.358***	4	3	-9.286***	YES***
(18)	ARDL(1,0,1,3,2)	71.234***	4	3	-18.799***	YES***
(19)	ARDL(1,0,0,0,4,3)	36.647***	5	3	-14.398***	YES***
(20)	ARDL(1,0,1,1,1,0)	39.251***	5	3	-14.650***	YES***
(21)	ARDL(2,0,0,0,2,0)	34.184***	5	3	-12.212***	YES***
(22)	ARDL(1,1,0,0,0,3)	90.444***	5	3	-19.623***	YES***
(23)	ARDL(1,1,0,1,0,1)	43.968***	5	3	-16.018***	YES***
(24)	ARDL(2,3,2,0,0,0)	32.954***	5	3	-12.390***	YES***
(25)	ARDL(1,0,0,2,1,0)	42.697***	5	3	-14.776***	YES***
(26)	ARDL(1,0,0,2,0,0)	103.946***	5	3	-22.411***	YES***
(27)	ARDL(1,0,0,0,3,0)	33.831***	5	3	-13.907***	YES***
(28)	ARDL(1,0,0,0,0,0	32.383***	5	3	-13.798***	YES***
(29)	ARDL(1,4,0,0,0,4)	50.065***	5	3	-15.640***	YES***
(30)	ARDL(1,0,0,0,1,0)	28.666***	5	3	-13.012***	YES***

For the bounds test, the asymptotic critical value bounds are taken from Pesaran et al. (2001) and presented by Kripfganz & Schneider (2022), with unrestricted intercept and no trend, with max lags K in the dependent variable and regressors equal to 5. ***, **, * statistically significant at 1%, 5%, and 10%, respectively.

4.2.1. Short-term Estimates

Table 4 – Short-run estimation results for the ARDL (Equation #7 to Equation #12)

Short Run	Eq. #7	Eq. #8	Eq. #9	Eq. #10	Eq. #11	Eq. #12
LD sp	-0.1501112**					
L2D sp	-0.0643459					
LD csi						
L2D csi						
L3D csi						
LD sti					-0.1929308***	
LD kospi						0.1007507
D1 epu.us	-0.0090165					
LD epu.us	-0.0222207***					
D1 epu.jap		-0.000474**				
LD epu.jap		-0.0002648				
D1 epu.kor						-0.0001033
D1 epu.sing					-0.000225***	
D1 cci.us	-0.1141516					
LD cci.us	-6.397935					
L2D cci.us	8.969588**					
L3D cci.us	-9.35608***					
D1 cci.jap		0.1733654***				
LD cci.jap		-0.2634314***				
L2D cci.jap		0.1403256***				
D1 cci.chi			0.0261754**			
D1 cci.kor						0.0462837***
D1 ipi.us	0.8497033***					

LD ipi.us	0.862068***					
L2D ipi.us	1.463907***					
L3D ipi.us	-3.671622***					
D1 ipi.jap		0.0000921***				
D1 cpi.chi			0.0010846*			
D1 cpi.kor						2.24e-06***
Constant	-28.59702	0.3730605	0.2095883	0.257666**	-0.0029082	0.0895591
ECT-1	-0.9864267***	-1.072256***	-1.0113***	-1.000512***	-0.8299508***	-1.395813***
R^2	0.8614	0.6786	0.5292	0.5066	0.5666	0.6582
Adjust R^2	0.8479	0.6601	0.5124	0.4992	0.5556	0.6405

Note: The ***, **, and * represent the number of breaks detected according to the critical values 1%, 5%, and 10% respectively. L connotes lags and D connotes differences

The short-run results presented in Table 4, Table 5, Table 6 and Table 7. The short-run results from the ARDL estimates consistently reveal, across most specifications (Equations #7–#30), a negatively signed and statistically significant error correction term (ECT−1), indicating the existence of cointegration and a relatively rapid adjustment of short-run deviations towards long-run equilibrium. Exceptions to this pattern are observed in Equations #13 and #14, in which the ECT−1 fails to achieve statistical significance, suggesting a less pronounced short-run adjustment in these specifications.

In Equation #7, where the dependent variable is the S&P500 within a specification that incorporates uncertainty measures and USA economic indicators, negative and statistically significant coefficients for LD sp and LD epu.us stand out, as well as the significance of several lags of USA industrial production (D1, LD, L2D, L3D ipi.us). These results point to a short-run mean-reversion pattern in S&P500 returns and a negative sensitivity to increases in USA economic policy uncertainty, while both contemporaneous and lagged variations in industrial production exert economically relevant effects, sometimes with mixed signs, reflecting immediate growth effects and delayed expectation-adjustment effects. The large magnitude of the ECT−1 in this equation suggests that shocks are almost entirely corrected within the following month.

Equation #8, focused on the Nikkei index, shows that D1 epu.jap and LD cci.jap are negative and significant, whereas D1 cci.jap, L2D cci.jap, and D1 ipi.jap display positive and significant effects. This pattern implies that sudden increases in Japanese policy uncertainty immediately depress stock prices, while contemporaneous rises in consumer confidence and industrial production lift the index, consistent with the theory that confidence and activity perceptions support profit expectations.

In Equation #9, referring to the Chinese CSI, the significant coefficients on D1 cci.chi and D1 cpi.chi are positive, suggesting that contemporaneous improvements in consumer confidence and moderate increases in CPI are interpreted by market participants as signs of economic strength, thereby boosting stock prices in the short run.

Equation #10 presents a positive and significant intercept (at the 5% level), while other relevant terms indicate regional and energy-related adjustment mechanisms affecting the Hang Seng and related markets. The positive constant term may reflect a trend or an unobserved shock not captured by the explanatory variables in that specific specification.

In Equation #11, modelling Singapore's STI, LD sti and D1 epu.sing emerge as negative and statistically robust determinants, indicating that changes in the previous level of the index and increases in domestic uncertainty compress Singapore’s market returns in the short run. This finding aligns with the greater exposure of Singapore’s financial market to political and confidence shocks that influence capital flows.

Equation #12, for the KOSPI, reveals positive and highly significant coefficients associated with D1 cci.kor and D1 cpi.kor, indicating that contemporaneous improvements in confidence and moderate increases in consumer prices support the South Korean stock market. Meanwhile, the presence of energy price-related effects underlines the index’s vulnerability to energy costs.

Table 5 – Short-run estimation results for the ARDL (Equation #13 to Equation #18)

Short Run	Eq. #13	Eq. #14	Eq. #15	Eq. #16	Eq. #17	Eq. #18
LD sp						
L2D sp						
LD csi			-0.2559958**			
L2D csi			-0.2155358**			
L3D csi			-0.1807388***			
LD sti					-0.146029**	
LD kospi						
D1 lwti	1.951472		0.0495562	0.1065329**	0.1085832***	
LD lwti	4.835883		0.0513155	0.0924691**		
L2D lwti	33.81385***		-0.0278539			
L3D lwti	-28.41354***		-0.1333198**			
D1 lcoal	-2.574382	-0.0015249		0.0538813		0.0119507
LD lcoal	0.6627924	0.011708		-0.1121038**		-0.0325595
L2D lcoal	-11.14176**	0.1256087**				0.0867624***
L3D lcoal		-0.926439*				
D1 lbrent		0.1287601***				0.1142142***
LD lbrent						
L2D lbrent						
L3D lbrent						
D1 lgas			-0.089361**			-0.027034
LD lgas						-0.0695084***
Constant	15.39611	-0.0171289	0.1508089**	0.1414018**	0.0398935	0.1210425***
ECT-1	-0.9758516	-0.9658101	-0.7814283***	-1.063582***	-0.9265085***	-1.276617***
R^2	0.7006	0.5066	0.5615	0.5418	0.5396	0.6654
Adjust R^2	0.6819	0.4812	0.5317	0.5207	0.5232	0.6463

Note: The ***, **, and * represent the number of breaks detected according to the critical values 1%, 5%, and 10% respectively. L connotes lags and D connotes differences.

Equation #13, despite incorporating energy variables such as L2D lwti and L3D lwti, as well as lags of local fuel prices (L2D lcoal), does not show a significant ECT−1, suggesting that, in the specification considered, short-run adjustment towards long-run equilibrium is less evident. Nevertheless, the significance of longer lags in energy prices indicates that shocks in this dimension have delayed effects on the S&P500, with opposite signs depending on the lag horizon, possibly reflecting interactions between global demand expectations and cost effects.

In Equation #14, the significance of local fuel price lags (L2D lcoal, L3D lcoal) and D1 lbrent points to spillovers between energy markets and the Nikkei. The non-significant ECT−1 reinforces the idea that not all specifications capture a homogeneous short-run adjustment, possibly due to structural shocks or lag specifications that weaken the identification of the correction process.

Equation #15, in which multiple lags of the CSI and energy components (particularly L3D lwti and L3D lbrent) appear significant and negatively signed, suggests feedback between energy prices and Chinese stock performance. Increases in oil and derivative prices tend to deteriorate the CSI with a lag, reflecting impacts on production costs and corporate margins.

Equation #16, centred on the Hang Seng, identifies D1 lwti, LD lwti, and LD lcoal as significant variables, with the first two showing positive effects and the latter a negative one. This pattern indicates that contemporaneous and short-term variations in oil prices may initially be interpreted as a signal of global economic recovery, benefitting the HSI, while high and persistent local fuel prices exert downward pressure on the index through increased costs.

Equation #17 highlights LD sti and D1 lwti as significant determinants of the STI, with the former reducing and the latter raising the index. This combination reflects the interaction between internal index dynamics and contemporaneous energy shocks.

In Equation #18, for the KOSPI, L2D lcoal, D1 lbrent, and LD lgas appear significant at the 1% level, with L2D lcoal and D1 lbrent exerting positive effects, and LD lgas a negative one. This suggests that immediate Brent shocks and specific lags of local fuel prices may have heterogeneous impacts on the Korean market, while gas prices represent a persistent source of downward pressure.

Table 6 – Short-run estimation results for the ARDL (Equation #19 to Equation #24)

Short Run	Eq. #19	Eq. #20	Eq. #21	Eq. #22	Eq. #23	Eq. #24
D1 sr.hk	-0.9889052***	-0.6834111***				
LD sr.hk	-0.9605321***	-0.6888501***				
D1 sr.sing	1.019149		-1.802324***			-0.6236971
LD sr.sing			-1.747057***			
L2D sr.sing			-1.307211***			
D1 sr.jap					0.0163049	
LD sr.jap					0.0338538*	
L2D sr.jap					0.0412966**	
L3D sr.jap					0.0406393***	
D1 sr.kor					0.0379177*	
LD sr.kor					0.0374891**	
L2D sr.kor					0.0408151*	
L3D sr.kor					0.03400216*	
Constant	-1.888493	0.9667336	0.7594573	1.712727	-0.1439892	-4.037507**
ECT-1	-0.9606416***	-1.003112***	-0.9506346***	-0.9815438***	-1.023367***	-0.9220549***
R^2	0.6324	0.8064	0.5160	0.4965	0.6354	0.4678
Adjust R^2	0.6153	0.7984	0.4935	0.4812	0.6084	0.4488

Note: The ***, **, and * represent the number of breaks detected according to the critical values 1%, 5%, and 10% respectively. L connotes lags and D connotes differences.

Equations #19 and #20, which explore the role of Hong Kong's Sharpe ratio (sr.hk) in external markets, show that D1 sr.hk and LD sr.hk are negative and highly significant. These results indicate that changes in risk-adjusted performance in Hong Kong are transmitted to other markets. In particular, the observed effects imply that relative improvements in sr.hk may trigger portfolio reallocations and selling pressures in markets such as the USA and Japan, revealing channels of regional and global financial spillovers.

Equation #21, incorporating lags of Singapore's Sharpe ratio, shows that D1 sr.sing, LD sr.sing, and L2D sr.sing are negative and significant, indicating that shocks to Singapore's risk–return compensation have an adverse effect on the CSI.

Equations #22 and #23, examining the HSI with lags of sr.jap and sr.kor, show that lagged domestic Sharpe ratios for Japan and Korea are positive and significant. This suggests that improvements in risk–return relations in neighbouring markets tend to support the Hang Seng. Similarly, the presence of multiple significant lags highlights that the effects are not exhausted immediately but distributed over several periods.

Equation #24 presents a negative and statistically significant intercept, as well as a negative ECT–1, reinforcing the overall adjustment pattern, although the negative constant may capture unmodelled trends or specific shocks during that sample window.

Table 7 – Short-run estimation results for the ARDL (Equation #25 to Equation #30)

Short Run	Eq. #25	Eq. #26	Eq. #27	Eq. #28	Eq. #29	Eq. #30
D1 sr.hk	-0.9889052***	-0.6834111***				
LD sr.hk	-0.9605321***	-0.6888501***				
D1 sr.sing	1.019149		-1.802324***			-0.6236971
LD sr.sing			-1.747057***			
L2D sr.sing			-1.307211***			
D1 sr.jap					0.0163049	
LD sr.jap					0.0338538*	
L2D sr.jap					0.0412966**	
L3D sr.jap					0.0406393***	
D1 sr.kor					0.0379177*	
LD sr.kor					0.0374891**	
L2D sr.kor					0.0408151***	
L3D sr.kor					0.0340216*	
Constant	-1.888493	0.9667336	0.7594573	1.712727	-0.1439892	-4.037507**
ECT-1	-0.9606416***	-1.003112***	-0.9506346***	-0.9815438***	-1.023367***	-0.9220549***
R^2	0.6324	0.8064	0.5160	0.4965	0.6354	0.4678
Adjust R^2	0.6153	0.7984	0.4935	0.4812	0.6084	0.4488

Note: The ***, **, and * represent the number of breaks detected according to the critical values 1%, 5%, and 10% respectively. L connotes lags and D connotes differences.

Equations #25 to #30 largely replicate the patterns observed in Equations #19 to #24 when the dependent variable is a domestic Sharpe ratio (USA, Japan, China, Hong Kong, Singapore, Korea). In particular, Equations #25 and #26 confirm that D1 sr.hk and LD sr.hk exert a negative effect on the USA and Japanese Sharpe ratios, respectively, reaffirming Hong Kong's role as a transmission channel for risk–return adjustments.

Equations #27 and #29 show that shocks in sr.sing and lags of sr.jap/kor negatively and positively affect, respectively, the Sharpe ratios of China and Singapore. This highlights heterogeneity in the directional spillovers between markets and the existence of portfolio substitution mechanisms that vary with local conditions. Equations #28 and #30, integrating the same family of variables, maintain the pattern of a negative ECT and significant neighbouring Sharpe ratio lags, underlining the robustness of the interconnectivity signal across financial hubs.

Taken together, the results suggest that developed markets (the USA and Japan) respond more strongly to variations in political uncertainty and real activity indicators, while Asian markets (China, Korea, Singapore, and Hong Kong) exhibit greater sensitivity to shocks in energy commodity prices and regional risk–return measures. The negative effects of gas prices and specific lags of oil and local fuel prices on Asian economies indicate that the cost-transmission channel is a relevant mechanism affecting stock returns. Moreover, the recurrent significance of regional Sharpe ratios denotes transmission channels through portfolio allocation and relative risk perception, with direct implications for international asset management.

4.2.2. Long-term Estimates

Table 8 – Long-run estimation results for the ARDL

Long Run	(7)	(8)	(9)	(10)	(11)	(12)
sr.us	-0.003668					
sr.jap		0.0002058				
sr.chi			0.0012369***			
sr.hk				0.0001975		
sr.sing					0.004106***	
sr.kor						0.0001266
epu.us	0.0240677***					
epu.jap		-0.0002437				
epu.chi			0.0000802			
epu.hk				-0.0001541**		
epu.sing					0.0000217	
epu.kor						0.0000139
cci.us	0.3398387					
cci.jap		-0.0012311				
cci.chi			-0.0017134			
cci.kor						-0.0005458
cpi.us	0.017861					
cpi.chi			-0.0000763			
cpi.kor						1.31e-07
ipi.us	0.10106					
ipi.jap		-2.03e-06				
ipi.kor						-1.88e-07
R^2	0.8614	0.6786	0.5292	0.5066	0.5666	0.6582
Adjust R^2	0.8479	0.6601	0.5124	0.4992	0.5556	0.6405

Long Run	(13)	(14)	(15)	(16)	(17)	(18)
lwti	-8.556126	-0.1134987	-0.0546277	-0.0318558	-0.0228974	0.0112729
lbrent	4.358628	0.1187602	0.0251118	0.0133507	0.0141991	-0.0262887
lcoal	0.1729916	0.0058208	-0.0139612	-0.0132176	0.000818	-0.0048968
lgas	1.180123	-0.0250147	-0.0028675	0.005946	-0.0086873	-0.0015561
R^2	0.7006	0.5066	0.5615	0.5418	0.5396	0.6654
Adjust R^2	0.6819	0.4812	0.5317	0.5207	0.5232	0.6463
Long Run	(19)	(20)	(21)	(22)	(23)	(24)
sr.us		-0.1404038***	-0.0007348	-0.0134443		-0.0128516
sr.jap	-1.014634***		-0.0153552	-0.0247442	0.0202705	0.008942
sr.chi	0.0148178	-0.0115385		0.027972	-0.0071061	0.002193
sr.hk	1.006965***	0.6747777***	0.0116067	-0.0001388	0.0114744	-0.0060611
sr.sing	1.839847*	0.3718704	1.827884***	0.579363	0.0296503***	1.261448**
sr.kor	-0.0259339	0.0022103	-0.0001547	-0.0033359	-0.0212267	
R^2	0.6324	0.8064	0.5160	0.4965	0.6354	0.4678
Adjust R^2	0.6153	0.7984	0.4935	0.4812	0.6084	0.4488
Long Run	(25)	(26)	(27)	(28)	(29)	(30)
sr.us		-0.1404038***	-0.0007348	-0.0134443	0.0296503***	-0.0128516
sr.jap	-1.014634***		-0.0153552	-0.0247442	0.0202705	0.008942
sr.chi	0.0148178	-0.0115385		0.027972	-0.0071061	0.002193
sr.hk	1.006965***	0.6747777***	0.0116067		0.0114744	-0.0060611
sr.sing	1.839847*	0.3718704	1.827884***	0.579363		1.261448**
sr.kor	-0.0259339	0.0022103	-0.0001547	-0.0033359	-0.0212267	
R^2	0.6324	0.8064	0.5160	0.4965	0.6354	0.4678
Adjust R^2	0.6153	0.7984	0.4935	0.4812	0.6084	0.4488

Note: The ***, **, and * represent the number of breaks detected according to the critical values 1%, 5%, and 10% respectively.

The long-run results presented in Table 8 reinforce the existence of structural and persistent relationships between financial markets and energy markets, as well as the presence of significant inter-regional linkages among the Sharpe ratios of the main financial centres analysed. The magnitude and sign of the estimated coefficients confirm that the interdependencies identified in the short run tend to persist over the long run, although with intensities and directions that vary according to market type and the level of economic development.

In Equations #7 to #12, corresponding to long-run estimates for individual equity markets, the USA economic policy uncertainty index (epu.us) exerts a positive and highly significant impact (at the 1% level) on the S&P500. At first glance, this result may appear counterintuitive, as a negative relationship between uncertainty and market performance would be expected. However, it may reflect the role of the USA market as a global “safe haven”. During periods of heightened political and economic uncertainty, investors tend to shift capital towards USA assets, increasing demand and thereby raising the index. Moreover, the diversified and globally integrated structure of S&P500 firms may allow the market to benefit in the long run from capital flows originating in more volatile regions.

Similarly, in the initial equations, the Chinese Sharpe ratio (sr.chi) displays a positive and significant coefficient at the 1% level (Equation #9), indicating that risk-adjusted performance in the domestic market has a direct and stable relationship with the long-run behaviour of the CSI index. This evidence suggests that risk–return efficiency and the perception of financial stability are key determinants of the sustained appreciation of the Chinese equity market, reflecting the country’s growing role in the Asian and global financial system.

Comparably, in Equation #11, Singapore’s Sharpe ratio (sr.sing) is positive and highly significant, demonstrating that efficiency in the risk–return balance is central to the long-term appreciation of the STI. This finding corroborates the idea that well-regulated, transparent financial markets with robust risk management mechanisms attract durable investment. By contrast, Hong Kong’s economic policy uncertainty index (epu.hk) exhibits a negative and significant coefficient at the 5% level (Equation #10), indicating that high levels of political uncertainty exert persistent downward pressure on the Hang Seng index. This result aligns with the literature linking political instability to reduced capital flows and increased risk premia demanded by investors.

Equations #13 to #18, which include long-run energy variables (WTI and Brent crude oil, coal, and natural gas), show considerable heterogeneity in signs and magnitudes. In general, the WTI coefficients (lwti) are negative across most specifications, whereas Brent coefficients (lbrent) tend to be positive. This asymmetry may reflect structural differences in the composition of energy trade, with Brent more associated with the Asian and European markets, and WTI more relevant to North America. Thus, sustained increases in Brent prices may be interpreted as a signal of global recovery, benefiting exporting markets integrated into the Asian energy chain, while persistent increases in WTI may represent higher production costs for the USA, adversely affecting its equity market.

Additionally, coal (lcoal) and natural gas (lgas) prices display mixed and modest signs, with limited significance, suggesting that their long-run impact is relatively minor, possibly absorbed by energy diversification and structural adaptation within the analysed economies. Nonetheless, negative signs in some specifications (for example, lcoal and lgas in Equations #15–#18) indicate that persistent increases in energy costs tend to exert contractionary effects on growth and, consequently, on equity performance.

Equations #19 to #24 examine long-run interdependence among the Sharpe ratios of different markets, highlighting channels of transnational risk transmission and financial efficiency. Equation #19 shows that the Japanese Sharpe ratio (sr.jap) has a negative and highly significant impact on the S&P500, while the Sharpe ratios of Hong Kong and Singapore are positive and significant. This pattern suggests that improvements in risk-adjusted performance in Japan are associated with long-term portfolio reallocations towards Asia, reducing the relative attractiveness of the USA market. Conversely, the robustness of Hong Kong and Singapore appears to support S&P500 performance, reflecting financial complementarities and integration within global capital flows.

Equation #20 reinforces this interconnectedness, as the USA Sharpe ratio (sr.us) has a negative and highly significant coefficient on the Nikkei, whereas Hong Kong's (sr.hk) has a positive and equally significant effect. Economically, this implies that when the USA market improves its risk-adjusted performance, the Japanese market tends to lose relative appeal, possibly due to global portfolio substitution. Conversely, a strengthening of Hong Kong benefits Japan, reflecting regional linkages and complementarities between these two developed Asian economies.

In Equations #21 and #22, Singapore's Sharpe ratio exhibits positive and statistically significant effects on the CSI and KOSPI indices, with stronger impacts in these markets. This suggests that Singapore's efficient performance serves as a regional benchmark of stability and confidence, transmitting long-run positive effects to other Asian economies, particularly those heavily reliant on regional trade and international financial flows.

Equations #25 to #30, modelling long-run relationships among the Sharpe ratios themselves, confirm the existence of bilateral and multilateral financial transmission channels. In Equation #25, the Sharpe ratios of Japan, Hong Kong, and Singapore are significant in explaining the USA Sharpe ratio. Specifically, the Japanese Sharpe ratio exerts a negative effect, whereas Hong Kong's and Singapore's are positive. Thus, improvements in risk–return performance in Asian financial centres contribute to the sustained appreciation of USA risk-adjusted performance, reflecting long-run integration and co-movement. The negative effect of Japan again indicates portfolio substitution and direct competition among developed markets.

In Equation #26, the USA and Hong Kong Sharpe ratios are significant for Japan, with negative and positive signs, respectively, confirming the asymmetric nature of linkages between the two financial markets. In Equation #27, Singapore's Sharpe ratio positively and significantly affects China's, signalling a regional transmission channel from a stable financial hub to an emerging economy. Complementarily, Equation #29 shows that the USA Sharpe ratio positively impacts Singapore's, suggesting feedback between developed economies and Asian financial hubs. Finally, in Equation #30, Singapore's Sharpe ratio has a positive and significant effect on South Korea's, reinforcing Singapore's role as a primary transmitter of stability and a benchmark for risk-adjusted performance in East Asia.

Overall, the long-run estimates reveal a complex and persistent network of financial and energy interconnections. Developed markets, particularly the USA and Japan, influence global risk–return flows, whereas Asian hubs such as Hong Kong and Singapore act as regional transmission channels, propagating both stability and shocks. Emerging markets (China and Korea) are predominantly recipients of these dynamics, reflecting their growing integration as well as their vulnerability to external shocks and energy price developments.

From an economic perspective, the results confirm that financial globalisation and energy interdependence create long-run transmission mechanisms that transcend regional borders. Significant interactions among Sharpe ratios indicate that risk–return efficiency in one market structurally influences others.

4.3. Results of the Time-Varying Granger Causality Test

Time-varying Granger causality test, including trend, were conducted. The complete results of the Wald tests of Granger causality are presented in Table B. 1 in the Appendix B and may be consulted to support the graphical interpretation provided. The graphical analysis of the rolling window was selected since it yields the most robust results, as suggested by Shi et al. (2016).

According to the following graphs obtained from the results of the causality Granger test, the following facts can be highlighted:

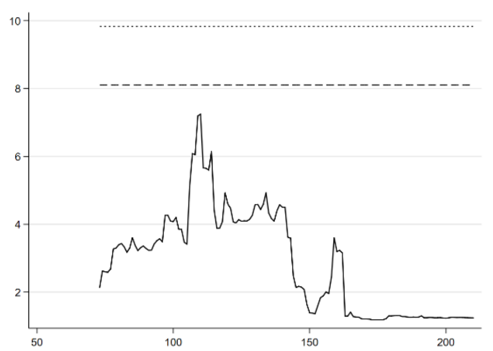


Figure 2 – Nikkei recursive S&P 500

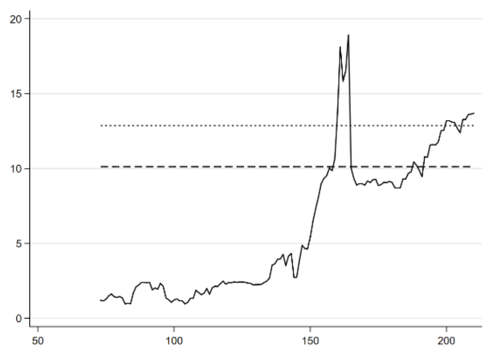


Figure 3 – S&P 500 recursive Nikkei

Figure 2 and Figure 3 reveal a unidirectional causality from the S&P 500 to the Nikkei, indicating that shocks in the USA equity market influence movements in the Japanese stock market. This effect is observed from October 2018 to May 2020, and again from December 2021 until the end of the analysed period. The first episode coincides with the USA and China trade tensions and the onset of the COVID-19 pandemic, both heightened global volatility and strengthened the transmission of financial shocks from the USA to other markets. The renewed causality in late 2021 may reflect the post-pandemic monetary tightening in the USA, which generated cross-market spillovers as global investors adjusted portfolios in response to changing risk and liquidity conditions. In general, these results emphasise the central role of the USA market in driving international financial dynamics, particularly during periods of uncertainty and policy shifts.

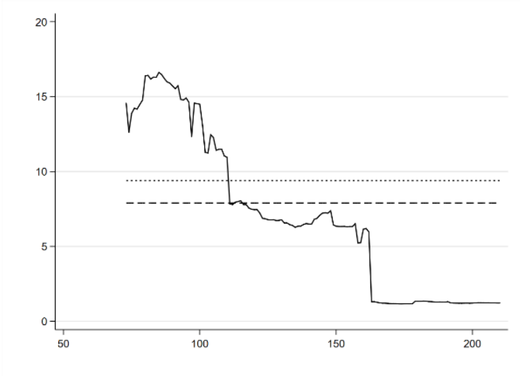


Figure 4 – CSI recursive S&P 500

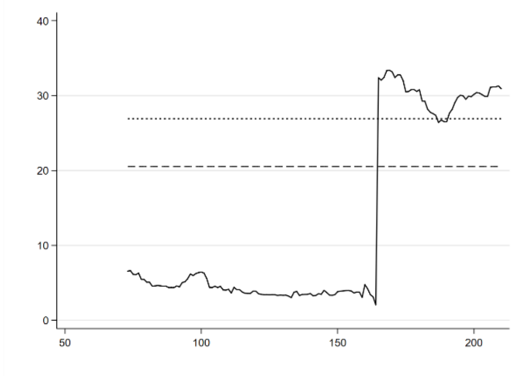


Figure 5 – S&P 500 recursive CSI

Figure 4 and Figure 5 reveal a bidirectional causality between the CSI and the S&P 500, though occurring in distinct periods. The CSI exerts influence on the S&P from January 2007 to April 2015, marked by China's rapid economic expansion and increasing integration into global financial markets. Conversely, the S&P drives the CSI from 2019 to June 2024, coinciding with escalating trade tensions between the USA and China, the COVID-19 pandemic, and subsequent shifts in global monetary policy. These dynamics suggest that while China's market once played a leading role during its growth and globalisation phase, recent years have reinforced the dominance of the USA market as a transmitter of global financial shocks.

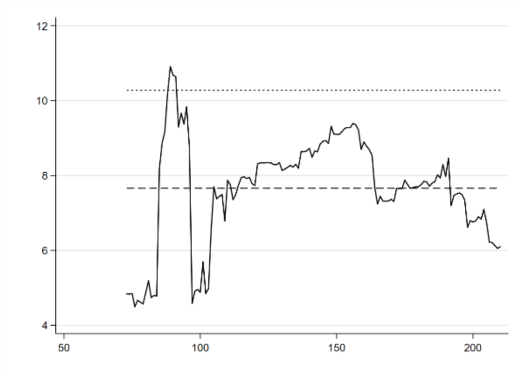


Figure 6 – CSI recursive Nikkei

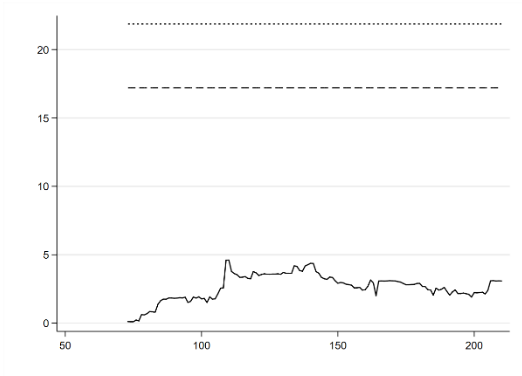


Figure 7 – Nikkei recursive CSI

Figure 7 shows no statistical evidence of causality from the Nikkei to the CSI. Conversely, Figure 6 reveals a reverse dynamic, wherein the CSI influences the Nikkei at several points in time, specifically in August 2013, April 2015, between February 2016 and May 2020, and again from December 2021 to August 2023. These periods coincide with phases of heightened economic activity and policy shifts in China, which likely transmitted to Japan's market through trade and financial channels, reinforcing the CSI's role as a regional driver during episodes of increased market interdependence.

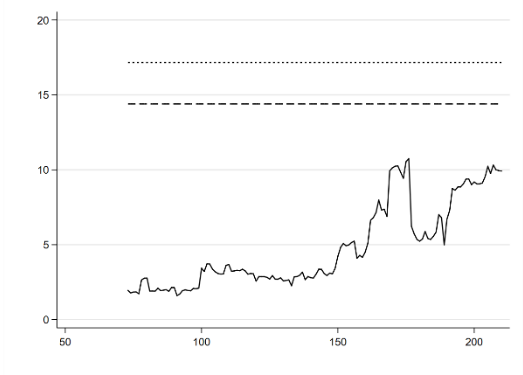


Figure 8 – STI recursive HSI

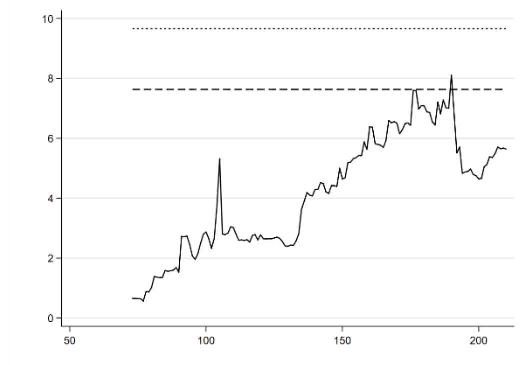


Figure 9 – HSI recursive STI

Figure 8 does not present statistical evidence indicating a causal relationship. The results in Figure 9 indicate a brief causality period from the HSI to the STI, observed only between December 2021 and January 2022. This short-lived relationship may reflect temporary regional market adjustments linked to post-pandemic recovery dynamics and shifts in investor sentiment across Asian financial markets.

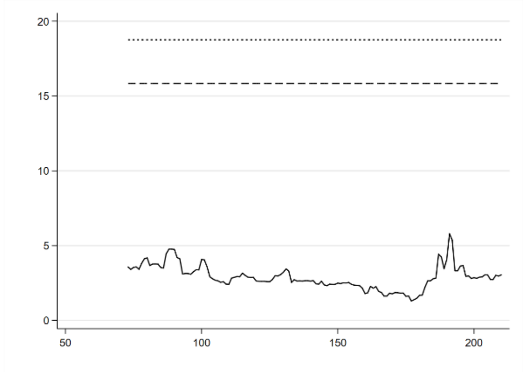


Figure 10 – Kospi recursive HSI

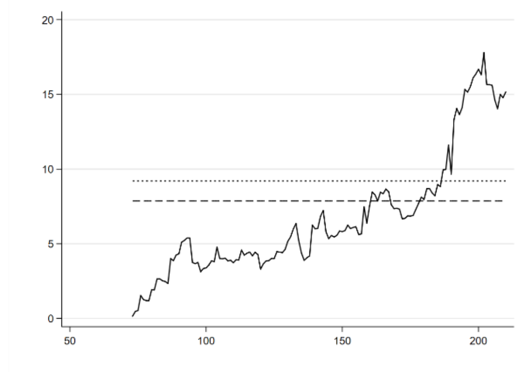
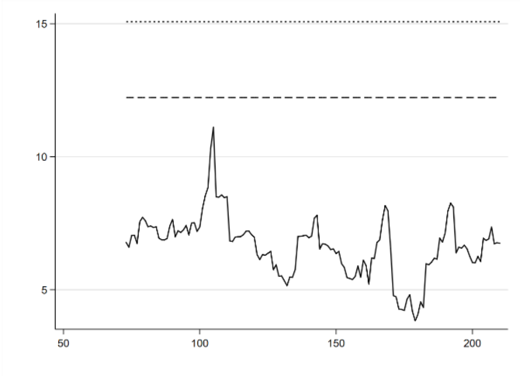


Figure 11 – HSI recursive Kospi

Figure 10 does not present evidence for causality from KOSPI to HIS. A unidirectional causality is observed from the HSI to the KOSPI (see Figure 11), beginning in April 2020 and persisting until the end of the observed period. This pattern likely reflects the spillover of market dynamics during the COVID-19 recovery phase, when shifts in Hong Kong's financial environment influenced broader regional markets such as South Korea.



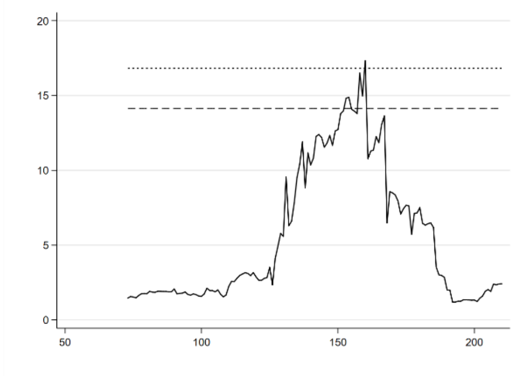
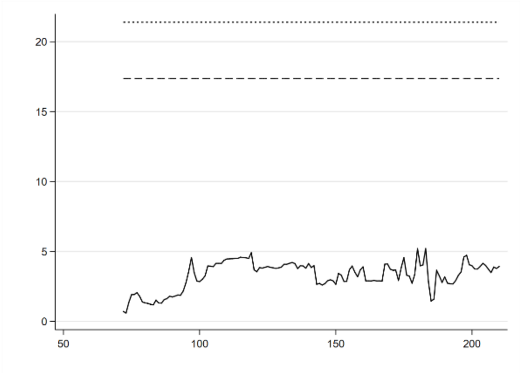


Figure 12 – Kospi recursive STI

Figure 13 – STI recursive Kospi

Figure 12 does not show any evidence for causality between KOSPI and STI. The results in Figure 13 reveal a brief unidirectional causality from the STI to the KOSPI between June 2019 and May 2020. This indicates a short-lived transmission of market dynamics from Singapore to South Korea, possibly reflecting global trade tensions and shifting investor sentiment.



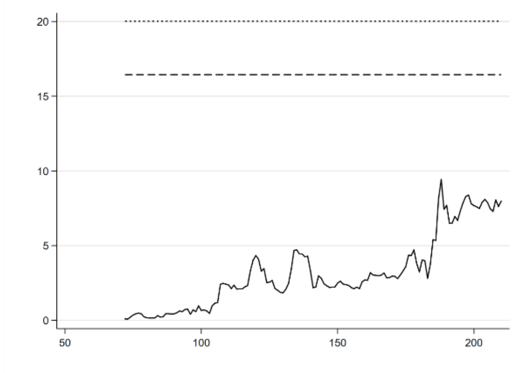


Figure 14 – Brent recursive wti

Figure 15 – Wti recursive brent

There is no statistical evidence of causality between Brent and WTI (see Figure 14 and Figure 15) throughout the observed period, which the strong interconnection and efficiency of global oil markets may explain. Both benchmarks tend to react almost simultaneously to standard shocks such as geopolitical tensions, fluctuations in global demand, and changes in production policies from major oil producers. As a result, price movements in Brent and WTI often occur in parallel, reducing the possibility of detecting directional causality. This behaviour suggests that information is quickly transmitted between the two markets, reflecting their high degree of integration and co-movement in the international crude oil system.

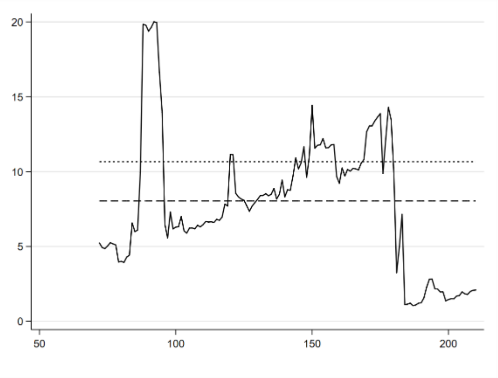


Figure 16 – Coal recursive wti

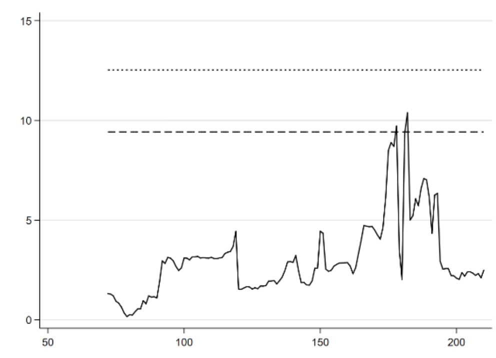


Figure 17 – Wti recursive coal

The results indicate a bidirectional causality between coal and WTI (see Figure 16 and Figure 17). The influence of coal on WTI occurs across multiple periods, from August 2013 to April 2015, again between October 2017 and August 2018, and finally from August 2018 to December 2021. Conversely, the causality from WTI to coal is limited to a brief interval between February and July 2021, possibly reflecting short-term adjustments in fossil fuel markets driven by demand recovery and energy price volatility.

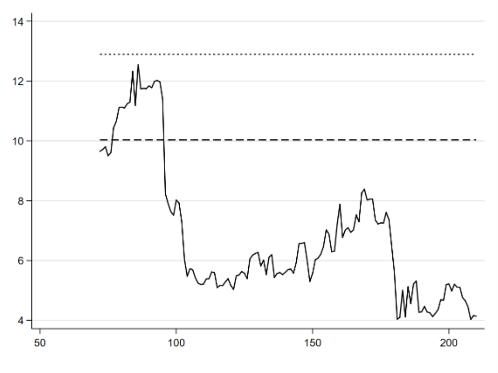


Figure 18 – Gas recursive wti

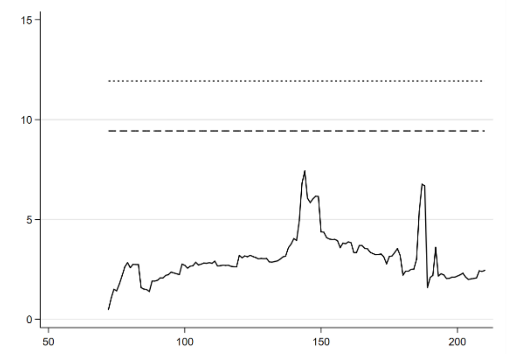


Figure 19 – Wti recursive gas

The analysis reveals a unidirectional causality from gas to WTI (see Figure 18), occurring between October 2012 and April 2015, suggesting that fluctuations in gas prices influenced crude oil markets during this period, likely reflecting interconnected dynamics in fossil fuel demand and production costs. However, no causality exists between WTI and gas (see Figure 19).

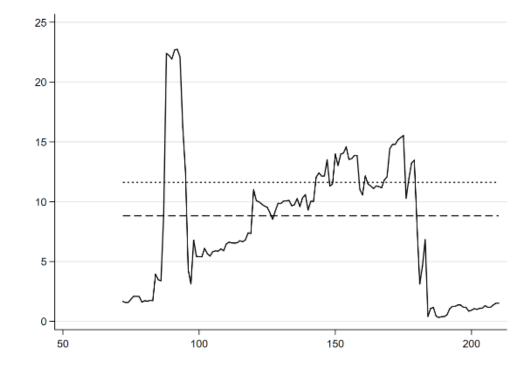


Figure 20 – Coal recursive brent

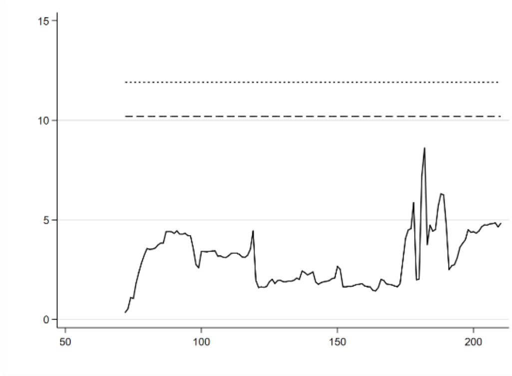


Figure 21 – Brent recursive coal

Figure 20 reveals a unidirectional causality from coal to Brent, occurring between August 2013 and April 2015 and from December 2016 to December 2021. This pattern suggests that variations in coal prices influenced Brent crude oil dynamics during these periods. From an economic standpoint, this relationship may reflect the substitutability between coal and oil in global energy markets, where fluctuations in coal supply or demand conditions can induce corresponding oil price adjustments. Moreover, the renewed causality observed from 2016 to 2021 coincides with a period marked by increasing environmental regulation and a gradual transition toward cleaner energy sources, potentially strengthening interdependencies among fossil fuel markets through energy policy and consumption behaviour shifts. On the other hand, Figure 21 points to the absence of causality between Brent and coal.

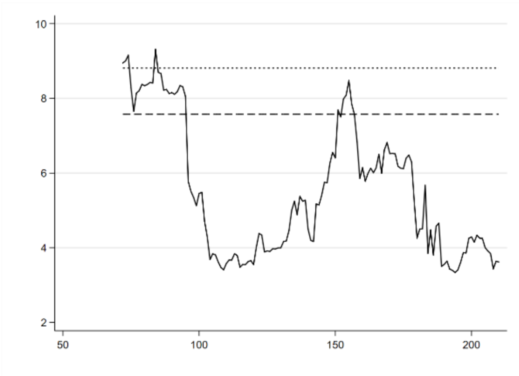


Figure 22 – Gas recursive brent

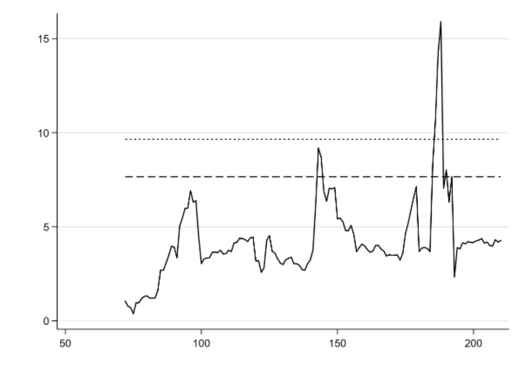


Figure 23 – Brent recursive gas

The results (see Figure 22 and Figure 23) reveal a bidirectional causality between natural gas and Brent. Specifically, gas influenced Brent between October 2012 and April 2015 and from June 2019 to April 2020. Conversely, Brent affected gas prices between August 2018 and January 2019, and again from February to July 2021. This reciprocal relationship suggests a strong interdependence between the two markets, reflecting the integrated nature of global energy pricing. The periods identified coincide with significant fluctuations in oil demand, major producers' production adjustments, and increased substitution effects between gas and oil in energy consumption. These dynamics likely amplified the transmission of shocks between both commodities, reinforcing their mutual influence within the global energy system.

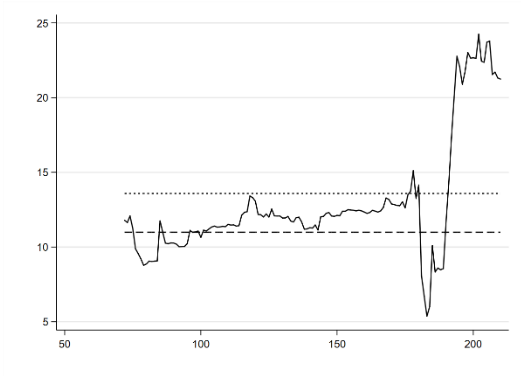


Figure 24 – Gas recursive coal

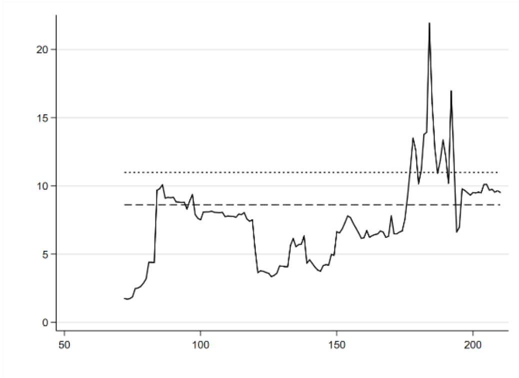


Figure 25 – Coal recursive gas

The results indicate an intense and persistent bidirectional causality between gas and coal throughout most of the observed period (see Figure 24 and Figure 25). The influence of gas on coal is evident for nearly the entire timeframe, with exceptions between March and August 2013 and again from July to December 2021. Conversely, coal exhibits causality toward gas from October 2012 to April 2015 and again between April 2020 and August 2023, with only a brief interruption before resuming in October and continuing until the end of the sample. This pattern suggests a close interaction between the two markets, likely driven by their substitutability in electricity generation and industrial use. Periods of intensified causality may reflect shifts in relative prices or policy-driven transitions in the energy mix, where changes in gas supply or coal demand propagate across both markets, reinforcing their long-term interdependence.

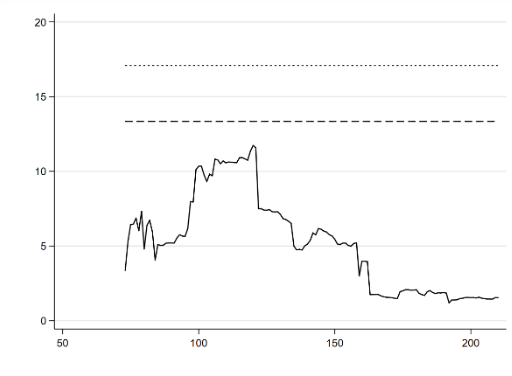


Figure 26 – Wti recursive S&P 500

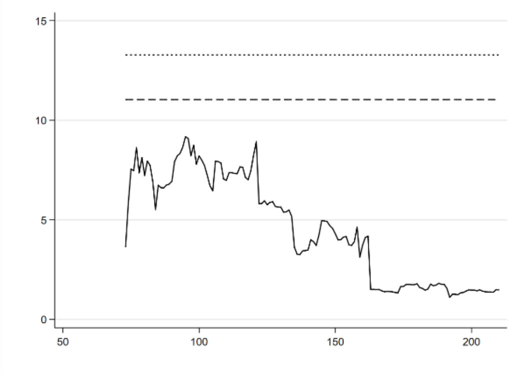


Figure 27 – Brent recursive S&P 500

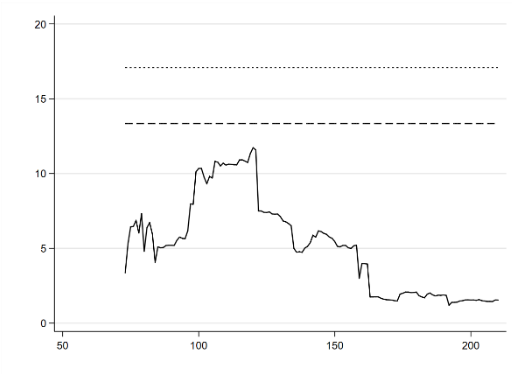


Figure 28 – Coal recursive S&P 500

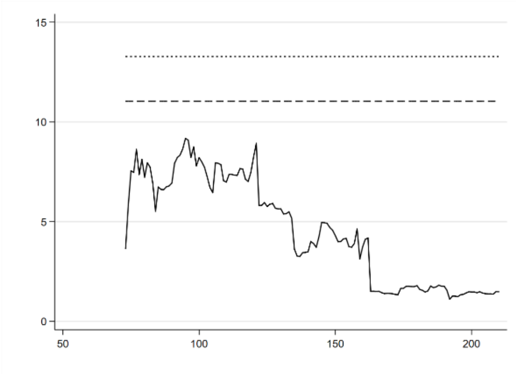


Figure 29 – Gas recursive S&P 500

Figure 26, Figure 27, Figure 28 and Figure 29 show no statistical evidence of causality between WTI and the S&P 500, Brent and the S&P 500, Coal and the S&P 500, or Gas and the S&P 500.

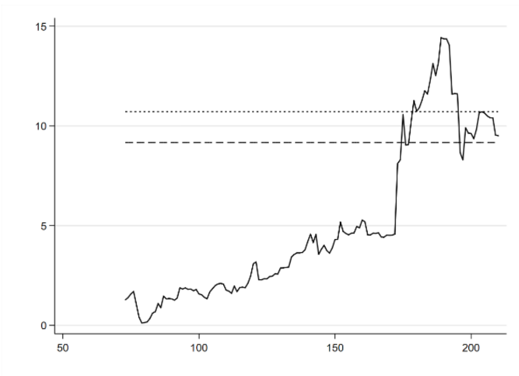


Figure 30 – Wti recursive Nikkei

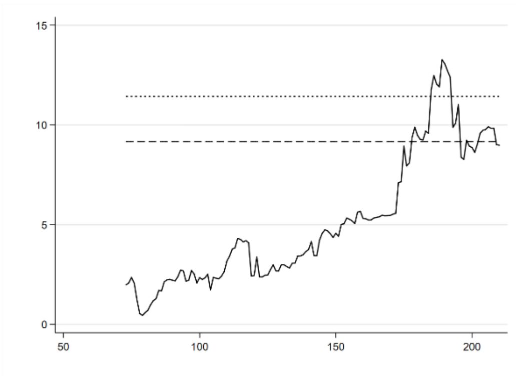


Figure 31 – Brent recursive Nikkei

A unidirectional causality from WTI to the Nikkei (see Figure 30) is observed from June 2019 until the end of the analysed period, indicating that fluctuations in oil prices influenced Japanese market dynamics during this time. A similar pattern is found between Brent and the Nikkei (see Figure 31). This suggests that Japan's equity market, given its dependence on energy imports, was sensitive to global oil price movements, particularly amid the economic uncertainties that followed the COVID-19 period.

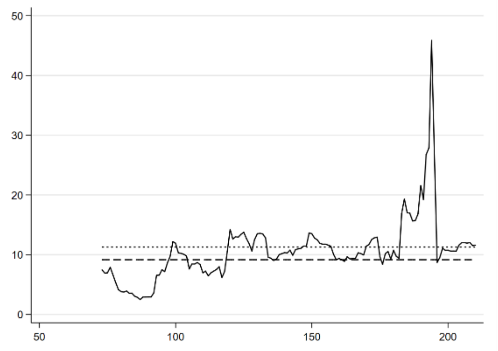


Figure 32 – Coal recursive Nikkei

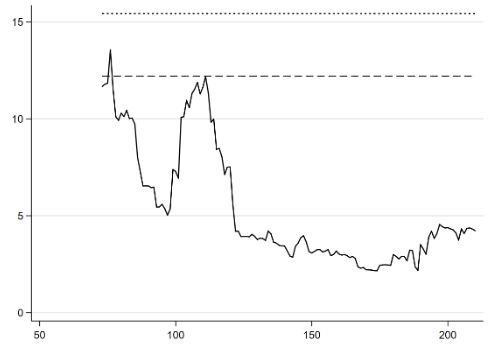


Figure 33 – Gas recursive Nikkei

Figure 32 show a causality from coal to the Nikkei is observed beginning in April 2015 and persisting throughout the analysed period, suggesting that Japan's equity market was influenced by movements in coal prices, likely reflecting the country's reliance on imported energy sources and the role of coal in its industrial sector. In contrast, the causality from gas to the Nikkei appears only briefly (see Figure 33), between October and November 2012, possibly capturing short-term market reactions to energy price fluctuations during that period.

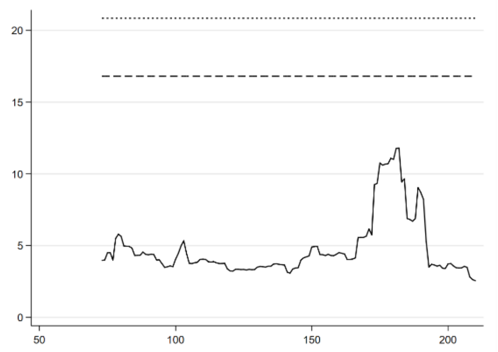


Figure 34 – Wti recursive CSI

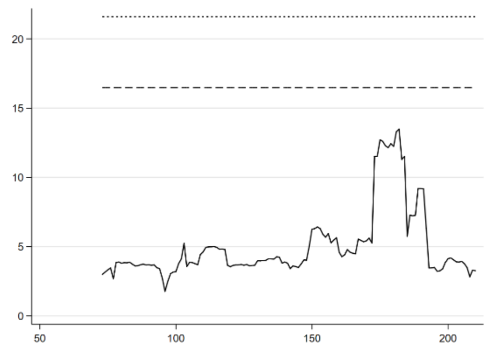


Figure 35 – Brent recursive CSI

There is no statistical evidence that points to a causality between the CSI and the oil markets in the observed period, as Figure 34 and Figure 35 point out, such a result. Is evidence that oil prices do not affect the Chinese market, which may be a result of the Chinese government's energy strategic change in the last decade.

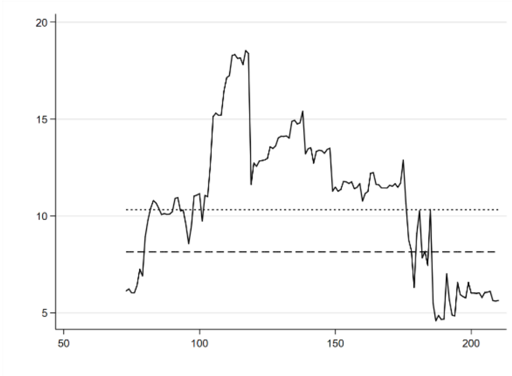


Figure 36 – Coal recursive CSI

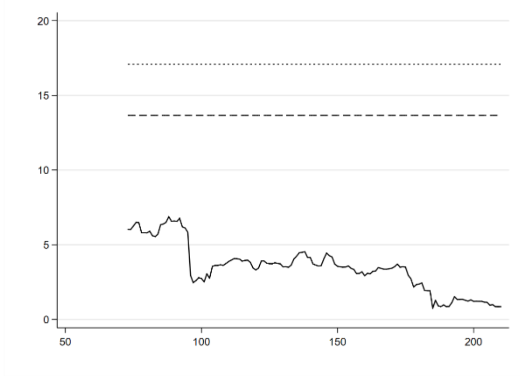


Figure 37 – Gas recursive CSI

A unidirectional causality from coal to the CSI is observed between December 2011 and April 2020, indicating that fluctuations in coal prices may have influenced the Chinese stock market during this period, as can be seen in Figure 36. A plausible result given China's dependence on coal as a major energy source and its impact on industrial production and economic growth. Conversely, there is no statistical evidence of causality between gas and the CSI, suggesting that natural gas prices did not play a significant role in shaping stock market dynamics over the same horizon (see Figure 37).

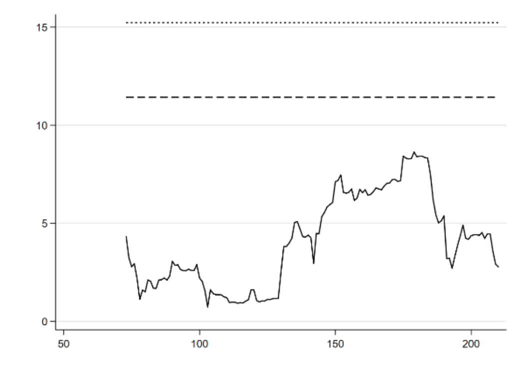


Figure 38 – Wti recursive HSI

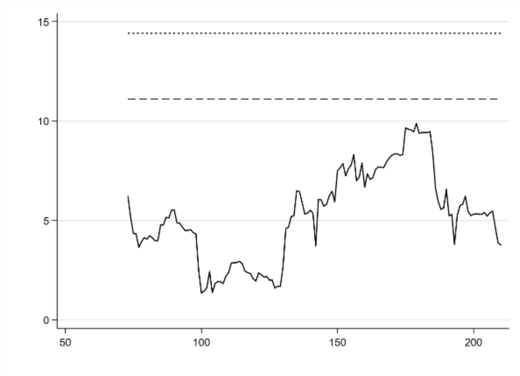


Figure 39 – Brent recursive HSI

There is no statistical evidence of a causal relationship between WTI and STI, nor between Brent and STI, as illustrated in Figure 38 and Figure 39. This absence of causality suggests that fluctuations in global oil prices did not significantly influence the Singaporean stock market during the analysed period, possibly reflecting the country's diversified economy and limited dependence on oil production or exports.

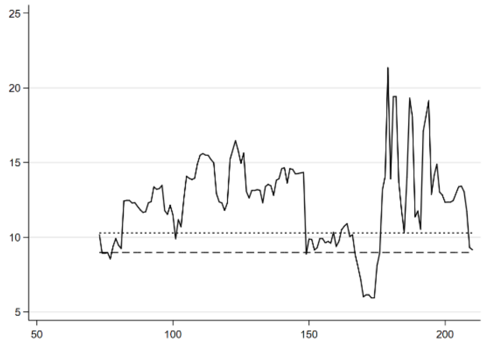


Figure 40 – Coal recursive HSI

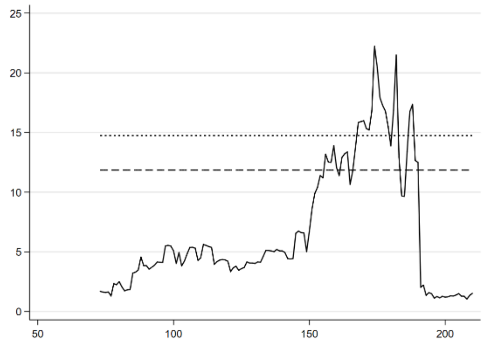


Figure 41 – Gas recursive HSI

There is no evidence of a causal relationship between coal and the HSI from April 2020 to February 2021 (see Figure 40). This reinforces the Japanese economy's dependence on fossil fuels, more specifically, coal, and the short period without the causal relationship is the peak period of the COVID pandemic. This absence must be due to the uncertainties that marked the period caused by the fall in global economic activity. In contrast, a unidirectional causality from gas to the HSI is observed (see Figure 41) between June 2019 and October 2022, suggesting that fluctuations in gas markets may have influenced the performance of the Hong Kong stock market during this period, likely reflecting broader global energy price dynamics and their impact on regional economic activity.

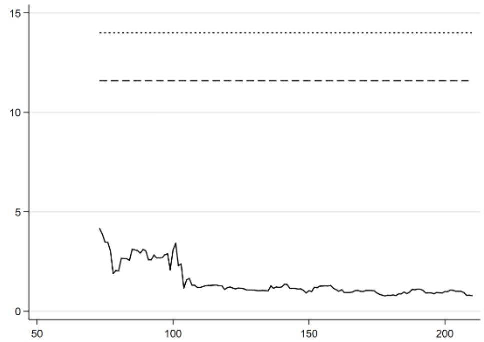


Figure 42 – Wti recursive STI

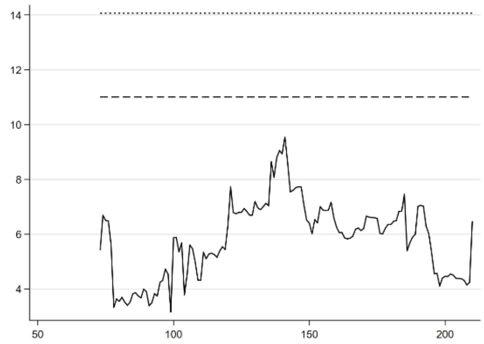


Figure 43 – Brent recursive STI

There is no statistical evidence of causality between WTI and STI (see Figure 42), nor between Brent and STI (see Figure 43), indicating that movements in crude oil prices did not significantly influence the Singapore stock market during the analysed period. This absence of causality may reflect the STI's relatively limited exposure to oil price shocks compared to economies more directly dependent on energy production or export.

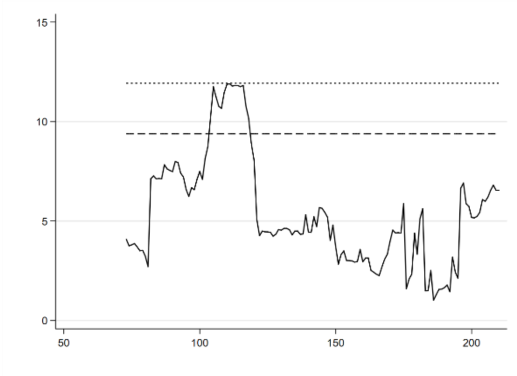


Figure 44 – Coal recursive STI

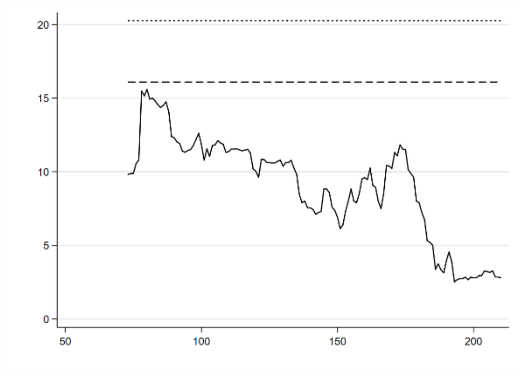


Figure 45 – Gas recursive STI

A unidirectional causality from coal to STI is observed between April 2015 and July 2021 (see Figure 44), suggesting that fluctuations in coal prices may have influenced the Singapore stock market during this period, possibly reflecting broader macroeconomic or energy-related effects on regional markets, considering that STI did not show causality with oil movements is coherent. Since the current production model requires energy capacity, there is evidence that Singapore's economy is sustained more by alternative energy than by other fossil sources. Conversely, no statistical evidence of causality is found between gas and STI, indicating a weaker or non-existent transmission of shocks from gas prices to the Singapore market (see Figure 45).

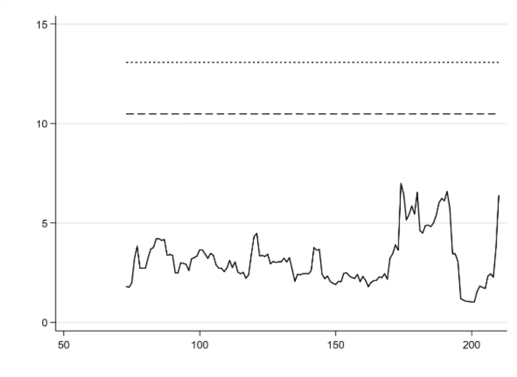


Figure 46 – Wti recursive Kospi

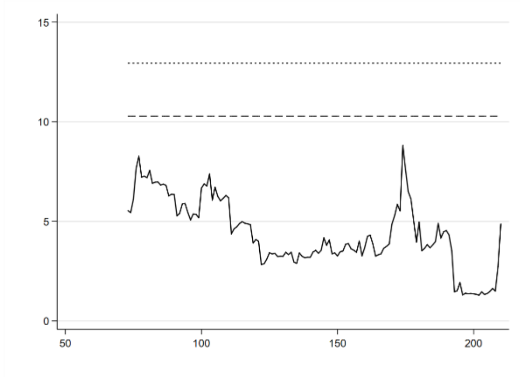


Figure 47 – Brent recursive Kospi

There is no statistical evidence between the KOSPI and oil (see Figure 46 and Figure 47), so external shocks to oil do not affect the economic activities captured by the KOSPI. Despite being an economy with a high consumption of fossil energies, its dependence does not seem to be linked to oil, but to other fossil alternatives.

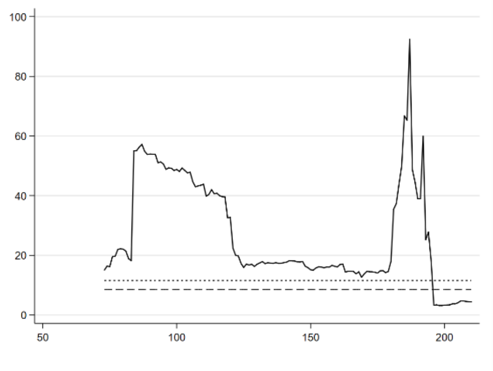


Figure 48 – Coal recursive Kospi

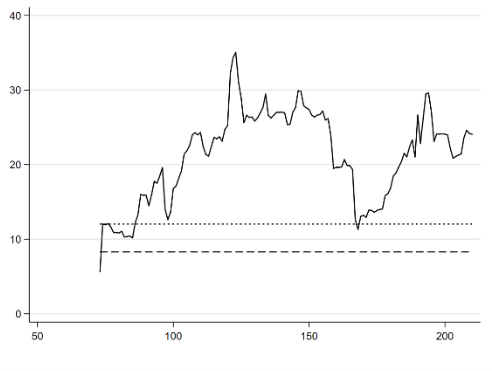


Figure 49 – Gas recursive Kospi

A persistent causality from coal to the Kospi is observed throughout nearly the entire sample period, ceasing only briefly in November 2022 (see Figure 48). Similarly, gas exhibits a continuous causal influence on the Kospi from December 2011 onward (see Figure 49), suggesting that energy market dynamics, particularly in coal and gas, played a significant role in shaping movements in the South Korean stock market over the analysed period. Reinforcing the idea that the Korean economy depends on fossil fuels, but not on oil.

5. Discussion

The econometric results obtained from the short-run and long-run estimations reveal complex and dynamic relationships among energy commodities, macroeconomic variables, and financial market indices across the United States, Japan, China, Hong Kong, Singapore, and South Korea. These relationships are consistent with the evidence reported in previous empirical studies, reinforcing the view that energy markets, macroeconomic indicators, and financial systems are increasingly integrated, particularly under conditions of economic uncertainty and global crises (Bonnier, 2021; Cheng & Xiong, 2014; Feng et al., 2023; Huseynli, 2022).

In the short run, the statistically significant and negative error correction terms (ECTs) in most equations confirm the existence of cointegration among the variables, indicating that deviations from long-run equilibrium are rapidly corrected, in some cases exceeding 100% adjustment speed. This suggests that financial markets tend to absorb shocks efficiently, quickly returning to equilibrium after short-term disturbances, which aligns with the hypothesis of increased market integration following the financialisation of commodities (Bonnier, 2021; Chan et al., 2011).

The analysis of short-run coefficients demonstrates the differentiated sensitivity of financial markets to domestic and international uncertainty factors. For instance, the USA Economic Policy Uncertainty Index (epu.us) exerts a negative short-run impact on the S&P 500 index (Equation #7), supporting Bloom (2014) and Yin et al. (2023), who argue that higher uncertainty discourages investment and raises the cost of capital, leading to reduced market performance. Similarly, in Japan, the EPU (epu.jap) negatively affects the Nikkei index (Equation #8), corroborating Lee et al. (2021), who note that uncertainty regarding future policy direction influences investor sentiment and asset prices.

In contrast, consumer and industrial production indicators in both the USA and Japan exhibit positive short-run effects on their respective stock indices. This relationship is consistent with Chevallier & Ielpo (2014), who emphasise that improved industrial output increases corporate profitability and investor confidence, driving market appreciation. Likewise, higher consumer confidence reinforces aggregate demand expectations, which are positively priced by investors (Engeloğlu & Yurdakul, 2025).

For China, both the Consumer Confidence Index (cci.chi) and the Consumer Price Index (cpi.chi) exert positive short-run effects on the CSI index (Equation #9). This finding aligns with (Ghosh, 2022; Saeed et al., 2023), who demonstrated a direct connection between inflationary expectations and stock performance, particularly in economies where energy price volatility strongly influences production costs. The positive link between inflation and the equity market may also reflect investor expectations of future price adjustments in the corporate sector.

In Singapore and South Korea, consumer and price indicators also contribute positively to stock market movements, particularly in the Kospi index (Equation #12), confirming the findings of Ghosh (2022) that improvements in consumer sentiment strengthen confidence in future corporate earnings, especially in post-crisis recovery phases.

Energy commodity variables also play a critical short-run role. The negative effects of lagged WTI and coal prices on the S&P 500 and Nikkei indices (Equations #13 and #14) reinforce the argument by Huseynli (2022) that rising energy costs erode firm profitability and suppress stock valuations, except for energy-producing sectors. Conversely, the positive short-run effects of Brent oil on the Nikkei and Kospi indices suggest that, for export-oriented economies, rising energy prices may signal higher global demand and, consequently, improved corporate revenues (Antonakakis et al., 2023).

The interdependence between Asian financial markets is further evidenced by the significance of Sharpe ratios across countries. The Hong Kong Sharpe ratio exerts a notable influence on both the USA and Japanese markets (Equations #19–20), confirming the argument of Du et al. (2023) that Hong Kong operates as a critical regional transmitter of financial risk. Similarly, the Singapore Sharpe ratio significantly affects the CSI, STI, and Kospi indices (Equations #21–22), suggesting that Singapore functions as a stabilising and integrating hub in the Asia-Pacific financial system (Sun et al., 2023).

In the long run, the persistence of the cointegrating relationships among commodities, uncertainty indices, and financial markets highlights the structural integration of these systems. The long-run dynamics corroborate the hypothesis that globalisation, financial liberalisation, and commodity financialisation have reinforced the transmission channels of shocks and volatility among markets (Bonnier, 2021; Rui-fengi et al., 2007).

The strong link between energy commodities (oil, gas, and coal) and stock indices supports the idea proposed by Cheng & Xiong (2014) and Mensi et al. (2021) who argue that commodities act as transmitters of financial risk. The long-run equilibrium suggests that commodity price movements are not merely transitory shocks but structural determinants of financial performance, particularly in economies with high energy dependency.

The Economic Policy Uncertainty (EPU) indices continue to play a crucial role in shaping long-term market behaviour. The negative long-run association between EPU and stock market indices reflects the theoretical framework advanced by Bansal et al. (2004) and Bloom (2014), where persistent uncertainty depresses investment and consumption decisions, thereby reducing economic output and asset valuations. Moreover, this relationship confirms that the effects of uncertainty are asymmetric, with adverse shocks generating stronger and more persistent impacts on financial performance (Boungou & Yatié, 2024; Zhou et al., 2022).

The Consumer Confidence Index (CCI) and Industrial Production Index (IPI) exhibit long-term positive relationships with stock indices, demonstrating the importance of domestic demand and industrial activity for financial market stability. This is consistent with the findings of Chevallier & Ielpo (2014) and Engeloğlu & Yurdakul (2025), who identified these indicators as leading signals of macro-financial health, particularly in open economies.

Finally, the long-run interdependence among Sharpe ratios across different markets suggests that investor sentiment and risk perception are globally integrated. This finding resonates with behavioural finance literature, which highlights the influence of psychological and emotional factors in shaping global market trends (Altuntaş & Ersoy, 2021; Shu & Chang, 2015). The significant transmission of Sharpe ratios between the United States, Japan, China, Singapore, and Korea demonstrates the increasing synchronisation of global investor behaviour, especially under conditions of heightened uncertainty and economic shocks (Fang, 2025; W. Zhang & Hamori, 2021).

6. Conclusion and Policy Implications

The primary objective of this study is to examine the contagion effects between financial markets and key energy commodities. For this purpose, the Autoregressive Distributed Lag (ARDL) model and the time-varying causality test, including trend methodology, were employed. The analysis spans the period from January 2007 to June 2024, thereby encompassing key major global economic events. This temporal scope enables the assessment of contagion dynamics across diverse crisis contexts, including financial, health-related, and geopolitical.

The findings are directly related to different strands of financial theory, particularly with respect to market efficiency, contagion theory, and the role of political uncertainty and investor sentiment as non-linear determinants of asset behaviour.

Firstly, the evidence that the prices of energy commodities such as oil, coal, and natural gas exert a significant influence on stock indices across different economies suggests that the assumptions of the Efficient Market Hypothesis (EMH) are not fully upheld, especially in the short term. According to the EMH, all available information should already be reflected in prices, thereby reducing the impact of external shocks on market index performance. The results obtained, therefore, point to an asymmetric and time-varying response to fluctuations in energy commodities, highlighting that efficiency is dynamic and subject to both external and internal shocks. Furthermore, the negative influence exerted by political uncertainty indices resonates with behavioural finance theory, which questions the homogeneous rationality of economic agents and acknowledges the cognitive limitations and biases inherent in investment decision-making. The fact that market indices such as the Nikkei and the CSI display sensitivity to behavioural variables reinforces the presence of noise traders, whose decisions amplify volatility and hinder the efficient adjustment of prices.

Within the framework of contagion theory, the results show that stock indices and risk/return indicators, such as the Sharpe ratio, in certain economies negatively affect the performance of other markets, both in the short and long run. This evidence confirms the existence of contagion effects, in line with the notion that investors draw on information from other markets when making their own decisions.

Additionally, the temporal analysis strengthens the view that relationships between assets do not follow linear and stable paths, but rather dynamic patterns. This behaviour is consistent with the application of chaos theory to financial markets, which posits that small disturbances, such as shocks in energy commodities, shifts in investor confidence indices, or variations in political uncertainty, may trigger disproportionate effects across different economic contexts. The presence of time-varying cointegration and causality shows that markets operate under complex interactions that elude linear predictability.

The results obtained from both the ARDL models and the time-varying Granger causality tests offer a set of practical implications of relevance to policymakers and investors alike, particularly within a context of increasing integration between financial and energy markets. First, the pronounced sensitivity of Asian markets to shocks in oil and coal prices highlights the need for a strategic reassessment of energy policies. Diversifying the energy consumption mix, through the expansion of renewable sources and the strengthening of the role of natural gas, emerges as a priority in mitigating macroeconomic vulnerability to international commodity price fluctuations. In parallel, the establishment of strategic reserves and the systematic use of hedging instruments, such as futures contracts or energy swaps, can serve as effective buffers during periods of heightened volatility, thereby ensuring greater economic resilience.

Additionally, the rise in spillovers between financial and energy markets observed during periods of crisis underscores the need for more robust macroprudential policies. Regulators should consider imposing limits on the exposure of funds and financial institutions to highly volatile energy assets, thereby reducing potential contagion effects. The implementation of stress tests based on energy-shock scenarios, alongside the continuous monitoring of dynamic correlations across markets, may support preventive responses capable of mitigating systemic risks and preserving both regional and global financial stability.

Another central aspect concerns the role played by the Economic Policy Uncertainty (EPU) index. Its significance in the results demonstrates that governmental communication constitutes a crucial instrument for market stabilization. Transparent and predictable policies, accompanied by appropriate communication protocols during crisis periods, help to reduce speculation and anchor economic agents' expectations. The regular disclosure of macroeconomic scenarios and clear energy strategies strengthens investor confidence and limits potential negative impacts on commodity prices and financial markets.

Finally, evidence suggests that international diversification may lose its effectiveness in contexts of high uncertainty and strong market correlations. In light of this, it becomes essential for investors to adopt more dynamic risk management strategies. In this regard, the use of derivatives, such as options and futures, to hedge portfolios exposed to shocks in the energy sector proves particularly relevant. Incorporating alternative assets, such as gold or instruments linked to the energy transition, can further enhance portfolio resilience. Moreover, the active monitoring of political uncertainty indicators and energy market volatility measures allows for proactive adjustments in allocation, mitigating potential losses and reinforcing the stability of returns.

One limitation of this analysis is the use of monthly rather than high-frequency data, such as daily observations. ECMs with adjustment coefficients near 100% may give the impression of complete adjustment within a single period, not necessarily reflecting instantaneous convergence but rather the limited temporal resolution of the data. High-frequency data would allow a more accurate characterization of shock dissipation and the speed of adjustment.

For future investigations, it would be pertinent to incorporate additional raw materials and further variables of a financial and macroeconomic nature, in order to assess the impact of different financial markets on various indicators. Moreover, the analysis of risk transmission and co-movements between financial markets and the energy commodities market could be deepened through the application of alternative methodologies, such as the estimation of Conditional Value-at-Risk (CoVaR) via quantile regression. The adoption of this approach would allow for an examination of the extent to which the main energy commodities act as sources of systematic risk or, conversely, contribute to its mitigation. In addition, it is recommended that data be explored at different temporal frequencies, for instance on a daily basis, so as to capture short-term dynamics that could complement the analysis undertaken.

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Appendixes

Appendix A – Variables

Table A. 1 – Source of EPU variables

Variable	Source
epu.us	Measuring Economic Policy Uncertainty' by Scott Baker, Nicholas Bloom and Steven J. Davis at www.PolicyUncertainty.com.
epu.jap	"Policy Uncertainty in Japan" by Elif C. Arbatli Saxegaard, Steven J. Davis, Arata Ito, and Naoko Miake.
epu.chi	'Economic Policy Uncertainty in China Since 1949: The View from Mainland Newspapers," by Steven J. Davis, Dingqian Liu and Xuguang S. Sheng, 2019. www.policyuncertainty.com
epu.hk	www.policyuncertainty.com
epu.sing	Davis, Steven J., 2016. "An Index of Global Economic Policy Uncertainty," Macroeconomic Review, October.
epu.kor	'Measuring Economic Policy Uncertainty' by Scott Baker, Nicholas Bloom and Steven J. Davis at www.PolicyUncertainty.com.

Table A. 2 – Dataset description

Variables		Description	Unit	Source
Energy commodities	wti	Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma	Barrel	Federal Reserve
	brent	Crude Oil Prices: Brent - Europe	Barrel	Federal Reserve
	coal	Global Price of Coal, Australia	Metric Ton	Federal Reserve
	gas	Global Price of Natural Gas, US Henry Hub Gas	MMBtu[1]	Federal Reserve
EPU	epu.us	Economic Policy Uncertainty Index for US	Index	Policy Uncertainly
	epu.jap	Economic Policy Uncertainty Index for Japan	Index	Policy Uncertainly
	epu.chi	Economic Policy Uncertainty Index for China	Index	Policy Uncertainly
	epu.hk	Economic Policy Uncertainty Index for Hong Kong	Index	Policy Uncertainly
	epu.sing	Economic Policy Uncertainty Index for Singapore	Index	Policy Uncertainly
	epu.kor	Economic Policy Uncertainty Index for Korea	Index	Policy Uncertainly
CCI	cci.us	Consumer Confidence Index for US	Index [6]	OECD
	cci.jap	Consumer Confidence Index for Japan	Index[6]	OECD
	cci.chi	Consumer Confidence Index for China	Index[6]	OECD
	cci.kor	Consumer Confidence Index for Korea	Index [6]	OECD
CPI	cpi.us	Consumer price indices, all items	Index, National	OECD
	cpi.chi	Consumer price indices, all items	Index, National	OECD
	cpi.kor	Consumer price indices, all items	Index, National	OECD
IPI	ipi.us	Production volume, Industry (except construction)	Index, 2015[5]	OECD
	ipi.jap	Production volume, Industry (except construction)	Index, 2015[5]	OECD

	ipi.kor	Production volume, Industry (except construction)	Index, 2015[5]	OECD
Stock index	sp	S&P 500 (^GSPC)[2]	Price Index	investing.com
	nikkei	Nikkei Stock Average[2]	Price Index	yahoo!finance
	csi	CSI 300 Index[3]	Price Index	Seeking Alpha
	hsi	Hang Seng Index[2]	Price Index	yahoo!finance
	sti	Straits Times Index[2]	Price Index	yahoo!finance
	kospi	KOSPI Composite Index[2]	Price Index	yahoo!finance
Bonds	10yb.us	United States 10-Year Bond Yield	Price	investing.com
	10yb.jap	Interest Rates: Long-Term Government Bond Yields: 10-Year: Main (Including Benchmark) for Japan	Percent[4]	Federal Reserve[7]
	10yb.chi	China 10-Year Bond Yield	Price	investing.com
	10yb.hk	Hong Kong 10-Year Bond Yield	Price	investing.com
	10yb.sing	Singapore 10-Year Bond Yield	Price	investing.com
	10yb.kor	Interest Rates: Long-Term Government Bond Yields: 10-Year: Main (Including Benchmark) for Korea	Percent[4]	Federal Reserve[8]

Note: [1]Million Metric British Thermal Units; [2]Adjusted Close Prices; [3]Close Prices; [4]Not Seasonally Adjusted; [5]Calendar and seasonally adjusted; [6]Amplitude adjusted; [7] https://fred.stlouisfed.org/series/IRLTLT01KRM156N; [8] https://fred.stlouisfed.org/series/IRLTLT01KRM156N

Table A. 3 – Main descriptive statistics of the variables used in the empirical models

Variable	Mean	Median	Max.	Min.	SD.	Skew.	Kurt.	JB
wti	72.982	73.510	133.880	16.550	22.395	0.113	2.400	3.595
brent	77.946	75.525	132.720	18.380	24.958	0.118	2.089	7.753*
coal	117.491	96.158	467.784	51.383	79.272	2.807	11.065	844.843*
gas	3.935	3.312	12.682	1.700	1.940	1.739	6.290	200.624*
epu.us	153.024	139.881	503.963	44.783	66.177	1.954	9.024	451.1305*
epu.jap	113.739	108.926	239.061	63.482	30.015	1.335	5.682	125.3409*
epu.chi	188.054	138.750	661.800	29.000	119.618	1.234	4.343	69.054*
epu.hk	160.334	146.214	425.362	36.272	70.590	0.781	3.335	22.31301*
epu.sing	179.578	157.330	428.558	52.886	79.320	0.655	2.633	16.205*
epu.kor	167.794	152.066	538.177	37.306	74.554	1.181	5.472	102.257*
cci.us	99.270	99.120	101.650	96.220	1.510	-0.033	1.829	12.033*
cci.jap	99.187	99.507	101.855	95.482	1.281	-0.692	2.934	16.801*
cci.chi	99.445	99.024	104.401	93.668	2.916	-0.147	2.416	3.738
cci.kor	100.063	100.138	102.844	95.790	1.267	-0.807	4.342	38.571*
cpi.us	103.467	100.449	132.554	85.401	12.011	0.869	2.944	26.438*
cpi.chi	669.065	634.314	841.331	570.949	82.144	0.568	1.952	20.898
cpi.kor	115907.400	112896.200	166504.000	74831.380	19697.340	0.498	3.706	13.047*
ipi.us	2.657	2.522	5.027	0.533	1.020	0.260	2.456	4.96
ipi.jap	0.591	0.491	1.903	-0.280	0.568	0.452	1.957	16.664*
ipi.kor	115834.200	113865.900	163618.900	69357.630	20572.430	0.071	3.301	0.970
sp	32868.710	17746.780	2642832.000	7062.930	181182.9	14.336	207.012	371375.600*
nikkei	2131541.000	2091865.000	6370105.000	650554.600	1205649.000	1.162	4.530	67.649*
csi	23277.900	23505.010	42698.180	11387.920	6300.310	0.323	2.874	3.793
hsi	177858.200	177321.100	257264.000	99353.730	30026.290	0.003	2.956	0.017
sti	4126.858	4175.287	5512.176	2469.018	491.622	-0.457	5.116	46.502*
kospi	2421667.000	2296319.000	3864601.000	1280657.000	577113.000	0.616	2.724	13.935

sr.us	-2.692	0.232	139.696	-546.179	42.848	-10.180	128.603	140318.8*
sr.jap	2.426	0.166	257.434	-18.546	22.395	9.686	101.165	86766.60*
sr.chi	0.773	0.077	200.235	-89.124	17.120	7.128	95.120	75307.37*
sr.hk	1.713	0.205	351.971	-117.126	26.024	11.354	161.422	221979.4*
sr.sing	0.011	0.134	11.930	-26.006	4.080	-2.911	21.407	3230.187*
sr.kor	-4.324	-1.136	6.908	-293.634	22.583	-10.822	133.547	151761.800*

Notes: The number of observations is equal to 210; Max. Stands for Maximum; Min. for Minimum; SD. for Standard Deviation; Kurt. for Kurtosis; Skew. for Skewness and JB for the Jarque-Bera test statistic

Appendix B – Test Results

Table B. 1 – Summary table of the interpretation of Wald tests of Granger causality

Direction of causality	Window	Test statistics	95th percentile	99th percentile	Interpretation
r2 → r1	Max Wald FE	3.763	8.837	12.946	NR
	Max Wald RO	7.194	9.662	13.456	NR
	Max Wald RE	7.247	9.834	13.801	NR
r3 → r1	Max Wald FE	14.722**	9.217	16.376	R
	Max Wald RO	14.560**	8.987	15.626	R
	Max Wald RE	16.611**	9.395	16.376	R
r3 → r2	Max Wald FE	7.195	9.356	13.408	NR
	Max Wald RO	10.909**	10.175	15.352	R
	Max Wald RE	10.909**	10.279	15.410	R
r1 → r2	Max Wald FE	13.070**	11.629	18.621	R
	Max Wald RO	16.613**	12.259	19.164	R
	Max Wald RE	18.916**	12.865	19.627	R
r1 → r3	Max Wald FE	30.687**	25.232	37.906	R
	Max Wald RO	9.535	24.320	37.906	NR
	Max Wald RE	33.387**	26.914	38.052	R
r2 → r3	Max Wald FE	1.653	20.338	26.954	NR
	Max Wald RO	4.603	20.723	28.974	NR
	Max Wald RE	4.617	21.872	29.161	NR
r5 → r4	Max Wald FE	2.245	15.942	24.422	NR
	Max Wald RO	9.597	16.962	26.572	NR
	Max Wald RE	10.742	17.160	26.572	NR
r6 → r4	Max Wald FE	4.168	17.757	23.018	NR
	Max Wald RO	4.906	18.156	22.403	NR
	Max Wald RE	5.791	18.760	23.018	NR

r6 → r5	Max Wald FE	7.500	14.399	19.215	NR
	Max Wald RO	7.856	14.573	20.146	NR
	Max Wald RE	11.105	15.073	20.722	NR
r4 → r5	Max Wald FE	3.256	8.649	13.745	NR
	Max Wald RO	5.711	9.612	15.574	NR
	Max Wald RE	8.113	9.661	15.574	NR
r4 → r6	Max Wald FE	7.699	7.807	10.721	NR
	Max Wald RO	14.423*	8.852	12.747	R
	Max Wald RE	17.796*	9.203	13.274	R
r5 →r6	Max Wald FE	1.914	15.858	25.665	NR
	Max Wald RO	16.287	16.821	25.958	NR
	Max Wald RE	17.318**	16.821	27.017	R
x2 → x1	Max Wald FE	1.984	20.946	31.367	NR
	Max Wald RO	4.731	20.715	28.961	NR
	Max Wald RE	5.213	21.392	31.367	NR
x3 → x1	Max Wald FE	7.841	9.951	14.994	NR
	Max Wald RO	19.835*	10.398	16.693	R
	Max Wald RE	20.013*	10.666	16.713	R
x4 → x1	Max Wald FE	11.054	12.319	18.317	NR
	Max Wald RO	12.326**	12.273	18.586	R
	Max Wald RE	12.550	12.894	19.970	NR
x3 → x2	Max Wald FE	5.482	10.366	15.787	NR
	Max Wald RO	22.402*	11.107	15.511	R
	Max Wald RE	22.737*	11.617	16.014	R
x4 → x2	Max Wald FE	8.989**	8.497	14.899	R
	Max Wald RO	9.318**	8.541	16.244	R
	Max Wald RE	9.318**	8.813	16.790	R

$x1 \rightarrow x2$	Max Wald FE	1.383	19.195	27.081	NR
	Max Wald RO	8.383	19.633	26.323	NR
	Max Wald RE	9.429	20.016	27.081	NR
$x4 \rightarrow x3$	Max Wald FE	15.976**	11.586	18.081	R
	Max Wald RO	23.898*	13.373	20.768	R
	Max Wald RE	24.245*	13.587	21.001	R
$x1 \rightarrow x3$	Max Wald FE	1.317	11.779	16.103	NR
	Max Wald RO	4.732	11.933	17.270	NR
	Max Wald RE	10.386	12.531	17.270	NR
$x2 \rightarrow x3$	Max Wald FE	3.825	11.566	14.788	NR
	Max Wald RO	3.343	11.495	15.046	NR
	Max Wald RE	8.604	11.910	17.652	NR
$x1 \rightarrow x4$	Max Wald FE	3.209	10.957	14.899	NR
	Max Wald RO	6.904	11.746	16.043	NR
	Max Wald RE	7.429	11.932	17.370	NR
$x2 \rightarrow x4$	Max Wald FE	1.232	8.925	13.060	NR
	Max Wald RO	14.777*	9.248	13.060	R
	Max Wald RE	15.896*	9.646	13.894	R
$x3 \rightarrow x4$	Max Wald FE	2.912	10.117	15.116	NR
	Max Wald RO	16.983*	10.924	15.284	R
	Max Wald RE	21.929*	10.994	15.293	R
$x1 \rightarrow r1$	Max Wald FE	4.889	16.176	22.142	NR
	Max Wald RO	8.335	16.605	24.819	NR
	Max Wald RE	11.731	17.087	26.252	NR
$x2 \rightarrow r1$	Max Wald FE	3.978	12.027	19.920	NR
	Max Wald RO	7.934	12.823	19.081	NR
	Max Wald RE	9.177	13.281	19.920	NR

x3 → r1	Max Wald FE	11.344**	9.990	16.331	R
	Max Wald RO	16.693*	10.339	16.331	R
	Max Wald RE	28.361*	10.851	16.984	R
x4 → r1	Max Wald FE	3.432	10.475	16.815	NR
	Max Wald RO	11.686**	10.279	17.265	R
	Max Wald RE	12.652**	10.691	20.927	R
x1 → r2	Max Wald FE	1.868	10.176	14.065	NR
	Max Wald RO	13.737**	10.341	14.107	R
	Max Wald RE	14.425**	10.717	15.041	R
x2 → r2	Max Wald FE	3.471	10.541	17.190	NR
	Max Wald RO	10.886	11.425	17.465	NR
	Max Wald RE	13.272**	11.430	17.934	R
x3 → r2	Max Wald FE	11.676**	10.441	17.411	R
	Max Wald RO	32.936*	10.868	19.292	R
	Max Wald RE	45.859**	11.281	19.659	R
x4 → r2	Max Wald FE	12.950	14.389	22.391	NR
	Max Wald RO	12.454	14.203	21.812	NR
	Max Wald RE	13.553	15.433	22.391	NR
x1 → r3	Max Wald FE	5.798	19.913	28.935	NR
	Max Wald RO	9.253	20.049	28.312	NR
	Max Wald RE	11.796	20.847	31.594	NR
x2 → r3	Max Wald FE	5.252	20.368	29.112	NR
	Max Wald RO	11.517	20.357	31.550	NR
	Max Wald RE	13.489	21.594	32.435	NR
x3 → r3	Max Wald FE	13.981**	9.013	14.235	R
	Max Wald RO	9.053	10.176	14.415	NR
	Max Wald RE	18.539*	10.324	14.685	R

x4 → r3	Max Wald FE	6.879	17.085	25.023	NR
	Max Wald RO	13.173	17.303	25.028	NR
	Max Wald RE	13.759	17.805	27.576	NR
x1 → r4	Max Wald FE	4.319	13.942	19.094	NR
	Max Wald RO	5.584	14.952	19.996	NR
	Max Wald RE	8.630	15.223	20.593	NR
x2 → r4	Max Wald FE	6.219	13.519	21.733	NR
	Max Wald RO	6.485	14.126	21.993	NR
	Max Wald RE	9.883	14.417	21.993	NR
x3 → r4	Max Wald FE	14.758**	9.904	17.332	R
	Max Wald RO	19.420*	10.026	16.493	R
	Max Wald RE	21.348**	10.286	17.332	R
x4 → r4	Max Wald FE	2.995	14.044	20.477	NR
	Max Wald RO	22.232*	14.467	19.797	R
	Max Wald RE	22.232*	14.746	21.333	R
x1 → r5	Max Wald FE	4.164	14.000	23.135	NR
	Max Wald RO	7.286	14.739	22.805	NR
	Max Wald RE	7.286	15.270	23.135	NR
x2 → r5	Max Wald FE	5.434	12.501	18.491	NR
	Max Wald RO	6.692	13.448	19.934	NR
	Max Wald RE	9.549	14.063	20.148	NR
x3 → r5	Max Wald FE	4.802	11.446	16.990	NR
	Max Wald RO	8.877	11.718	20.124	NR
	Max Wald RE	11.900	11.931	20.124	NR
x4 → r5	Max Wald FE	9.810	19.198	26.881	NR
	Max Wald RO	15.479	18.843	24.998	NR
	Max Wald RE	15.592	20.258	26.881	NR

x1 → r6	Max Wald FE	2.147	12.769	19.833	NR
	Max Wald RO	6.993	12.559	19.226	NR
	Max Wald RE	6.993	13.080	20.315	NR
x2 → r6	Max Wald FE	6.855	12.134	19.353	NR
	Max Wald RO	8.813	12.580	18.883	NR
	Max Wald RE	8.813	12.944	19.353	NR
x3 → r6	Max Wald FE	57.185*	10.677	14.804	R
	Max Wald RO	55.025*	11.022	17.484	R
	Max Wald RE	92.399*	11.567	17.559	R
x4 → r6	Max Wald FE	10.485	10.521	16.547	NR
	Max Wald RO	15.987**	10.964	17.051	R
	Max Wald RE	35.036*	12.027	17.988	R

Note: x → y indicates that the direction of Granger causality being tested runs from x to y. The study period is January 2007 to June 2024. It follows that NR denotes failure to reject H_0, implying the absence of Granger causality. Conversely, R denotes rejection of H_0 at the 5% significance level (95% confidence), thereby providing evidence of Granger causality. The level of statistical significance of 1% is denoted by ***, 5% by ** and 10% by *.