Spillovers of US Monetary Policy on Emerging Market Equities, Currencies, and Energy Stocks

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Thesis presented for the degree of Doctor of Philosophy in Economics

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August 2026

Abstract

This research investigates the effects of US monetary policy shifts and dollar movements on financial markets in both the US and Emerging Market Economies (EMEs). The first paper analyses the impact of local and US interest rate levels and volatilities on EME stock markets using a multiplicative GARCH(1,1) model. Results indicate: (i) local and US interest rates often exert opposite effects on returns; (ii) stock return volatility is more sensitive to local rate changes than to US rate changes; and (iii) US interest rate volatility has asymmetric and stronger effects on stock market volatility compared to local volatility. The second paper examines the dynamics between US dollar appreciation and EME currency depreciation using DCC-GARCH(1,1) and Cross-Quantilogram (CQ). Findings show: (i) the conditional correlation between dollar appreciation and EME depreciation is positive and time-varying; and (ii) CQ results vary with internal and external shocks (e.g., COVID-19, currency crises), as well as time lags and quantile choices. The third paper investigates the responses of clean and brown energy stock markets to a shock in both short-run and long-run US monetary policy rates using Structural VAR and Local Projections. A shock in short-term policy rates generates immediate and statistically significant positive effects on both markets. In contrast, a shock in long-term policy rates produces negative effects, with the clean energy market more adversely affected. This suggests that high energy transition costs amplify sensitivity to long-term interest rates. Overall, the findings provide important insights for investors and policymakers in the US and EMEs on managing financial stability and supporting sustainable market development.

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Acknowledgements

I would like to express my deepest gratitude to my supervisors and mentors, Prof. Peter G. Moffatt and Dr Gustavo Fruet Dias, for their continuous support, encouragement, and invaluable guidance throughout my PhD journey. Their mentorship has been instrumental in shaping both the direction and the quality of this thesis.

I am also profoundly indebted to Dr Martin Bruns and Dr Fuyu Yang for serving as discussants during my internal seminar presentations of each chapter. Their insightful comments and constructive feedback greatly enriched my work and helped refine the ideas presented here.

Throughout my PhD studies, I have acquired a wide range of skills essential for both the academic profession and the broader job market—ranging from technical expertise to multitasking, networking, and collaboration. I am deeply grateful for the freedom, trust, and support provided by my supervisors and colleagues, which enabled me to grow both intellectually and personally.

I wish to extend my sincere appreciation to the University of East Anglia for awarding me a full scholarship to pursue my doctoral studies at the School of Economics. Coming from a low-income background, this opportunity would not have been possible without such generous financial support. Being part of such a collaborative, stimulating, and welcoming academic community has been a truly extraordinary experience. My development has been shaped not only by formal mentorship and teaching but also by the many engaging discussions with colleagues and the camaraderie shared with fellow PhD students.

Finally, my deepest gratitude goes to my family and friends for their unwavering love, patience, and support. At no point did I feel alone in this journey, and this accomplishment is as much theirs as it is mine.

Chapter 1

Introduction

The 1929 Wall Street Crash, followed by the Great Depression, and the recent Global Financial Crisis underscore the pivotal role of financial markets in sustaining economic stability and expose the extensive reliance of global economies on the US. A substantial body of literature has analysed the reaction of financial markets to monetary policy changes (for instance, Bernanke and Kuttner, 2005; Bjørnland and Leitemo, 2009). The following two areas have received increased attention in recent financial research: (i) the dependence of financial markets in Emerging Market Economies (EMEs) on the macroeconomic policies of Advanced Economies, especially on the US monetary impulses, and (ii) the evolving dynamics of green and brown financial markets as global warming and climate change become more pressing concerns worldwide.

Limited studies have investigated the effect of US monetary shifts on the financial markets in other countries, especially in EMEs. Camara et al. (2025) document that the US monetary tightening has more pronounced adverse effects on EMEs than on advanced economies. Uribe and Yue (2006) find that an impulse in US interest rates accounts for approximately 20% of the variability in the aggregate outputs of EMEs. Obstfeld and Zhou (2023) reveal that US dollar appreciation has adverse effects on the aggregate demand and financial strength of EMEs, affecting them through the terms of trade. Even within a country, a sector-wise comparison of financial market performance to monetary shocks needs further investigation due to heterogeneity among financial markets. For evidence, clean energy markets have received increased attention among investors, policymakers, and governments across the world and differ from the brown energy markets. Recent asset pricing models differentiate asset prices for clean energy from those for brown energy (for instance, Pedersen et al., 2021; Pástor et al., 2021). Investigating the monetary policy shock on the clean and brown energy sectors has policy implications for investors and energy transition policy regulators. To the best of my knowledge, the following questions have not been addressed in the existing literature: (i) Are stock markets in Emerging Market Economies (EMEs) more sensitive to the US interest rate than to their respective local interest rate? (ii) Does the strengthening of the US dollar matter for currency movements in the Global South? (iii) Does the response of the clean energy stock market to a US monetary policy shock differ from the responses of the brown energy stock market?

Chapter 2 addresses the first question, which is motivated by the studies of Camara et al. (2025), Hoek et al. (2020) and Uribe and Yue (2006). They claim that US monetary policy decisions do matter in EMEs. Following the study of Elyasiani and Mansur (1998), we utilise the GARCH(1,1) model to examine the level and volatility of both local and US interest rates on the stock market returns and volatility in the EMEs. We select 15 EMEs, including countries from Asia, Africa, and Europe, and use daily series data from 9th November 2003 to 30th June 2025. Main findings in Chapter 2 are: (i) The local interest rate tends to have a negative and significant effect on the stock market returns in many EMEs. In contrast, the US interest rate tends to have positive and significant effects on them. (ii) The conditional volatility of the stock market returns is more sensitive to positive and/or negative changes in the local interest rate than to those changes in the US interest rate. (iii) The volatility of the US interest rate is found to have a more pronounced effect on stock market volatilities compared to the volatility of the local interest rate. (iv) The volatilities of local and US interest rates have asymmetric effects on stock market volatilities.

The second question is addressed in Chapter 3 and triggered by a recent empirical study by Obstfeld and Zhou (2023) which shows that US dollar strengthening has more adverse effects on output, investment, consumption, public expenditure, and the financial position of EMEs. This chapter employs a Dynamic Conditional Correlation-GARCH(1,1) model and Cross-Quantilogram (CQ) approach using daily data from 1st January 2015 to 31st October 2024. The CQ approach introduced by Han et al. (2016) allows us to explore the causality from one variable to another at various quantiles and time lags. This study selects four EMEs which faced severe currency crises after the COVID-19 pandemic: Turkey, Pakistan, Sri Lanka, and Bangladesh. Key findings in Chapter 3 are: (i) The dynamic conditional correlation between US dollar appreciation and currency depreciation in EMEs is positive and varies over time. (ii) Turkish currency depreciation accounts for a higher correlation with US dollar appreciation compared to South Asian currency depreciation. (iii) The CQ approach provides mixed effects of the strengthening of the US dollar on the currency depreciation of the EMEs depending on the internal and external turmoils (such as the COVID-19 pandemic and local currency crisis) and the selection of the time lags and quantile probabilities.

In Chapter 4, we explore the third question. Notably, Chapter 2 and Chapter 3 focus on US monetary transmission to the financial markets in other countries, while Chapter 4 explores US monetary transmission to the financial markets within the US. The motivation for this chapter is that demand for clean energy over brown energy has increased dramatically in recent decades. For instance, global clean energy investment surged from US$0.565 trillion in 2019 to US$1.77 trillion in 2023. This chapter employs Structural Vector Autoregressive (SVAR) and Local Projections models with monthly series data from November 2005 to March 2025. This chapter investigates the responses of clean and brown energy stock markets to a shock in short-run and long-run monetary policy rates. This chapter presents interesting findings. We show that an impulse in short-term monetary policy rates has a statistically significant positive immediate effect on both clean and brown energy stock markets. In contrast, a shock in the long-term monetary policy rate has negative effects on both markets. Noticeably, the shock in the long-term rates has a stronger and statistically significant negative effect on the clean energy market than on the brown energy market. This underlines that higher upfront costs for energy transitions might induce the long-term interest rate to have a more adverse effect on clean energy markets than on brown energy markets. The findings in this study have significant implications for policymakers striving to navigate energy transitions through financial market dynamics via monetary policy.

The last chapter in this thesis concludes all the previous chapters and provides suggestions for future research.

Chapter 2

Stock Market Return and Volatility in Emerging Market Economies: Local and US Interest Rates

Abstract

This paper investigates how stock markets in emerging market economies (EMEs) respond to changes in and the volatility of both local and US interest rates. We employ a GARCH(1,1) model using daily data for 15 EMEs covering the period from 9 November 2003 to 30 June 2025. The study presents several key findings. First, local interest rates tend to have a negative and statistically significant effect on stock market returns in many EMEs. In contrast, US interest rates tend to have a positive and statistically significant effect. Second, changes in local interest rates have a greater impact on the conditional volatility of stock market returns than changes in US interest rates. Third, US interest rate volatility has a more pronounced effect on the conditional volatility of stock market returns than local interest rate volatility. Fourth, the effects of both local and US interest rates on stock market returns and their conditional volatility vary across the EMEs.

Keywords:
Stock Market Returns and Volatility, US and Local Interest Rates, and Monetary Policy Shocks

2.1 Introduction

The US interest rate plays a crucial role not only in the US economy but also in the global economy, particularly in emerging market economies (EMEs). For example, changes in the US interest rate explain approximately 20% of the variability in EMEs' economic output (Uribe and Yue, 2006). Moreover, an increase in US interest rates has a more pronounced adverse impact on EMEs than on advanced economies (Camara et al., 2025). Financial markets in EMEs are also sensitive to US interest rate risk, with the degree of sensitivity influenced by the level of domestic macroeconomic instability (Hoek et al., 2020) as they are sensitive to domestic interest rate risk (For instance, Thorbecke, 1997; Elyasiani and Mansur, 1998; Rigobon and Sack, 2004; Bernanke and Kuttner, 2005; Faff et al., 2005; Jones et al., 2005; Bjørnland and Leitemo, 2009; Galí and Gambetti, 2015; Gospodinov and Jamali, 2015). Therefore, the effects of US and domestic interest rate risks on financial market asset price movements in EMEs have become a major area of interest for investors, policymakers, and researchers worldwide, particularly in those EMEs.

Many empirical studies have examined the effect of domestic interest rate risk on stock markets (Thorbecke, 1997; Elyasiani and Mansur, 1998; Rigobon and Sack, 2004; Bernanke and Kuttner, 2005; Faff et al., 2005; Jones et al., 2005; Bjørnland and Leitemo, 2009; Galí and Gambetti, 2015; Gospodinov and Jamali, 2015) and vast majority of them analyses US interest rate risk on US stock markets (Thorbecke, 1997; Elyasiani and Mansur, 1998; Rigobon and Sack, 2004; Bernanke and Kuttner, 2005; Bjørnland and Leitemo, 2009; Galí and Gambetti, 2015; Gospodinov and Jamali, 2015). However, a limited number of studies have extended the US interest rate spillovers on stock markets beyond the US. Ammer et al. (2010) and Laeven and Tong (2012) have attributed the sensitivity of global stock prices to US monetary policy surprises. Kim (2023) examines the reaction of the Korean stock market to the US interest rate hikes and finds that stock firms with the largest market capitalisation, larger export sales, and more foreign ownership outperform during the Federal funds hike. These studies have employed panel regression with the assumption of constant error variance in their investigation.

The usual model with constant error variances may not fit the stock market returns series well, as they often show heteroskedasticity over time. The Generalised Autoregressive Conditional Heteroskedasticity (GARCH) approach introduced by Bollerslev (1986) is the most common approach to capture the conditional heteroskedasticity variances in financial market asset returns. Only a few studies have employed it to explore interest rate risk on stock market returns and volatility

(Elyasiani and Mansur, 1998; Faff et al., 2005), and their scope is limited to within a country. For example, Elyasiani and Mansur (1998) and Faff et al. (2005) explore interest rate risk spillovers on stock markets within the US and Australia, respectively.

To the best of our knowledge, no studies have examined US interest rate risk spillover on stock markets in EMEs using GARCH-type frameworks. Therefore, this study examines the effects of US interest rate risk on stock market return and volatility in emerging market economies (EMEs) and compares them with the effects of domestic interest rates using a threshold GARCH model. In this study, we test this theoretical expectation using a heteroskedastic GARCH (1,1) model with daily series data of 15 EMEs from 9 November 2003 to 30 June 2025. Due to the high uncertainty about the future, financial market returns are more sensitive to internal and external factors and often show volatility clusters over time and a fat-tailed distribution. The GARCH framework deals with these data features. In addition, the conditional mean and variance models of the GARCH framework allow us to examine the effect of explanatory variables on stock market returns and volatility.

This study contributes to the existing literature in several ways. First, the existing literature focuses on the effect of US interest rates on firm-level stock prices (see Ammer et al., 2010; Laeven and Tong, 2012; Kim, 2023). In this, it investigates how local and US interest rates affect country stock market returns as well as stock market volatilities in EMEs. Second, previous studies related to our study have applied a panel regression framework. Still, to the best of my knowledge, no prior studies have examined the effect of US interest rates on stock market returns and volatilities. Third, our study provides empirical evidence of how the effect of US interest rates on the financial markets in EMEs depends on country, region, macroeconomic vulnerability, and level of interdependency on the US.

The key findings are as follows: (i) Local interest rates tend to have a negative and statistically significant effect on stock market returns in many EMEs, whereas US interest rates tend to have a positive and statistically significant effect. (ii) The conditional volatility of stock market returns is more sensitive to changes in local interest rates than to changes in US interest rates. (iii) US interest rate volatility has a more pronounced effect on stock market volatility than local interest rate volatility. (iv) The volatilities of local and US interest rates exert asymmetric effects on stock market volatility.

Financial market uncertainty can severely affect economic conditions. Effective financial market risk management is therefore essential for maintaining economic stability, as financial market crashes can trigger economic recessions. Historically, there is substantial evidence that financial market crashes have led to major economic downturns. The 1929 Wall Street Crash, followed by the Great Depression, is one major example. Other notable examples include the 1997-1998 Asian Financial Crisis and the 2007-2008 Global Financial Crisis. This study investigates how stock market returns and volatility are associated with changes in local and US interest rates. The findings provide valuable insights for policymakers in managing financial market risks arising from both domestic and international monetary policy changes. In addition, the results can assist investors in managing their investment portfolios more effectively, enabling them to maximise returns while mitigating the adverse effects of heightened economic and financial uncertainty.

The rest of this paper is organised as follows. Section 2.2 reviews the related literature. Section 2.3 describes the variables and data. Section 2.4 illustrates our empirical framework. Section 2.5 presents and discusses our empirical results. Section 2.6 concludes our study.

2.2 Review of Related Studies

In theory, interest rates have a negative effect on stock market returns through demand and credit channels. The demand channels emphasise that a fall in interest rates leads to a rise in aggregate demand by increasing spending on capital and consumer goods. Then, increased demand and market activities can boost financial market activities, including stock markets. On the other hand, a rise in interest rates lowers aggregate demand by reducing spending on capital and consumer goods and then reduces stock market returns. The credit channels demonstrate that monetary policy has a crucial role in credit markets through altering interest rates. For example, higher interest rates limit the supply of credit provided by financial intermediaries and then reduce financial market returns due to the increased cost of capital. On the flip side, falling interest rates increase the supply of credit and can lead to flourishing stock market activity. The demand and credit channels emphasise the negative effect on the stock markets. Further, foreign interest rates, especially US interest rates, can also negatively influence financial markets in the EMEs through the balance sheet and the international credit channels. A fall in US aggregate demand due to a rise in US interest rates can significantly deteriorate EME financial markets by weakening their balance sheets. At the same time, a rise in US interest rates shrinks the global credit market and then has a more adverse effect on the countries that rely more on foreign financing.

On theoretical grounds, the effects of both local and foreign interest rates on stock market volatility differ from their effects on stock market returns. Local and foreign interest rate changes, either positive or negative, increase stock market volatility as future interest rate changes become unpredictable. Positive changes in interest rates increase volatility more than negative changes. Financial market volatility in more macroeconomically vulnerable countries increases in response to changes in local or US interest rates. Similarly, countries with greater reliance on the United States tend to experience higher financial market volatility in response to US interest rate changes compared to those with lower levels of dependence.

Early studies focused on the impact of domestic interest rates on equity returns. Dinenis and Staikouras (1998), Elyasiani and Mansur (1998), Rigobon and Sack (2004), Bernanke and Kuttner (2005), Faff et al. (2005),Jones et al. (2005), Bjørnland and Leitemo (2009), Maio (2013), Ferrer et al. (2016), Maio and Santa-Clara (2017), Zaremba et al. (2023), and Beckers and Bernoth (2024) are only some of the evidences. A negative effect of domestic interest rate on stock market return is quite a common finding in empirical literature. However, there is some literature showing evidence for a positive effect (Faff et al., 2005; Jones et al., 2005; Jarociński and Karadi, 2020). For instance, Faff et al. (2005) finds positive and statistically significant effects on Australian financial sector equity returns during January 1978 - November 1983, especially during the regulatory controls in their banking sector. Further, Jarociński and Karadi (2020) provide evidence for a positive effect and argue that it is possible because of the central bank's information shock. Central banks also convey information about their assessment of the economic outlook when they announce monetary policy rates. This information shock biases the effect of a monetary policy shock on a country's macroeconomy, including stock market returns.

Relatively few studies address the effect of interest rate sensitivity on stock market volatility. Elyasiani and Mansur (1998) find that interest rate volatility has a negative and significant effect on stock return volatility for money-centre and large banks in the United States. Faff et al. (2005) also report a negative effect of interest rate volatility on stock market return volatility in Australia. In their study, small banks and finance companies show statistically significant results, whereas large banks do not. Jones et al. (2005) document that monetary policy change has a positive but not statistically significant effect on the conditional volatility of the equity market in the UK. Kasman et al. (2011) document that interest rate sensitivity (measured by taking the square of the risk-free interest rate return) has a positive and highly statistically significant effect on the conditional volatility of bank stock returns in Turkey.

Majority of previous empirical studies in the relevant domain have concentrated US interest rate with the US stock markets, for examples, Campbell and Ammer (1993), Thorbecke (1997), Elyasiani and Mansur (1998), Rigobon and Sack (2004), Bernanke and Kuttner (2005), Bjørnland and Leitemo (2009), Maio (2013), Maio and Santa-Clara (2017), Lakdawala and Schaffer (2019), Beckers and Bernoth (2024). In all these studies, short-run interest rates are selected except Elyasiani and Mansur (1998) and Beckers and Bernoth (2024), where long-run interest rates (10-year US Treasury rates) are utilised to explore the stock market reactions in the US.

A limited number of studies have extended the effect of US interest rates on the stock markets in other countries. Ammer et al. (2010) find that a 25 basis point unexpected rise in the federal funds rate lowers US and foreign equity prices by 1.59% and 1.71%, respectively, employing pooled OLS regression. Another similar study by Laeven and Tong (2012), using panel regression, reports that a change in federal funds has a strong negative effect on global stock prices, and the effect is more pronounced if countries align with the US in their domestic monetary policy decisions. Jones et al. (2005) report that the change in the federal funds rate has positive and negative effects on equity (FTSE 100) return and its conditional volatility, respectively, in the UK by using linear regression and GARCH(1,1) models. The federal funds rate is one of the best measures of short-run interest rates. Our research examines the impact of US long-run interest rates on equity markets in emerging market economies (EMEs).

The recent literature has begun to explore the effect of US interest rate change on EMEs. Camara et al. (2025) document that US monetary tightening leads to a substantial fall in US imports and contracts EMEs more than advanced economies. Uribe and Yue (2006) find that around 20% of the variability in the whole economic activities of EMEs is explained by US interest rate shocks. However, Hoek et al. (2020) report that a rise in US interest rates can be good news for EMEs, depending on the source driving the rise, namely monetary and growth shocks. They find that growth and monetary shocks around FOMC announcements have positive and negative spillovers, respectively, on equity prices in EMEs, and that the magnitude of the spillovers is larger for monetary shocks than for growth shocks. In their study, shocks are defined based on the comovements between the S&P 500 index and the 2-year US Treasury yield around FOMC announcements and US employment report releases: a positive comovement indicates a growth shock, whereas a negative comovement indicates a monetary shock.

In the context of examining the effect of interest rate on stock markets, many previous empirical studies have employed linear regression including pooled and panel setup (Dinenis and Staikouras, 1998; Ammer et al., 2010; Laeven and Tong, 2012; Zaremba et al., 2023) and vector autoregressive (VAR) models (Bjørnland and Leitemo, 2009; Maio, 2013) with the assumption of constant error variance. However, few studies applied GARCH models, which assume heteroskedastic variance over time, to explore the impact of interest rate on stock markets. Elyasiani and Mansur (1998), Faff et al. (2005) and Jones et al. (2005) utilised GARCH(1,1) models, where the first two studies explore domestic interest rates with US and Australian stock markets. In contrast, the latter study analyses both domestic and US monetary policy rates with the UK equity market. Our study employs a GARCH model to illustrate the effects of both domestic and US interest rates on stock markets in EMEs.

2.3 Data and Variables

This study investigates how stock market returns and their volatility in EMEs respond to changes in local and US interest rates. The sample comprises 15 EMEs representing South Asia (India, Pakistan, and Sri Lanka), East Asia (China, Taiwan, Hong Kong, and South Korea), Southeast Asia (Malaysia, Thailand, and Indonesia), Africa (Kenya, Morocco, and South Africa), Eurasia (Turkey) and Europe (Hungary).

For each EME, we collect data on stock market indices, local exchange rates against the US dollar, and local interest rates (the government benchmark 1-Year bond bid yield in %). In addition, we include US interest rates (five-year constant maturity Treasury yield), the trade-weighted US dollar index, the West Texas Intermediate (WTI) crude oil price, and the gold price per troy ounce quoted by the London Bullion Market Association (LBMA). All data are obtained from Refinitiv Workspace and cover the period from 9 November 2003 to 30 June 2025.

Furthermore, we include dummy variables to capture the effects of the Global Financial Crisis (GFC; 1 July 2007 to 30 June 2009), the COVID-19 pandemic (1 February 2020 to 31 December 2021), the Russia-Ukraine war (22 February 2022 to 30 June 2023) and day-of-the-week effects.

All continuous variables, except the local and US interest rates, are transformed into daily percentage returns using the standard logarithmic return formula:

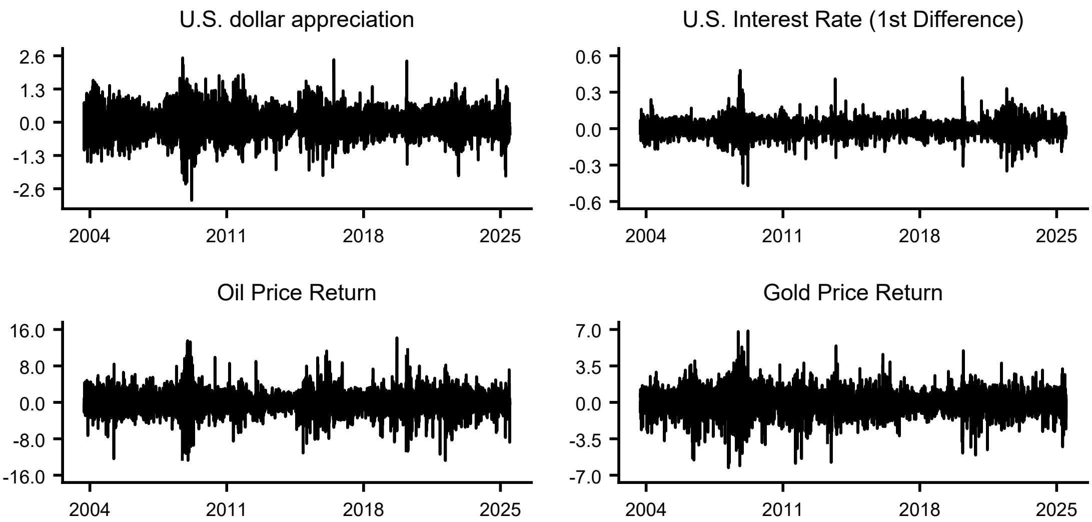
$$y_t = \left(logP_t - logP_{t-1}\right) * 100\% \tag{2.1}$$

where $logP_t$ is the logarithm of a variable at time t, and $logP_{t-1}$ is its one-period lagged value. The variable (y_t) denotes the daily percentage return of a series.

For the local and US interest rates, we use first differences ($P_t - P_{t-1}$) rather than logarithmic returns because interest rates are already expressed as percentages. The transformed series for all foreign variables are presented in Figure 2.1. At the same time, the daily stock returns of the EMEs are displayed in Figure 2.2. The figures shows volatility clusters around the periods of global financial crisis 2007-2008, Covid-19 (2020-2021) and Ukraine-Russia war (2022-2023). This id further validate the inclusion of dummy variables to represent those major events in our modelling.

Table 2.1 reports the descriptive statistics for all continuous variables used in this study. The average daily stock returns are positive for all EMEs, with India (0.05%) and Turkey (0.07%) recording the highest mean daily returns among the sample countries. The standard deviations indicate that the stock markets of Turkey and China are more volatile than those of the other EMEs. The skewness suggests that stock returns are generally fairly symmetric across the EMEs, whereas the kurtosis statistics indicate the presence of leptokurtic distributions.

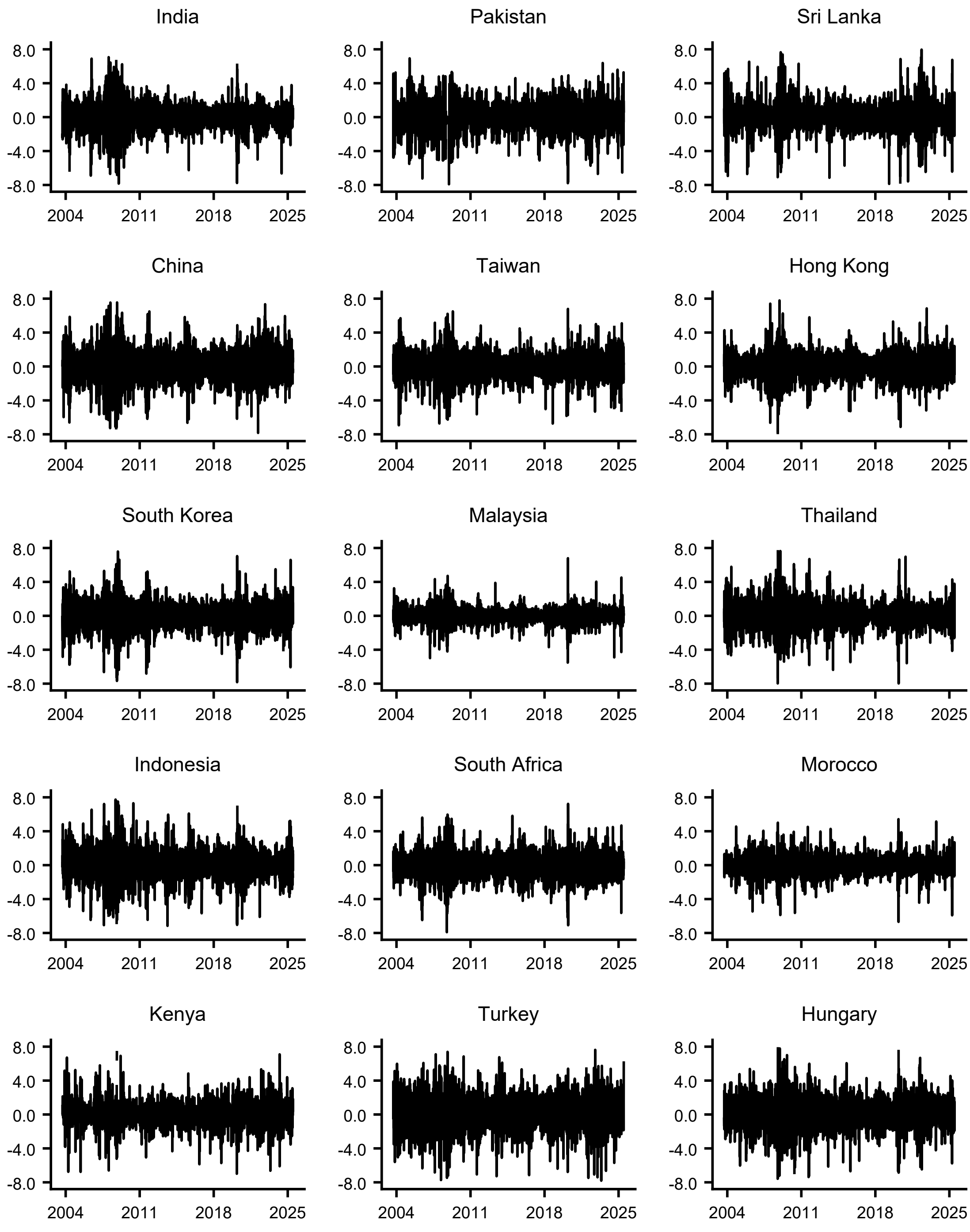
Figure 2.1: Return series of international variables



Note: U.S. constant 5-year treasury rate is obtained to represent the U.S. interest rate. All the variables are per daily basis and in terms of percentages

Table 2.1 also reports the results of the Augmented Dickey–Fuller (ADF) and ARCH tests, which examine stationarity and the presence of conditional heteroskedasticity, respectively. The ADF test statistics are statistically significant at the 1% level for all variables, providing strong evidence that the series are stationary. Likewise, the ARCH test statistics are significant at the 1% level in all cases, indicating the presence of conditional heteroskedasticity. These findings justify the application of the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) framework in this study.

Figure 2.2: Stock Market Returns in Emerging Market Economies



Note: All stock market returns are expressed as % daily change

Table 2.1: Descriptive statistics

Variable	Mean	Std.	Minimum	Maximum	Skewness	Kurtosis	ADF test	ARCH test
Stock Market Returns in % (y)								
India	0.049	1.324	-13.74	16.42	-0.416	13.40	-16.55	686.3
Pakistan	0.012	1.450	-12.89	9.33	-0.388	4.74	-16.20	998.8
Sri Lanka	0.020	1.396	-16.05	14.31	-0.306	20.99	-16.29	592.1
China	0.025	1.651	-13.78	14.04	-0.063	7.46	-18.00	1038.0
Taiwan	0.023	1.238	-10.30	8.99	-0.376	5.17	-17.68	610.3
Hong Kong	0.015	1.249	-12.56	10.45	-0.262	7.38	-17.76	1155.5
South Korea	0.024	1.289	-10.97	11.72	-0.351	7.04	-18.35	1072.7
Malaysia	0.009	0.747	-10.24	6.79	-0.651	12.42	-18.29	460.2
Thailand	0.012	1.314	-18.09	11.44	-0.843	16.49	-17.56	730.1
Indonesia	0.039	1.466	-11.45	14.44	-0.208	7.61	-17.59	665.2
South Africa	0.035	1.226	-9.48	7.23	-0.333	4.60	-19.51	1430.2
Morocco	0.016	0.892	-10.30	5.42	-0.536	8.54	-16.72	939.2
Kenya	0.029	1.160	-10.08	9.56	-0.006	7.27	-17.95	818.9
Turkey	0.069	1.744	-10.76	12.72	-0.201	3.99	-17.19	310.0
Hungary	0.030	1.634	-16.11	15.11	-0.486	9.87	-17.44	1095.4
Local Currency Depreciation against US dollar in % (LCD)								
India	0.011	0.413	-3.550	3.694	0.167	7.68	-17.17	865.0
Pakistan	0.028	0.437	-5.410	7.960	3.049	73.38	-19.62	172.6
Sri Lanka	0.020	0.421	-5.595	11.953	8.053	244.73	-14.14	1660.7
China	-0.003	0.187	-2.241	1.838	-0.265	13.88	-15.65	351.7
Taiwan	-0.003	0.309	-5.157	2.765	-1.379	24.74	-15.87	1970.1
Hong Kong	0.000	0.039	-0.653	0.337	-1.691	27.34	-17.76	642.8
South Korea	0.003	0.650	-10.945	10.216	-0.108	32.60	-17.95	1650.8
Malaysia	0.002	0.369	-3.596	2.026	-0.451	6.26	-16.32	701.2
Thailand	-0.004	0.462	-11.034	10.951	0.346	127.56	-16.77	2066.7
Indonesia	0.011	0.438	-6.471	7.617	0.836	35.23	-15.15	199.3
South Africa	0.015	1.055	-6.776	16.172	0.901	12.29	-19.05	742.1
Morocco	-0.001	0.445	-2.788	3.309	0.025	2.85	-17.04	617.6
Kenya	0.009	0.404	-4.088	5.489	0.175	25.74	-14.69	1064.3
Turkey	0.059	0.978	-19.520	14.756	-0.046	50.07	-16.04	686.3
Hungary	0.007	0.880	-5.650	7.739	0.255	3.72	-17.63	860.7
Local Interest Rate Change (π_1)								
India	0.000	0.071	-0.749	0.920	0.484	21.28	-15.38	304.3
Pakistan	0.002	0.094	-1.470	1.370	0.106	67.93	-14.27	204.1
Sri Lanka	0.000	0.215	-7.597	5.000	-2.342	409.32	-16.84	82.3
China	0.000	0.073	-0.973	0.800	0.225	33.83	-15.62	1270.8
Taiwan	0.000	0.036	-0.700	0.700	0.247	100.09	-16.84	1312.8
Hong Kong	0.000	0.051	-0.800	0.820	0.035	37.26	-17.57	501.4
South Korea	0.000	0.039	-0.420	0.570	1.651	44.95	-15.53	149.1
Malaysia	0.000	0.031	-0.500	0.570	-1.293	93.52	-18.05	87.0
Thailand	0.000	0.035	-0.880	0.900	1.247	177.93	-16.08	3.4
Indonesia	-0.001	0.246	-3.202	3.039	0.176	44.86	-19.54	1571.0
South Africa	0.000	0.130	-3.915	3.915	-0.082	324.59	-18.16	1653.4
Morocco	-0.001	0.367	-6.375	6.125	-0.138	80.85	-25.08	629.1
Kenya	0.001	0.262	-3.260	4.750	2.171	66.46	-16.31	68.4
Turkey	0.000	0.494	-8.230	6.410	0.031	65.74	-18.41	419.9
Hungary	-0.001	0.100	-1.530	2.720	4.545	134.61	-15.35	592.2
International Price Returns (%)								
OPR	0.015	2.566	-28.138	31.286	-0.106	17.98	-17.59	1745.8
GPR	0.038	1.070	-10.162	6.865	-0.476	5.47	-18.46	343.7
π_2	0.000	0.066	-2.140	0.840	-5.808	204.80	-17.95	32.6
UDA	0.000	0.475	-3.056	2.520	-0.098	2.15	-17.35	418.8

Note: OPR, GPR, UDA, and π_2 denote oil price returns, gold price returns, U.S. dollar appreciation, and changes in the U.S. interest rate, respectively. The Augmented Dickey–Fuller (ADF) test is employed to examine the presence of a unit root in each time series, while the ARCH test is used to detect conditional heteroskedasticity. In all cases, the test statistics from both the ADF and ARCH tests are statistically significant at the 1% level.

2.4 Methodology

Bollerslev (1986) introduced the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) framework, building on the earlier work of Engle (1982), to model the conditional variance of financial market returns based on past squared residuals and past conditional volatility. The GARCH(1,1) model is the most widely used approach in financial volatility modelling and can be written as follows for a return series y_t:

$$y_t = \mu + u_t \; ; \qquad u_t = \sigma_t \varepsilon_t \tag{2.2}$$

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{2.3}$$

where the mean and variance equations of the GARCH(1,1) model are given in (2.2) and (2.3) respectively. In the mean equation, μ denotes the intercept, and u_t is the residual term. σ_t^2 represents the conditional variance of y_t. The term ε_t is a standardised residual assumed to follow a standard normal distribution with zero mean and unit variance, $\varepsilon_t \sim N(0,1)$.

The variance equation (2.3) expresses conditional volatility as a function of both past squared shocks (u_{t-1}^2) and past conditional variance (σ_{t-1}^2). The parameters α and β capture the effects of past shocks and past volatility, respectively, and are assumed to be non-negative. When $\alpha + \beta$ is close to one, volatility persistence is high in y_t. The stationarity condition of the GARCH(1,1) model requires that $\alpha + \beta \leq 1$. The intercept term ω is assumed to be positive.

Glosten et al. (1993) extend the variance specification by introducing an additional term to capture the leverage effect of past shocks on conditional volatility. The leverage effect implies that financial market returns tend to be more volatile in response to bad news than to good news. The variance equation in (2.3) is therefore modified as follows:

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \eta I_{\{u_{t-1}>0\}} u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{2.4}$$

where $I\{\cdot\}$ is an indicator (dummy) variable that takes the value one if $u_{t-1} > 0$ and zero otherwise. The coefficient η captures the leverage effect and is expected to be negative, given that the indicator is defined for positive shocks. A negative estimate of η implies that increases in volatility are similar following positive shocks compared to negative shocks. In other words, bad news (positive shocks) increase financial market volatility more than good news (negative shocks).

Under this specification, the stationarity condition becomes $\alpha + \eta/2 + \beta \leq 1$. Moreover, the model exhibits high volatility persistence when $\alpha + \eta/2 + \beta$ is close to one.

The GARCH family of models can be combined with a multiplicative component to examine the effects of explanatory variables on conditional volatility (see, for further details, Harvey, 1976; Judge et al., 1985). A large number of empirical studies employ GARCH models with multiplicative components to analyse the dynamics of conditional volatility in financial asset returns in response to explanatory variables (Elyasiani and Mansur, 1998; Eichengreen and Tong, 2003; Hwang and Satchell, 2005; Apergis and Rezitis, 2011; Curto and Serrasqueiro, 2022).

Following this literature, this study employs a GARCH model with a multiplicative component to investigate the effects of local and US interest rates on stock market volatility in EMEs. The revised specification of the model is written as follows:

$$y_t = \mu + \sum_{k=1}^{q_1} \psi_k y_{t-k} + \sum_{i=0}^{q_2} \rho_{1i}\pi_{1,t-i} + \sum_{j=1}^{q_3} \rho_{2j}\pi_{2,t-j} + \ G \ + u_t \ ; \quad u_t = \sigma_t \varepsilon_t \tag{2.5}$$

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \eta I_{\{u_{t-1}>0\}} u_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{2.6}$$

where

$$\omega = exp(\omega_0 + \phi_1 \pi_{1,t}^{+} + \phi_2 \pi_{1,t}^{-} + \phi_3 \pi_{2,t}^{+} + \phi_4 \pi_{2,t}^{-} + \phi_5 \sigma_{\pi_{1,t}}^2 + \phi_6 \sigma_{\pi_{2,t}}^2 + Q) \tag{2.7}$$

$$G = \sum_{s=1}^{q_4} \sum_{m=0}^{q_5} \theta_{sm} X_{s,t-m} \ + \ \sum_{n=1}^{q_6} \delta_n D_n \quad , \quad Q = \sum_{s=1}^{g_1} \sum_{m=0}^{g_2} \varphi_{sm} X_{s,t-m} \ + \ \sum_{n=1}^{g_3} \lambda_n D_n.$$

The mean equation in (2.2) extends the basic specification by incorporating explanatory variables to explain stock market returns (y_t). In this framework, we are particularly interested in ρ_1 and ρ_2, which capture the effects of local interest rates (π_1) and US interest rates (π_2) on stock market returns, respectively. The coefficients ψ_k represent the effects of lagged stock market returns (y_{t-k}).

The term G captures the effects of control variables on stock market returns and consists of continuous variables (X_s) and categorical variables (D_n). The continuous variables in X_s include oil price returns, gold price returns, local currency depreciation against the US dollar, and US dollar appreciation against the currencies of its major trading partners.

Dummy variables (D_n) are included in the GARCH framework to capture structural breaks in stock markets over the sample period. Financial market returns are often sensitive to global crises. Empirical evidence shows that the global financial crisis (2007-2008) (Schwert, 2011; AM Al-Rjoub and Azzam, 2012), the COVID-19 pandemic

(2020-2021) (Narayan et al., 2021), and Russia-Ukraine war (2022) (Izzeldin et al., 2023; Boubaker et al., 2022) had significant negative effects on stock market returns in many EMEs. These crises can include structural breaks in stock market returns, which may bias parameter estimates if ignored (Perron, 1989).

Many empirical studies include dummy variables in the mean equation of the GARCH framework to account for such structural shifts and improve estimation accuracy (for instance, Elyasiani and Mansur, 1998; Faff et al., 2005). Accordingly, this study includes dummy variables representing the global financial crisis, the COVID-19 pandemic, and the Russia-Ukraine war. In addition, day-of-the-week dummy variables are included, as previous studies provide evidence of such effects on stock market returns (Cross, 1973; Brusa et al., 2000; Zhang et al., 2017).

The effects of the continuous variables (X_s) and the dummy variables (D_n) are represented by the coefficients φ_s and λ_n, respectively. In the variance equation (2.6), the intercept term ω is replaced by the multiplicative component, as specified in (2.7). The specification enables us to examine the effects of (i) positive and negative changes in local interest rates, (ii) positive and negative changes in US interest rates, (iii) local interest rate volatility, and (iv) US interest rate volatility on stock market volatility.

Changes in both local and US interest rates are classified into three categories: positive changes, negative changes, and no changes. The "no change" category is used as the reference (base) group for both interest rate variables. In equation (2.7), ϕ_1 and ϕ_2 measure the effects of positive (π_1^+) and negative (π_1^-) changes in local interest rates, respectively, relative to the reference group. Similarly, ϕ_3 and ϕ_4 measure the effects of positive (π_2^+) and negative (π_2^-) changes in US interest rates, respectively, relative to their corresponding reference group.

We also examine the effects of interest rate volatility on stock market volatility. The coefficients ϕ_5 and ϕ_6 capture the effects of the conditional volatilities of local interest rates ($\sigma^2_{\pi_{1,t}}$) and US interest rates ($\sigma^2_{\pi_{2,t-1}}$), respectively. The term Q [1] represents the effects of the control variables included in the variance equation and consists of the same continuous and dummy variables as those included in the mean equation.

In empirical research, the normality assumption is widely used when estimating econometric models. However, this assumption is often inappropriate for financial return series, which typically exhibit excess kurtosis and fat tails (Mandelbrot, 1963; Fama, 1965; Cont, 2001). When Bollerslev (1986) introduced the GARCH model, he

[1] For the US interest rate, we use its one-period lagged values to account for the time zone differences between the US and the selected EMEs

assumed that the residuals of the mean equation (u_t) followed a normal distribution. Subsequently, (1987) adopted the t-distribution to estimate GARCH models using speculative price series. Baillie and Bollerslev (2002) argue that the normality assumption is generally inappropriate for daily financial data and recommend using the Student's t-distribution instead.

The kurtosis values of the stock market returns examined in this study are substantially higher than the benchmark value of three for a normal distribution (see Table 2.1). Therefore, we assume that the residual (u_t) in equation (2.5) follows a Student's $t-$distribution.

We first estimate the conditional volatilities of both local and US interest rates ($\sigma^2_{\pi_{1,t}}$, $\sigma^2_{\pi_{2,t}}$, respectively) using a standard GARCH(1,1) model, following Elyasiani and Mansur (1998), as these variables are included as explanatory variables in (2.7). Next, all parameters of the GARCH framework with multiplicative component, as specified in equations (2.5) - (2.7), are jointly estimated by maximising the log likelihood function.

The optimum lag orders of the Autoregressive (AR) process in the mean equation (2.5) are selected using the Box-Pierce-Ljung statistic (Box and Jenkins (1976)). In contrast, the lag order of the variance equation (2.6) is selected using the ARCH-LM test (Engle, 1983). Accordingly, an AR(10) specification is selected for the mean equation. A lag order of one is adopted for ARCH (u_{t-1}), leverage ($I_{\{u_{t-1}>0\}}u^2_{t-1}$), and GARCH ($\sigma^2_{t-1}$) terms in the variance equation (2.6).

2.5 Empirical Results and Discussion

2.5.1 Stock Market Returns: Local and US Interest Rates

The primary objective of this study is to examine the effects of local and US interest rates on stock market returns in the selected emerging market economies. In Table 2.2, the rows labelled $\pi_{1,t}$ and $\pi_{1,t-1}$ present the effects of changes in local interest rates and their lagged values, respectively, on conditional stock market returns. Similarly, the rows labelled $\pi_{2,t}$ and $\pi_{2,t-1}$ show the effects of changes in the US interest rate and its lagged values, respectively, on stock market returns.

We begin by examining the effects of local interest rates on stock market returns. The results indicate that local interest rates have a negative and statistically significant effect on daily stock market returns in India, Pakistan, Hong Kong, and Turkey. From a theoretical perspective, a negative relationship between interest rates and stock market returns is expected through the cost-of-capital channel. Higher interest rates increase the cost of borrowing, raising firms' financing costs and reducing investors' expected returns. Consequently, stock market returns tend to decline. Our finding is consistent with a large body of empirical literature. For example, Thorbecke (1997), Elyasiani and Mansur (1998), Elyasiani and Mansur (1998), Rashid Sabri (2004), Rigobon and Sack (2004), Bernanke and Kuttner (2005), Bjørnland and Leitemo (2009), and Galí and Gambetti (2015) all provide strong evidence of a significant negative relationship between interest rates and stock market returns.

Interestingly, this study also finds evidence of a positive effect of local interest rates on stock market returns in Sri Lanka, China, Malaysia, Indonesia, Morocco, and South Korea. However, the effect is highly statistically significant only in South Korea. This finding is contrary to the prediction of conventional asset pricing theory, which generally suggests a negative relationship between interest rates and stock market returns. Nevertheless, few recent studies have documented a positive relationship between interest rates and stock market returns. For example, Jarociński and Karadi (2020) argue that such a positive relationship may arise through the central bank information channel.

The information channel plays an important role in generating a positive relationship between interest rates and stock market returns (Jarociński and Karadi, 2020). When central banks announce changes in policy rates, whether tightening or easing monetary policy, they simultaneously provide information about economic outlook, future economic conditions, and policy expectations. These announcements often contain additional information that influences investors' expectations beyond the policy rate itself. For example, a central bank may announce an increase in the policy interest rate while simultaneously providing an optimistic assessment of future economic growth. If investors interpret this information as a signal of stronger future economic performance, the positive information effect may outweigh the negative impact of higher interest rates. As a result, stock prices may increase despite the rise in interest rates. Such information effects may therefore weaken or even reverse the conventional negative relationship between interest rates and stock market returns. The positive effects identified in this study are consistent with the findings of Jarociński and Karadi (2020).

We also observe that local interest rates have a negative and statistically significant effect on stock market returns in Hungary on the day of the interest rate change. In contrast, the lagged effects become positive and statistically significant on the following trading day. This finding is not surprising, as several empirical studies have documented negative contemporaneous effects and positive delayed effects of interest rate changes on stock market returns (see, for example, Melcangi and Sterk, 2024; Bernanke and Kuttner, 2005). However, we find no statistically significant evidence of the effects of local interest rates on stock market returns in Taiwan, Thailand, South Africa, or Kenya.

The effect of US interest rates on stock market returns in the selected EMEs is among the main focuses of this study and is reported in Table 2.2. The results provide evidence of asymmetric effects of US interest rates on the stock market returns across the selected EMEs. Interestingly, we find that increases in US interest rates generally have positive effects on stock market returns in most EMEs, with the exceptions of Sri Lanka, Morocco, and Kenya. However, these positive effects are statistically significant only in China, India, Turkey, Hungary, and Hong Kong.

The positive effects of US interest rates can also be explained through the information channel. As discussed earlier, information shocks associated with US Federal Reserve policy announcements may generate positive spillover effects on stock markets in emerging market economies. Federal Reserve announcements provide investors not only in the US but also around the world with valuable information regarding future US economic conditions (Jarociński and Karadi (2020)). Because emerging market economies are closely linked to the US economy through international trade and financial markets, positive signals regarding future US economic performance may improve expectations about global economic activity. Consequently, increases in US interest rates may be interpreted as reflecting a stronger US economy, thereby improving investor confidence and generating positive effects on stock market returns in emerging market economies. These findings are consistent with those of Faff et al. (2005), who reported a positive relationship between interest rates and the stock returns of large banks during the pre-deregulation period in Australia.

In contrast, the results indicate that US interest rates have a negative and statistically significant effect on stock market returns in Sri Lanka. This finding is also economically plausible. Sri Lanka is a relatively small open economy that depends heavily on foreign capital. Moreover, the country experienced more than three decades of civil war, during which it relied substantially on external borrowing to finance both military expenditures and broader government spending. Under these circumstances, increases in US interest rates raise global borrowing costs and tighten international financial conditions, thereby increasing the cost of external financing. These factors can adversely affect economic activity and, consequently, reduce stock market returns.

2.5.2 Stock Market Volatility: Local and US Interest Rates

We now shift our focus to the next main objective of this study: examining how stock market volatility responds to changes in local and US interest rates. Table 2.3 presents the estimated results of the variance model (2.6). Specifically, we investigate the effects of (i) increases and decreases in local interest rates ($\pi^{+}_{1,t}$ and $\pi^{-}_{1,t}$), (ii) increases and decreases in US interest rates ($\pi^{+}_{2,t}$ and $\pi^{-}_{2,t}$), and (iii) the volatilities of local and US interest rates ($\sigma^2_{\pi_{1,t}}$ and $\sigma^2_{\pi_{2,t}}$) on stock market volatility in each emerging market economy.

First, we examine how increases and decreases in local interest rates affect stock return volatility. The rows corresponding to $\pi^{+}_{1,t}$ and $\pi^{-}_{1,t}$ in Table 2.3 report the effects of positive and negative changes in local interest rates, respectively. We find that an increase in local interest rates significantly raises the conditional volatility of stock market returns in India, Pakistan, Thailand, Indonesia, Kenya, and Hungary. At the same time, it has no statistically significant effect in the remaining emerging market economies included in this study.

The results also reveal asymmetric responses of stock market volatility to declines in local interest rates. Specifically, decreases in local interest rates significantly reduce conditional stock market volatility in China, significantly increase volatility in India, Sri Lanka, Hong Kong, Thailand, Indonesia, Kenya, and Hungary, and have no statistically significant effect in Pakistan, Taiwan, South Korea, Malaysia, South Africa, Morocco, and Turkey. These findings are consistent with Gospodinov and Jamali (2015), who report that S&P 500 volatility is sensitive to changes in the federal funds rate. However, their study does not distinguish between positive and negative interest rate changes. In contrast, our study separately examines the effects of increases and decreases in local interest rates, providing a more nuanced understanding of the asymmetric responses of stock market volatility.

Second, we examine the effects of changes in US interest rates on stock market volatility. The rows corresponding to $\pi^{+}_{2,t}$ and $\pi^{-}_{2,t}$ in Table 2.3 report the effects of increases and decreases in US interest rates, respectively. We find that increases in US interest rates tend to reduce stock market volatility in China, India, Hong Kong, and Morocco, although these effects are not statistically significant. In contrast, increases in US interest rates tend to raise stock market volatility in the remaining emerging market economies, with statistically significant effects observed only in India, Turkey, and Hungary. On the other hand, declines in US interest rates generally increase stock market volatility across the EMEs, except in India, Sri Lanka, and Thailand. However, statistically significant evidence is found only for

South Korea. These asymmetric responses are expected because US interest rates influence stock markets through several transmission channels, including demand and credit channels, as discussed by Ammer et al. (2010).

Third, we investigate the effects of the volatilities of local and US interest rates on stock market volatility. The rows labelled $\sigma^2_{\pi_{1,t}}$ and $\sigma^2_{\pi_{2,t}}$ in Table 2.3 present the estimated effects of local and US interest rate volatility on the daily conditional volatility of stock market returns.

The results indicate both positive and negative effects of local interest rate volatility across the EMEs. Positive responses are observed in India, Sri Lanka, China, Indonesia, South Africa, and Turkey, whereas negative responses are found in the remaining countries. However, only the positive effect in Indonesia and the negative effect in Hungary are statistically significant. These asymmetric effects are consistent with the findings of Kasman et al. (2011), Elyasiani and Mansur (1998) and Faff et al. (2005).

Similarly, US interest rate volatility exhibits asymmetric effects on stock market volatility. Negative responses are observed in India, Pakistan, Taiwan, South Korea, Malaysia, Thailand, South Africa, and Hungary, although only Pakistan, India and Thailand show statistically significant effects. Conversely, stock market volatility responds positively to US interest rate volatility in Sri Lanka, China, Hong Kong, Indonesia, Morocco, Kenya, and Turkey. Among these, only Sri Lanka, Morocco, and Turkey exhibit statistically significant positive effects.

We next compare the effects of local and US interest rates on stock market volatility using the results reported in Table 2.3. The findings indicate that stock market volatility is generally more sensitive to changes in local interest rates than to changes in US interest rates. In contrast, US interest rate volatility has a more pronounced effect on stock market volatility than local interest rate volatility. For example, in India, Pakistan, Sri Lanka, Thailand, Morocco, and Turkey, US interest rate volatility has larger and statistically significant effects on stock market volatility, whereas local interest rate volatility has relatively smaller and statistically insignificant effects.

These findings are consistent with Hoek et al. (2020) and Ammer et al. (2010). Hoek et al. (2020) show that US monetary policy shocks have stronger effects on economies with higher levels of macroeconomic instability. In our sample, Pakistan, Sri Lanka, and Turkey exhibit relatively high levels of macroeconomic uncertainty. Ammer et al. (2010) argue that US monetary policy has greater effects on economies that are highly integrated through trade and financial markets. Within our sample, India, Thailand,

and Morocco fall into this category.

An interesting finding of this study is that US interest rate volatility has a stronger effect on stock market volatility in the selected EMEs than local interest rate volatility. During periods of global economic stability, changes in local interest rates may exert a greater influence on stock market volatility because they directly affect domestic business activity and economic conditions. By contrast, changes in US interest rates often affect emerging economies indirectly, making their immediate impact on stock market volatility more responsive to changes in local interest rates than to changes in US interest rates.

However, interest rate volatility reflects uncertainty rather than the direction of policy changes. Higher interest rate volatility signals greater uncertainty, which may increase investor anxiety and lead to stronger reactions in stock markets. Consequently, stock market volatility may increase. Investors may respond more strongly to volatility in U.S. interest rates than to volatility in local interest rates because uncertainty surrounding U.S. monetary policy can generate widespread uncertainty across the global economy. Given the high degree of integration between the U.S. economy and the rest of the world, fluctuations in U.S. interest rate volatility can have substantial spillover effects on emerging markets.

Historical episodes such as the 1929 Wall Street Crash and the 2007–2008 Global Financial Crisis illustrate how financial disturbances originating in the United States can spread rapidly to other economies. Numerous empirical studies have documented the global influence of U.S. economic conditions and monetary policy (Miranda-Agrippino and Rey, 2020; Ahmed et al., 2024; Obstfeld and Zhou, 2023). These factors may explain why our results indicate that stock markets in the selected emerging market economies are more sensitive to U.S. interest rate volatility than to local interest rate volatility.

Table 2.2: Results of the mean model (2.5)

Variables	India	Pakistan	Sri Lanka	China	Taiwan	Hong Kong	South Korea	Malaysia	Thailand	Indonesia	South Africa	Morocco	Kenya	Turkey	Hungary
μ	0.149***	-0.074**	-0.083***	0.086***	0.043**	0.025*	0.023	-0.001	-0.045*	-0.000	0.062**	-0.010	0.008	0.190***	0.058**
	(0.025)	(0.029)	(0.022)	(0.031)	(0.020)	(0.015)	(0.028)	(0.009)	(0.025)	(0.000)	(0.026)	(0.019)	(0.021)	(0.047)	(0.028)
y_{t-1}	0.036***	0.102***	0.157***	0.018	-0.042***	-0.001	-0.054***	0.028**	-0.021	-0.004	-0.020	0.100***	0.255***	-0.036***	-0.005
	(0.013)	(0.014)	(0.013)	(0.013)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)	(0.014)	(0.012)	(0.014)	(0.013)
$\pi_{1,t}$	-0.441**	-0.816***	0.048	0.084	-0.051	-0.963***	0.950**	0.098	-0.016	0.001	-0.011	0.015	-0.026	-0.289***	-0.867***
	(0.190)	(0.141)	(0.063)	(0.241)	(0.472)	(0.277)	(0.397)	(0.312)	(0.361)	(0.001)	(0.097)	(0.024)	(0.035)	(0.044)	(0.192)
$\pi_{1,t-1}$	-0.268	-0.038	-0.085	-0.226	0.552	-0.539*	0.386	0.151	-0.360	-0.000	0.141	0.003	0.048	0.012	0.658***
	(0.173)	(0.170)	(0.067)	(0.252)	(0.446)	(0.277)	(0.387)	(0.257)	(0.325)	(0.001)	(0.091)	(0.021)	(0.035)	(0.045)	(0.195)
$\pi_{2,t-1}$	0.189	0.274	-0.232*	0.617*	0.165	0.467*	0.219	0.061	0.137	0.003	0.349	-0.157	-0.148	1.053***	0.707**
	(0.182)	(0.263)	(0.133)	(0.318)	(0.261)	(0.276)	(0.204)	(0.299)	(0.209)	(0.002)	(0.254)	(0.145)	(0.165)	(0.398)	(0.292)
$\pi_{2,t-2}$	0.414*	-0.146	-0.144	0.002	-0.002	0.140	0.252	0.118	0.082	0.001	-0.122	0.177	0.187	-0.120	-0.347
	(0.211)	(0.257)	(0.129)	(0.319)	(0.267)	(0.226)	(0.208)	(0.162)	(0.242)	(0.003)	(0.239)	(0.156)	(0.166)	(0.366)	(0.268)
LCD_t	-0.761***	-0.148***	0.004	-1.166***	-0.833***	-2.711***	-0.549***	-0.398***	-0.341***	-0.010***	-0.170***	-0.039	-0.112***	-0.697***	-0.636***
	(0.034)	(0.034)	(0.031)	(0.100)	(0.048)	(0.354)	(0.023)	(0.021)	(0.036)	(0.000)	(0.016)	(0.040)	(0.022)	(0.029)	(0.035)
LCD_{t-1}	-0.132***	-0.013	-0.037	-0.231**	-0.381***	-1.494***	-0.180***	-0.067**	-0.158***	-0.000	-0.087***	0.004	-0.025	-0.111***	-0.200***
	(0.033)	(0.038)	(0.037)	(0.096)	(0.049)	(0.359)	(0.024)	(0.029)	(0.032)	(0.000)	(0.015)	(0.039)	(0.024)	(0.027)	(0.033)
UDA_t	0.094***	0.015	0.006	-0.050	0.098***	-0.037	0.208***	0.017	0.013	0.001***	-0.013	0.036	-0.004	0.131***	0.740***
	(0.028)	(0.031)	(0.024)	(0.035)	(0.033)	(0.028)	(0.030)	(0.027)	(0.030)	(0.000)	(0.033)	(0.038)	(0.019)	(0.045)	(0.061)
UDA_{t-1}	-0.071***	-0.024	0.027	-0.250***	-0.106***	-0.197***	-0.101***	-0.008	-0.132***	-0.001*	-0.001	-0.030	-0.015	-0.065	0.214***
	(0.027)	(0.032)	(0.025)	(0.042)	(0.030)	(0.033)	(0.031)	(0.034)	(0.030)	(0.000)	(0.033)	(0.037)	(0.020)	(0.045)	(0.059)
OPR_t	0.035***	0.010	0.014***	0.052***	0.023***	0.035***	0.040***	0.006	0.048***	0.000***	0.061***	0.004	-0.002	0.041***	0.066***
	(0.006)	(0.006)	(0.005)	(0.008)	(0.006)	(0.004)	(0.006)	(0.006)	(0.005)	(0.000)	(0.006)	(0.004)	(0.004)	(0.009)	(0.008)
OPR_{t-1}	0.015***	0.027***	0.006	0.044***	0.028***	0.023***	0.039***	0.018**	0.029***	0.000***	0.020***	0.003	0.003	0.010	0.009
	(0.006)	(0.006)	(0.005)	(0.008)	(0.003)	(0.006)	(0.006)	(0.008)	(0.005)	(0.000)	(0.006)	(0.004)	(0.004)	(0.008)	(0.007)

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Table 2.2: Results of the mean model (2.5) (continued)

Variables	India	Pakistan	Sri Lanka	China	Taiwan	Hong Kong	South Korea	Malaysia	Thailand	Indonesia	South Africa	Morocco	Kenya	Turkey	Hungary
GPR_t	-0.005	0.004	-0.010	0.018	-0.007	0.025*	-0.009	0.005	-0.051***	-0.000	0.144***	0.003	0.002	0.027	0.003
	(0.013)	(0.014)	(0.010)	(0.017)	(0.013)	(0.014)	(0.013)	(0.006)	(0.014)	(0.000)	(0.014)	(0.009)	(0.009)	(0.021)	(0.019)
GPR_{t-1}	-0.010	0.009	-0.001	0.024	0.001	0.003	-0.014	-0.010	-0.006	0.000	-0.019	-0.002	0.004	-0.017	-0.003
	(0.013)	(0.015)	(0.010)	(0.017)	(0.008)	(0.015)	(0.014)	(0.017)	(0.013)	(0.000)	(0.014)	(0.009)	(0.009)	(0.019)	(0.017)
GFC	0.026	0.036	-0.138***	-0.032	-0.012	-0.027	0.039	-0.038	-0.013	0.001	-0.087	-0.005	-0.141***	-0.235***	-0.195***
	(0.079)	(0.075)	(0.034)	(0.097)	(0.068)	(0.057)	(0.060)	(0.054)	(0.067)	(0.001)	(0.059)	(0.039)	(0.048)	(0.078)	(0.072)
CVD	0.072*	-0.120**	-0.024	-0.075	0.044	-0.035	-0.004	-0.023	-0.017	-0.001*	-0.044	0.020	-0.007	0.067	0.039
	(0.037)	(0.054)	(0.056)	(0.064)	(0.040)	(0.047)	(0.044)	(0.032)	(0.036)	(0.000)	(0.046)	(0.028)	(0.048)	(0.060)	(0.055)
URW	-0.014	-0.155*	-0.208**	-0.095	-0.047	-0.111	-0.027	-0.043**	0.010	-0.000	-0.062	-0.029	-0.185***	0.290***	-0.095
	(0.053)	(0.081)	(0.100)	(0.103)	(0.069)	(0.068)	(0.061)	(0.018)	(0.039)	(0.001)	(0.066)	(0.047)	(0.068)	(0.106)	(0.083)
TUE	-0.053*	0.137***	0.039	-0.071	0.025	0.003	0.058	0.042**	0.100***	0.001**	-0.029	0.037	0.021	-0.101	-0.041
	(0.032)	(0.039)	(0.027)	(0.044)	(0.034)	(0.027)	(0.040)	(0.017)	(0.035)	(0.000)	(0.038)	(0.024)	(0.024)	(0.062)	(0.040)
WED	-0.102***	0.151***	0.116***	-0.034	-0.009	0.049*	0.004	0.007	0.111***	0.001***	-0.044	0.032	0.082***	-0.170***	0.034
	(0.033)	(0.040)	(0.030)	(0.048)	(0.029)	(0.027)	(0.038)	(0.023)	(0.034)	(0.000)	(0.038)	(0.025)	(0.027)	(0.061)	(0.045)
THU	-0.108***	0.115***	0.132***	-0.089*	-0.014	-0.017	-0.007	0.012	-0.001	0.000	-0.003	0.046*	0.066**	-0.037	0.006
	(0.036)	(0.041)	(0.030)	(0.047)	(0.034)	(0.024)	(0.040)	(0.018)	(0.034)	(0.000)	(0.037)	(0.025)	(0.027)	(0.063)	(0.045)
FRI	-0.127***	0.155***	0.141***	-0.072	-0.041	0.022	-0.023	0.022	0.056*	0.001	-0.056	0.048**	0.043*	-0.113*	-0.057
	(0.034)	(0.039)	(0.028)	(0.045)	(0.025)	(0.031)	(0.040)	(0.017)	(0.034)	(0.000)	(0.037)	(0.024)	(0.024)	(0.062)	(0.043)

Note: This table presents the effects of both local (π_1) and US (π_2) interest rates on stock market returns (y_t) along with the effects of control variables consisting of continuous and dummy variables. Local Currency Depreciation (LCD), US Dollar Appreciation (UDA), Oil Price Returns (OPR) and Gold Price Returns (GPR) are the continuous variables (X_t) in (2.5). The recent Global Financial Crisis (GFC), COVID-19 pandemic (CVD), Ukraine-Russia War-2022 (URW), Tuesday (TUE), Wednesday (WED), Thursday (THU), and Friday (FRI) are the dummy variables (D_t) in (2.5). The optimal lag length for estimating the mean model is selected based on the AIC. Further, *, ** and *** represent significance levels at 10%, 5% and 1% respectively.

Table 2.3: Results of the variance model (2.6)

Variables	India	Pakistan	Sri Lanka	China	Taiwan	Hong Kong	South Korea	Malaysia	Thailand	Indonesia	South Africa	Morocco	Kenya	Turkey	Hungary
ω_0	-4.578***	-3.226***	-2.616***	-2.336***	-3.434***	-3.883***	-4.938***	-4.608***	-4.299***	-11.58***	-3.702***	-2.919***	-1.768***	-2.509***	-3.066***
	(0.761)	(0.331)	(0.272)	(0.319)	(0.330)	(0.489)	(0.889)	(0.369)	(0.509)	(0.157)	(0.364)	(0.214)	(0.194)	(0.370)	(0.323)
$\pi^{+}_{1,t}$	1.824**	0.497**	0.315	-0.448	0.038	0.214	-0.523	0.335	1.230***	2.073***	-0.242	-0.062	0.332*	0.358	1.049***
	(0.733)	(0.216)	(0.219)	(0.345)	(0.359)	(0.641)	(0.735)	(0.553)	(0.450)	(0.131)	(0.455)	(0.397)	(0.199)	(0.221)	(0.245)
$\pi^{-}_{1,t}$	1.402*	0.048	0.478**	-0.634*	-0.104	0.958*	0.457	-0.054	1.006**	1.923***	0.218	-0.022	0.418**	-0.278	0.624***
	(0.765)	(0.269)	(0.198)	(0.345)	(0.414)	(0.515)	(0.445)	(1.021)	(0.482)	(0.129)	(0.331)	(0.415)	(0.172)	(0.274)	(0.232)
$\pi^{+}_{2,t}$	-0.006	1.014***	0.068	-0.862	0.066	-3.730	1.180	0.154	0.446	0.037	0.407	-0.339	0.270	0.600**	0.430*
	(0.270)	(0.317)	(0.239)	(0.605)	(0.434)	(11.742)	(0.850)	(0.522)	(0.512)	(0.084)	(0.429)	(0.290)	(0.183)	(0.306)	(0.253)
$\pi^{-}_{2,t}$	-0.209	0.262	-0.012	0.191	0.233	0.196	1.564*	0.640	-7.151	0.130	0.128	0.132	0.144	0.250	0.277
	(0.276)	(0.399)	(0.248)	(0.335)	(0.390)	(0.383)	(0.877)	(0.419)	(14.053)	(0.083)	(0.499)	(0.228)	(0.185)	(0.352)	(0.263)
$\sigma^2_{\pi_{1,t}}$	4.904	-0.066	0.098	1.396	-17.701	-41.980	-18.830	-90.614	-32.160	0.339*	0.144	-0.028	-0.061	0.071	-4.132**
	(9.042)	(1.366)	(0.173)	(5.622)	(24.560)	(38.586)	(42.036)	(57.466)	(127.803)	(0.186)	(1.256)	(0.034)	(0.447)	(0.058)	(2.065)
$\sigma^2_{\pi_{2,t}}$	-7.782**	-14.962*	3.913*	2.350	-3.084	0.864	-16.615	-5.050	-74.979*	1.740	-3.249	4.005**	1.308	4.024*	-0.791
	(3.240)	(8.575)	(2.052)	(3.351)	(3.471)	(5.024)	(11.371)	(4.842)	(41.904)	(1.527)	(6.115)	(1.956)	(2.399)	(2.386)	(2.328)
$\sigma^2_{LCD,t}$	-0.257	0.104***	0.013	-0.058	-2.158	-22.959	-0.888**	-0.796	0.169**	0.369***	0.098	0.601	0.098	0.042**	0.359***
	(0.347)	(0.023)	(0.023)	(1.969)	(1.329)	(55.758)	(0.423)	(0.516)	(0.083)	(0.119)	(0.060)	(0.915)	(0.120)	(0.020)	(0.117)
$\sigma^2_{UDA,t-1}$	1.220***	0.730	2.283***	1.881***	2.022***	2.022**	3.329***	1.354**	1.064	1.441***	0.061	0.683	-0.258	0.762*	0.912*
	(0.453)	(0.526)	(0.494)	(0.573)	(0.623)	(0.821)	(0.821)	(0.628)	(1.229)	(0.294)	(0.635)	(0.968)	(0.461)	(0.452)	(0.513)
OPR_t	0.112***	0.043	0.056	0.067***	0.084***	0.080***	0.119***	-0.074	-0.039	-0.011	0.089***	0.099***	0.028	0.073***	-0.054
	(0.015)	(0.044)	(0.050)	(0.013)	(0.013)	(0.016)	(0.021)	(0.169)	(0.265)	(0.027)	(0.014)	(0.017)	(0.024)	(0.014)	(0.084)
OPR_{t-1}	-0.124***	-0.043	-0.006	-0.086***	-0.115***	-0.105***	-0.164***	0.069	-0.075	0.013	-0.104***	-0.121***	-0.017	-0.092***	0.051
	(0.023)	(0.048)	(0.049)	(0.022)	(0.024)	(0.030)	(0.041)	(0.156)	(0.262)	(0.025)	(0.025)	(0.025)	(0.026)	(0.022)	(0.078)
GPR_t	0.226***	0.258***	-0.073	-0.123	0.078	-0.177	-0.027	-0.014	0.141	0.101**	0.082	0.279***	-0.119	0.162**	0.065
	(0.076)	(0.085)	(0.077)	(0.111)	(0.085)	(0.148)	(0.121)	(0.111)	(0.177)	(0.051)	(0.103)	(0.076)	(0.076)	(0.072)	(0.072)

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Table 2.3: Results of the variance model (2.6) (continued)

Variables	India	Pakistan	Sri Lanka	China	Taiwan	Hong Kong	South Korea	Malaysia	Thailand	Indonesia	South Africa	Morocco	Kenya	Turkey	Hungary
GFC_t	1.455***	0.661**	-0.832***	1.269***	1.196***	1.414***	1.447***	1.494***	2.507***	0.476***	0.798***	0.045	0.377*	0.181	0.296
	(0.207)	(0.302)	(0.236)	(0.274)	(0.250)	(0.352)	(0.350)	(0.307)	(0.552)	(0.139)	(0.299)	(0.222)	(0.215)	(0.228)	(0.189)
CVD_t	-0.087	0.272	0.983***	0.517**	0.412**	0.380	0.637***	1.001***	-0.293	0.367***	0.396*	-0.255	0.295*	0.002	0.380**
	(0.181)	(0.203)	(0.189)	(0.207)	(0.183)	(0.279)	(0.240)	(0.222)	(0.416)	(0.119)	(0.211)	(0.178)	(0.173)	(0.182)	(0.149)
URW_t	-0.248	-0.098	0.801***	0.737**	0.502**	0.794**	0.074	0.392	0.287	-0.349**	0.575**	0.059	0.435*	0.787***	-0.145
	(0.234)	(0.256)	(0.263)	(0.329)	(0.248)	(0.343)	(0.334)	(0.282)	(0.529)	(0.144)	(0.288)	(0.251)	(0.238)	(0.215)	(0.202)
u^2_{t-1}	0.179***	0.305***	0.480***	0.106***	0.095***	0.091***	0.096***	0.123***	0.121***	0.454***	0.127***	0.255***	0.327***	0.128***	0.154***
	(0.023)	(0.031)	(0.071)	(0.014)	(0.014)	(0.013)	(0.014)	(0.017)	(0.013)	(0.059)	(0.014)	(0.031)	(0.039)	(0.021)	(0.021)
$I_{\{u_{t-1}>0\}}$	-0.169***	-0.214***	-0.221***	-0.073***	-0.087***	-0.062***	-0.087***	-0.064***	-0.090***	-0.350***	-0.118***	-0.071**	-0.034	-0.054***	-0.110***
	(0.025)	(0.030)	(0.058)	(0.014)	(0.015)	(0.012)	(0.015)	(0.016)	(0.013)	(0.060)	(0.015)	(0.032)	(0.044)	(0.020)	(0.021)
σ^2_{t-1}	0.828***	0.753***	0.635***	0.889***	0.903***	0.914***	0.919***	0.865***	0.912***	0.105***	0.897***	0.698***	0.513***	0.827***	0.801***
	(0.022)	(0.018)	(0.025)	(0.014)	(0.014)	(0.013)	(0.013)	(0.019)	(0.008)	(0.024)	(0.013)	(0.024)	(0.032)	(0.026)	(0.030)
Λ	0.326***	1.150***	-0.137	0.318***	0.209***	0.229***	0.304***	0.186***	1.222***	0.575***	0.450***	0.628***	0.036*	0.302***	0.346***
	(0.027)	(0.125)	(0.164)	(0.027)	(0.026)	(0.028)	(0.027)	(0.029)	(0.116)	(0.129)	(0.028)	(0.125)	(0.022)	(0.026)	(0.027)
N	5685	5622	5645	5685	5685	5685	5685	5685	5685	5685	5685	5685	5685	5685	5685
AIC	15811	17970	15640	19459	16255	16393	16415	10069	16234	-34678	16433	12586	15048	20500	19072
BIC	16077	18235	15905	19725	16521	16659	16681	10335	16500	-34413	16698	12852	15314	20766	19338
LL	-7865.5	-8944.9	-7779.8	-9689.7	-8087.7	-8156.4	-8167.6	-4994.6	-8077.3	17379.2	-8176.3	-6253.0	-7483.9	-10210.1	-9496.0
χ^2	654.34	176.91	219.99	371.37	522.18	308.56	903.79	672.03	325.71	1066.62	617.35	71.55	508.95	886.23	529.02

Note: This table presents the effects of the changes and volatilities of both local (π_1) and US (π_2) interest rates on the volatilities of stock market returns in each EME, along with the effects of the control variables consisting of continuous and dummy variables. $\pi^+_{1,t}$ and $\pi^-_{1,t}$ denote positive and negative changes in local interest rates, respectively, while $\pi^+_{2,t}$ and $\pi^-_{2,t}$ represent the same for the case of US interest rates. The conditional volatilities of the local and US interest rates are denoted by $\sigma^2_{\pi_{1,t}}$ and $\sigma^2_{\pi_{2,t}}$, respectively. Conditional volatility of local currency depreciation ($\sigma^2_{LCD,t}$), conditional volatility of US dollar appreciation ($\sigma^2_{UDA,t}$), oil price returns (OPR), and gold price returns (GPR) are included in the multiplicative heteroskedasticity component (MHC) of (2.6). The recent global financial crisis (GFC), COVID-19 pandemic (CVD) and Ukraine-Russia war 2022 (URW) are the dummy variables (D_t) included in the MHC of (2.6). The optimum lag lengths of explanatory variables in the multiplicative heteroskedasticity component are selected based on the AIC. The residuals (u_t) in the mean model (2.5) are assumed to follow the Generalised Error Distribution (GED), and the corresponding shape parameter is noted by Λ in this table. The standard univariate GARCH(1,1) is utilized to obtain the following conditional volatilities: $\sigma^2_{\pi_{1,t}}$, $\sigma^2_{\pi_{2,t}}$, $\sigma^2_{LCD,t}$, and $\sigma^2_{UDA,t}$. LL and χ^2 show the log-likelihood and the Chi-Square values, respectively, of our GARCH estimation. Further, *, **, and *** represent significance levels at 10%, 5%, and 1%, respectively.

2.5.3 Stock Market Returns: Structural Breaks

Table 2.2 presents the results of the mean model (2.5) of the GARCH framework used in this study. Stock markets are sensitive to global turmoil, which can generate structural breaks over time. To account for these structural breaks, this study incorporates dummy variables representing the three major events that are expected to have affected stock market returns: the 2007-2008 global financial crisis, the COVID-19 pandemic, and the Ukraine-Russia war that began in February 2022. In Table 2.2, the rows labelled GFC, CVD and URW represent the effects of the 2007-2008 global financial crisis, the COVID-19 pandemic, and the Ukraine-Russia war, respectively, on stock market returns in the selected Asian countries.

We begin by examining the effects of the global financial crises. The results indicate that stock market returns in Sri Lanka, Kenya, Turkey and Hungary were significantly lower during the global financial crisis than during other periods. However, the findings suggest that Sri Lanka experienced a more severe decline in stock market returns than other selected countries during the crisis. Sri Lanka had been affected by a civil war for more than 30 years, which ended in May 2009. The period from 2008 to 2009 was particularly challenging for the country, as it had to cope simultaneously with the ongoing civil war and the global financial crisis. This may be the primary reason why Sri Lankan stock market returns declined dramatically during this period. Many previous empirical studies have reported that the global financial crisis had adverse effects on stock market returns worldwide, and these effects were more severe in Western countries than in Asian economies (Schwert, 2011; AM Al-Rjoub and Azzam, 2012). The responses of stock market returns to the global financial crisis are consistent with the findings of these earlier studies.

The row labelled CVD in Table 2.2 shows the behaviour of stock market returns in the selected Asian market economies during the COVID-19 pandemic. We find that stock market returns were lower in many countries during the pandemic; in particular, the decline was statistically significant in Pakistan and Indonesia. At the same time, this study finds increases in stock market returns in India, Taiwan, Morocco, Turkey, and Hungary, with India recording a statistically significant increase in returns. These mixed results are consistent with findings reported in earlier studies. Uddin et al. (2021) examined the direct and indirect effects of the COVID-19 pandemic on stock markets in 34 developed and emerging economies. They used the total number of COVID-19 cases and deaths to represent the severity of the COVID-19 pandemic in each country. They found that increases in both measures were associated with reductions in overall stock market returns. Similarly, Harjoto et al. (2021) revealed a strong association between stock market returns and the number of COVID cases using a multiple linear regression model based on data from 53 emerging markets and 23 developed countries. In contrast, Narayan et al. (2021) used a dummy variable to represent the COVID-19 pandemic and found that stock market returns in the G7 countries were higher during the pandemic period. The findings of our study are broadly consistent with the evidence reported in these previous studies.

The nature of the Ukraine-Russia war that began in 2022 differs from that of the 2007-2008 global financial crisis and the COVID-19 pandemic. The responses of stock market returns during the peak of the Ukraine-Russia war are displayed in the row labelled URW in Table 2.2. The results indicate that the Ukraine-Russia war had negative effects on stock market returns in all selected countries except in Turkey. These negative effects were statistically significant in Pakistan, Sri Lanka, Malaysia and Kenya. Interestingly, we find that the war had a positive and statistically significant effect on Turkish stock market returns. Previous empirical studies provide evidence of both positive and negative effects of the war on stock market returns in other countries. For example, Boubaker et al. (2022) found that the Ukraine-Russia war generated negative cumulative abnormal returns in global stock markets; however, stock markets in NATO countries experienced higher returns, consistent with the expected economic stimulus associated with increased military preparedness, as demonstrated through an event study.

2.5.4 Stock Market Returns: the Day-of-Week Effect

We now turn to the day-of-week effect on financial market returns, as shown by the rows labelled TUE, WED, THU and FRI in Table 2.2. The most widely documented pattern is the weekend effect, which suggests that returns on Mondays are lower than those on other trading days, often attributed to the accumulation of negative news over the weekend. In the early stages of financial markets, particularly before the rapid advancement of information and communication technologies, financial institutions often released bad news during weekends. As a result, this negative news tended to adversely affect stock market performance at the beginning of the following trading week.

In this study, we find evidence supporting both the weekend and the reverse weekend effect. The results presented in Table 2.2 indicate that stock markets in Pakistan, Sri Lanka, Thailand, Indonesia, and Kenya exhibit significantly higher returns on other weekdays compared with Mondays. This evidence strongly supports the weekend effect hypothesis and is consistent with the findings of Smirlock and Starks (1986) and Zhang et al. (2017). Furthermore, Malaysia, Hong Kong, and Morocco provide mild evidence for the weekend effect. In contrast, we find strong evidence of a reverse weekend effect in India and Turkey, where stock market returns are significantly higher on Mondays than on other trading days. China also shows mild evidence of this reverse weekend effect. In the empirical literature, Brusa et al. (2000) documented a reverse weekend effect in the US using the Dow Jones Industrial Average (DJIA). However, we find no significant evidence of any day-of-the-week effects in Taiwan, South Korea, South Africa, or Hungary.

2.5.5 Stock Market Returns: International Commodity Prices

This study considers crude oil price and gold prices as explanatory variables for stock market returns. The rows labelled OPR and GPR in Table 2.2 present the effects of oil price returns and gold price returns, respectively, on stock market returns. Changes in oil prices can have either positive or negative effects on stock market returns, depending on the sources of the oil price shocks. Positive oil price shocks driven by demand-side factors may have positive effects on stock market returns because stronger global demand is generally associated with improved economic conditions. This, in turn, can increase aggregate demand and stimulate stock market performance.

Our results indicate that oil price returns have a positive and statistically significant impact on stock market returns in all the selected countries except Morocco and Kenya, where the effects of oil price returns are not statistically significant. The empirical literature provides evidence of both positive and negative effects of oil price shocks on stock market returns (Kilian and Park, 2009; Degiannakis et al., 2013; Ready, 2017). These studies decompose oil price shocks into demand-side and supply-side shocks. Ready (2017) shows that demand-side shocks have a positive effect on stock returns, whereas supply-side shocks have a negative effect. Similarly, Degiannakis et al. (2013) find that supply-side shocks have a negative effect on stock market returns. In contrast, demand-side shocks can have either positive or negative effects, depending on the underlying conditions.

In this study, oil price returns are not decomposed into demand-side and supply-side shocks, as our objective is not to identify the specific effects of different types of oil price shocks. Nevertheless, our findings suggest that oil price returns have a positive effect on stock returns in the selected emerging market economies, except Morocco and Kenya.

Table 2.2 also presents the effect of gold prices (including its lagged term) on stock market returns, which are displayed in the rows labelled GPR_t and GPR_{t-1}. We find mixed effects of gold prices on stock markets. Investors in the financial markets also invest in gold markets, and the extent of these investments depends on the current level of uncertainty and expected future uncertainty.

Gold is considered a safe-haven asset because investors tend to shift their investment portfolios toward gold when they expect financial markets to become more vulnerable, especially in future. Historically, gold prices have shown an increasing trend, although they also exhibit fluctuations over time. The results indicate that gold price returns have positive and statistically significant effects on stock market returns in Hong Kong and South Africa, but negative and statistically significant effects in Thailand. However, we find no significant effects in the other cases considered in this study. These results are consistent with the findings of Raza et al. (2016).

The positive effects of gold price returns suggest that increases in gold prices tend to increase stock market returns. We observe these positive effects in South Korea and Hong Kong as we expected. South Africa is one of the world's major gold-producing countries, and increases in global gold prices can have positive effects on its economy because higher gold prices increase national earnings. This, in turn, increases aggregate demand and improves stock market performance. The positive effect of gold prices in Hong Kong is also expected because Hong Kong is an international financial centre. Increases in gold prices may lead to capital inflows into Hong Kong, which can boost stock market activity. In general, the negative effect of gold prices suggests that increases in gold prices reduce stock market returns. Rising gold prices may signal higher uncertainty in financial markets, leading investors to shift their portfolios toward safe-haven assets, including gold. This can negatively affect stock markets in Hong Kong. In all other countries, gold prices do not show any significant effects on stock market returns.

2.5.6 Stock Market Returns: Exchange Rates

This study also includes the local exchange rate against the US dollar and the US dollar Index, which measures the value of the US dollar against the currencies of its major trading partners, to explain stock market returns. In Table 2.2, the rows labelled LCD and UDA present the effects of local currency depreciation against the US dollar and US dollar appreciation against its major trading partners, respectively.

The results demonstrate that local currency depreciation has a negative and statistically significant effect on stock market returns in all selected countries except Sri Lanka and Morocco, where the effects remain negative but are not statistically significant. These negative effects are expected because currency depreciation can lead to higher inflation by increasing the prices of goods and services, particularly imported goods such as crude oil. Higher import prices increase production costs, which can slow economic activity and reduce stock market returns. The negative impact of currency depreciation on stock markets is consistent with the findings of previous empirical studies (see, for instance, He et al., 2023; Ajayi and Mougouė, 1996).

The effects of US dollar dynamics on stock market returns in the emerging market economies are also noteworthy. We find both positive and negative effects of US dollar appreciation on stock market returns. The results indicate that the immediate effect of US dollar appreciation is positive and statistically significant in India, Taiwan, South Korea, Indonesia and Turkey. However, these effects become negative and statistically significant at a later stage, particularly after one day. US dollar appreciation against its major trading partners generally reflects a strengthening of the US economy, which may send a positive signal to countries that export to the US. Consequently, stronger demand from the US market may have an immediate positive impact on stock market returns in these economies. However, over time, producers may face higher production costs and reduced international competitiveness, which can eventually exert downward pressure on stock market returns. In contrast, this study finds that both contemporaneous and lagged effects of US dollar appreciation are positive and statistically significant in Hungary. One possible explanation is that a stronger US economy contributes to greater stability in the global economy, thereby improving economic conditions in Hungary and supporting higher stock market returns. These findings are consistent with those of Zarei et al. (2019), who reported that currency appreciation has a positive effect on stock market returns. However, Obstfeld and Zhou (2023) reported that the strengthening of the US dollar has a more adverse effect on output and financial markets in emerging market economies, based on the evidence from a vector autoregression (VAR) framework.

2.5.7 Model Validation Diagnostics

A lag order of one is the most widely used specification for the ARCH and GARCH terms in the variance equation of the GARCH framework. Elyasiani and Mansur (1998), Faff et al. (2005) and Jones et al. (2005) employ the GARCH(1,1) model to illustrate stock market volatility in their studies. Bollerslev (1987) also demonstrates that the GARCH(1,1) model adequately captures the volatility of most univariate economic time series. Following this established literature, we estimate only the GARCH(1,1) specification with a threshold term in this study.

The GARCH framework assumes that the conditional volatility of stock market returns depends on both past squared shocks and past conditional volatility (Bollerslev, 1986). The effects of past squared shocks (u_{t-1}^2) and past conditional volatility (σ_{t-1}^2) are referred to as the ARCH and GARCH effects, respectively. These effects are reported in the rows corresponding to u_{t-1}^2 and σ_{t-1}^2 in Table 2.3.

The results show that the conditional volatility of stock market returns in all EMEs is significantly affected by both past shocks and past conditional volatility, as the estimated ARCH and GARCH coefficients are statistically significant at the 1% level. These findings are consistent with previous empirical studies, including Elyasiani and Mansur (1998),Faff et al. (2005), and Jones et al. (2005). In addition to the ARCH and GARCH effects, the row corresponding to $I_{\{u_{t-1}>0\}}$ in Table 2.3 reports the asymmetric effect on stock market volatility, commonly referred to as the leverage effect, which is denoted by η in variance model (2.6). The results indicate that stock market volatility responds more strongly to bad news than to good news in all EMEs except Kenya. Specifically, the estimated coefficients for $I_{\{u_{t-1}>0\}}$ are negative and statistically significant for all EMEs, indicating the presence of a leverage effect. In contrast, the coefficient for Kenya is negative but statistically insignificant.

Furthermore, for every EME, the sum of the ARCH, GARCH, and Leverage effects $(\alpha+\eta/2+\beta)$ is less than, but close to, one. This provides evidence that the estimated GARCH model satisfies the stationarity condition and the stock market exhibits a high degree of persistence over time.

For the estimation of the GARCH model, we assume that the residuals of the mean equation follow the Generalised Error Distribution (GED). The estimated parameter is reported in the row corresponding to Λ in Table 2.3. The estimated values are positive and statistically significant at the 1% level for all EMEs except Sri Lanka and Kenya. For Sri Lanka, the estimated coefficient is negative and statistically insignificant, while for Kenya it is positive and statistically significant only at the 10% level.

The estimates of Λ provide evidence of excess kurtosis and fat-tailed conditional distributions of stock market returns in nearly all EMEs included in this study. The exceptions are Sri Lanka and Kenya, for which the evidence is weak. In particular, Kenya provides only limited evidence of fat tails in the conditional distribution of its stock market returns.

2.6 Conclusion

Understanding the return-generating process and volatility of stock markets in emerging market economies, particularly their responses to both domestic and US interest rates, is crucial for investors seeking to manage their portfolios and design effective asset pricing and hedging strategies. It is also highly important for policymakers when formulating macroeconomic decisions aimed at ensuring economic prosperity and stability. This study investigates the role of domestic and US interest rates in shaping stock market returns and volatility in the selected emerging market economies.

This research differs from previous studies in two key respects. First, most prior work has focused on examining the impact of domestic interest rates on stock market returns and volatility. In contrast, our study extends beyond domestic interest rates by incorporating US interest rates into the analysis of stock market returns and volatility in emerging market economies. Unlike other studies, this study is mainly interested in examining whether (i) stock market returns in EMEs are more sensitive to US interest rates than local interest rates and (ii) stock market volatility is more reactive to US interest rate volatility than to local interest rate volatility. Second, although most previous studies have employed models that assume constant error variance, we apply a GARCH model allowing for heteroskedastic error variance.

The study presents several key findings. First, local interest rates tend to have a negative and statistically significant effect on stock market returns in many EMEs. In contrast, US interest rates tend to have a positive and statistically significant effect. Second, changes in local interest rates have a greater impact on the conditional volatility of stock market returns than changes in US interest rates. Third, US interest rate volatility has a more pronounced effect on the conditional volatility of stock market returns than local interest rate volatility. Fourth, the effects of both local and US interest rates on stock market returns and their conditional volatility vary across the EMEs.

Chapter 3

US Dollar Surge and Currency Depreciation in Emerging Market Economies

Abstract

We investigate dynamics between US dollar surges and currency values of Emerging Market Economies (EMEs) by using DCC-GARCH and Cross-Quantilogram (CQ) models and daily data from January 1, 2015, to October 31, 2024. This study selects four EME currencies (TRY, PKR, BDT, and LKR) that faced currency crises after the COVID-19 pandemic. This study provides some key findings. First, the depreciation of the selected currencies is positively correlated with US dollar appreciation over time. Second, the hedge ratio of the Turkish Lira against the US dollar index declines over time, particularly during the COVID-19 pandemic and Turkey's local currency crisis. Third, the hedge ratio for the selected South Asian currencies remains small with no significant changes during the COVID-19 pandemic, but doubled during the local currency crises compared to the COVID-19 period. Finally, the CQ analysis shows that the CQ correlation between present and past local currency depreciation in the selected country varies over time, especially during the COVID-19 pandemic and currency crisis, and has a strong correlation with US dollar appreciation.

3.1 Introduction

Exchange rate movements affect the trade balance through a valuation channel and contribute to capital gains and losses on foreign assets and liabilities (Lane and Shambaugh, 2010). The US dollar serves as the primary currency for international transactions in most global markets, and changes in its value can affect the economic and financial stability of Emerging Market Economies (EMEs). Obstfeld and Zhou (2023) explore how US dollar appreciation impacts the EMEs using panel local projection methods and quarterly data. They find that US dollar appreciation deteriorates the level of output, investment, public expenditure, consumption, and financial position in EMEs through a detrimental effect on terms of trade. As we know, a country's trade balance is directly linked to local currency values. Therefore, this study focuses on the US dollar surges and the EMEs' exchange rates.

Several studies have focused on the relationship between various currencies. Albulescu et al. (2018) examine the interaction among EUR, GBP, CAD, and JPY using daily data from 1999 to 2014. Meng and Huang (2019) focus on the comovements of Asian currencies between 1983 and 2017. Li (2011) investigates interconnections among the following currency combinations: AUD-NZD, SEK-EUR, SEK-GBP, GBP-EUR, and CAD-USD. Tamakoshi and Hamori (2014) study the comovements among the major European currencies before the introduction of the euro (EUR). A study by Kočenda and Moravcová (2019) investigate dynamic conditional correlation and volatility transmissions of new EU foreign exchange markets.

However, the focus on US dollar dynamics with EME currencies is limited in the existing literature. Hence, we strengthen the literature by examining the following four aspects. First, we analyse the dynamic conditional correlation between US dollar surges and EME currency depreciation. Second, we compute the time-varying hedge ratio and portfolio weight of US dollar surges to EMEs' depreciation. Third, we examine the effect of US dollar surges on EME currency depreciation. Finally, we investigate how the COVID pandemic and local currency crises in EMEs affect the above relationships. To the best of our knowledge, no previous study has investigated the dynamics of US dollar surges and EME currency depreciation.

The Dynamic Conditional Correlation (DCC) model, developed by Engle (2002), is the most common approach to exploring the time-varying conditional correlation between two time series variables. We begin our analysis with the DCC model and examine the time-varying comovements between US appreciation and EME currency depreciation over time. Our main interest is to investigate the directional predictability of US dollar appreciation on EME currency depreciation, motivated by the study of Obstfeld and Zhou (2023). The DCC model does not indicate the causal direction from one variable to another. Hence, we apply the cross-quantilogram (CQ) approach introduced by Han et al. (2016) to measure directional predictability.

We also examine how the dependency between the US dollar and the exchange rates of EMEs changed during the COVID-19 pandemic and the currency crises in EMEs. After the COVID-19 pandemic, the exchange rates of many EMEs have fallen more sharply against the U.S. dollar than before. Notably, some have faced currency crises — for instance, the exchange rates of Turkey, Pakistan, Sri Lanka, and Bangladesh have experienced significant currency value loss in recent years (see further details, Figure 3.1). A surge in the US dollar may severely deteriorate the trade balance of EMEs when they face a currency crisis. Hence, we aim to examine whether US dollar surges trigger currency depreciation in EMEs during such crises.

This study shows several key findings. First, the dynamic conditional correlation between US dollar appreciation and the depreciation of the selected countries' local currencies is positive and varies over time. Notably, the correlation increases significantly at a marginal level for Bangladesh only during the COVID-19 pandemic and decreases significantly for Turkey during the currency crisis. Second, the hedge ratio of the Turkish Lira against the US dollar index declines over time, particularly during the COVID-19 pandemic and Turkey's currency crisis. The hedge ratios for the South Asian currencies remain small with no significant changes during the COVID-19 pandemic and double during their currency crises compared to the COVID-19 pandemic. Third, the cross-quantilogram analysis shows that US dollar appreciation has the strongest effect on the Turkish Lira compared to South Asian currencies. During the COVID-19 pandemic and the local currency crisis period, US dollar appreciation led to a significantly stronger short-run depreciation of the Turkish Lira, consistent with Obstfeld and Zhou (2023). Finally, US dollar surges contribute to the short-run strengthening of the Pakistani and Bangladeshi currencies during their respective currency crises while weakening the Sri Lankan currency. Notably, during the COVID-19 pandemic, the surge in the US dollar led to an appreciation of the Sri Lankan Rupee in the medium term.

The rest of the paper is organised as follows: Section 3.2 presents a review of related literature; Section 3.3 provides data, descriptive statistics, and time trends of our study variables; Section 3.4 illustrates the DCC-GARCH model, Cross-Quantilogram, and other methodological aspects; Section 3.5 presents the empirical results; and Section 3.6 concludes our study.

3.2 Literature Review

Many empirical studies provide evidence of correlation between exchange rates (Li, 2011; Tamakoshi and Hamori, 2014; Meng and Huang, 2019; Kočenda and Moravcová, 2019). For instance, Meng and Huang (2019) show a high level of integration between the Japanese and Korean currencies. Li (2011) and Tamakoshi and Hamori (2014) account for the asymmetric and time-varying nature of exchange rate co-movements. In Central and Eastern Europe, currency interactions display different characteristics at each timescale, as noted by Alin Marius Andrieş and Tiwari (2016). Tamakoshi and Hamori (2014) find strong correlations among new EU currencies (CZK, PLN, and HUF) during their appreciation against the US dollar and weak correlations during the global financial crisis of 2007-2008.

In the empirical literature, various models have been utilised to investigate the interaction between exchange rates. For example, the dynamic conditional correlation GARCH model (Kočenda and Moravcová, 2019; Tamakoshi and Hamori, 2014), wavelet analysis (Li, 2011; Meng and Huang, 2019) and copula models (Albulescu et al., 2018) have been applied. These models are useful for analysing the comovements between variables but do not provide causal direction. Han et al. (2016) introduced a method called the coss-quantilogram (CQ) to measure the dependence structure with directional predictability at arbitrary quantile and lag selections. Furthermore, the CQ approach allows us to simultaneously quantify the magnitude and duration of the dependency between variables.

Overall, the field literature provides evidence of currency comovements and examines the impact of global financial turmoil on them. To the best of our knowledge, no previous study has focused on the effect of US dollar appreciation on the currency depreciation of EMEs or considers how a country-specific currency crisis affects currency comovements. This study fills this gap.

3.3 Data and Variables Description

We utilise daily data on the trade-weighted US Dollar Index (DIX) and four exchange rates of EMEs against the US dollar from January 1, 2015, to October 31, 2024. The four exchange rates are Turkish Lira (TRY), Pakistani Rupee (PKR), Bangladeshi Taka (BDT), and Sri Lankan Rupee (LKR). The aim of this study is to investgate the dynamics local currency rates agains US dollar. We have given more focus on the countries which faced severa currency issues after following COVID-pandemic because this can provide implication for investors and policy makers. Nature of the COVID pandemic is different from the nature of currency crisis periods. Therefore, identifying and comparing the the dynamics of local currency movements during the such different periods considering US dollar appreciation would provide implication for investors and policymakers. Therefore, we selected only four countries which faced severe currency issues after the COVID-19 pandemic.

DIX measures the value of the US dollar relative to the currencies of its major trading partners. An upward movement in the DIX indicates US dollar appreciation. For EME currencies, we first obtain the nominal exchange rates of TRY, PKR, BDT, and LKR against the US dollar and convert them into real terms by adjusting for the corresponding country's inflation rate, as shown:

$$x_t = n_t \times \left(\frac{1 + \pi_t^f}{1 + \pi_t} \right) \tag{3.1}$$

where n_t and x_t represent the nominal and real exchange rates for a selected EME and time t. Since we consider local currency rates against the US dollar, π_f represents the inflation rate of the US economy, while π_t refers to the inflation rate of the selected EME.

The return series of the DIX and the real exchange rates of TRY, PKR, BDT, and LKR are used for our analysis and computed using the following standard formula:

$$y_t = log(x_t) - log(x_{t-1}) \tag{3.2}$$

where $log(x_t)$ denotes the natural logarithm of the real exchange rate for a selected EME at time t, and $log(x_{t-1})$ represents the exchange rate in the previous period $(t-1)$. The returns series y_t captures the first difference of the logarithm of the real exchange rate x_t. To express returns as percentage changes, we multiply all y_t by 100. The return for the DIX reflects the US dollar appreciation rate, while the returns for TRY, PKR, BDT, and LKR indicate their respective depreciation rates.

3.4 Methodology

3.4.1 Dynamic conditional correlation GARCH (DCC-GARCH) model

We initially employ the Dynamic Conditional Correlation Generalised Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model, introduced by Engle (2002), to examine the co-movements between US dollar appreciation and the depreciation of selected EME currencies. The foundation of this model originates from the Autoregressive Conditional Heteroskedasticity (ARCH) framework proposed by Engle (1982), which models univariate conditional volatility based on lagged squared errors or shocks. Bollerslev (1986) later extended the ARCH model by developing the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) model, which captures conditional volatility by incorporating both past shocks and past conditional volatility. The DCC GARCH model can be expressed as follows:

$$\mathbf{y}_t = \boldsymbol{\mu}_t + \boldsymbol{\varepsilon}_t \qquad \boldsymbol{\varepsilon}_t|\mathcal{F}_{t-1} \sim N(\mathbf{0}, \mathbf{H}_t), \tag{3.3}$$

$$\boldsymbol{\varepsilon}_t = \mathbf{H}_t^{1/2}\mathbf{u}_t \qquad \mathbf{u}_t \sim N(\mathbf{0}, \mathbf{I}), \tag{3.4}$$

$$\mathbf{H}_t = \mathbf{D}_t\mathbf{R}_t\mathbf{D}_t, \tag{3.5}$$

$$\mathbf{D}_t = diag(h_{1,t}^{\frac{1}{2}}, ..., h_{k,t}^{\frac{1}{2}})', \tag{3.6}$$

where $\mathcal{F}_{t-1}$ is the information set available up to period $t-1$; $\mathbf{y_t}$, $\mu_\mathbf{t}$, ε_t, and u_t are the $k \times 1$ vectors representing the return series, conditional means, residuals, and standardised residuals, respectively. Similarly, $\mathbf{H_t}$, $\mathbf{D}_t$, and $\mathbf{R_t}$ are $k \times k$ matrices representing the conditional variance-covariance, conditional variance, and dynamic conditional correlation matrices, respectively. The residual term ε_t is normally distributed with zero mean and conditional variance-covariance matrix H_t. In contrast, the standardised residual u_t is normally distributed with zero mean and variance $\mathbf{I}$, which is a $k \times k$ identity matrix. Further, $\mathbf{D_t}$ is a diagonal matrix containing the square root of univariate conditional variances $(h_{1,t}, ..., h_{k,t})$ obtained from a univariate GARCH model.

The estimation of the dynamic conditional correlation ($\mathbf{R_t}$) requires a time-varying covariance matrix Q_t of standardised residuals u_t. In the first stage, the conditional variance $h_{i,t}$ is obtained using a GARCH (1,1) model, which is specified as follows:

$$h_{i,t} = \omega + \alpha\varepsilon_{i,t-1}^2 + \beta h_{i,t-1}. \tag{3.7}$$

In this model, ω is a constant term, α quantifies the effect of past squared residuals (referred to as the ARCH effect); β captures the impact of past conditional volatility (known as the GARCH effect). The unconditional variance is given by $\frac{\omega}{1-\alpha-\beta}$ and the condition $\alpha + \beta < 1$ is imposed to ensure stationarity.

In the second stage, the covariance matrix Q_t is computed as:

$$Q_t = (1 - a - b)\bar{Q} + au_{t-1}u_{t-1}^{'} + bQ_{t-1}, \tag{3.8}$$

where $\bar{Q}$ is the unconditional covariance matrix of the standardised residuals, a and b measures the impact of past shock and volatility persistence. The dynamic conditional correlation matrix R_t is obtained by standardizing Q_t as follows:

$$\mathbf{R}_t = diag(q_{1,t}^{-\frac{1}{2}}, ..., q_{k,t}^{-\frac{1}{2}})\ Q_t\ diag(q_{1,t}^{-\frac{1}{2}}, ..., q_{k,t}^{-\frac{1}{2}}), \tag{3.9}$$

Here, $\bar{Q}$ represents $k \times k$ unconditional variance-covariance matrices of standardized residuals of $u_t = (u_{1t}, u_{2t}, ..., u_{kt})'$; and $q_{ii,t}$ is a i^{th} diagonal element of Q_t. The scalar parameters a and b satisfy $a \geq 0$, $b \geq 0$ and $a + b < 1$. Parameter a accounts for the short-term effect of past shocks on the dynamic conditional correlations, whereas b reflects the persistence of past correlations. If the condition $a + b < 1$ is violated, then $\mathbf{R_t}$ remains constant over time, and the model converges to the constant conditional correlation GARCH (referred to as CCC-GARCH) model.

Our second objective in this study is to explore how the COVID-19 pandemic and the currency crisis in EMEs affect the dynamic conditional correlation between the dollar appreciation and EME currency depreciation ($\rho_{ij,t}$). To assess both effects, we apply an AR(1) process for the dynamic conditional correlations, following the framework of Chiang et al. (2007), which is displayed as follows:

$$\rho_{ij,t} = \phi_0 + \phi_1\rho_{ij,t-1} + \delta_1 D_{1,t} + \delta_2 D_{2,t} + e_t \tag{3.10}$$

where D_1 and D_2 are dummy variables representing the COVID-19 pandemic and the currency crisis periods, respectively. The $\rho_{ij,t}$ is ijth element of the dynamic conditional correlation matrix $\mathbf{R_t}$. In other words, the dynamic conditional correlation between US currency appreciation and the local currency depreciation of one of the selected EMEs is obtained using the DCC-GARCH framework. The coefficients ϕ_1 and ϕ_2 represent the impact of the COVID-19 pandemic and local currency crisis on the dynamic conditional correlation $\rho_{ij,t}$. The term e_t is the error term in the AR(1) model given (3.10).

3.4.2 Time-varying hedge ratios and optimal portfolio weights

This study also aims to explore the hedge ratio and portfolio weights in the context of the dynamic relationship between the US dollar and EME exchange rates. The estimates of the DCC-GARCH model are employed to compute the time-varying hedge ratio and portfolio weights. Following the methodology of Kroner and Sultan (1993), the conditional variance-covariance is utilised to estimate the time-varying hedge ratio, which is expressed as follows:

$$\theta_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}} \tag{3.11}$$

where $h_{ij,t}$ denotes the conditional covariance between US dollar appreciation and the depreciation of EME currency i, while $h_{jj,t}$ represents the conditional variance of US dollar appreciation (j). Time-varying optimal portfolio weight is computed based on the framework proposed by Kroner and Ng (1998), as defined below:

$$\lambda_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}} \tag{3.12}$$

where $\lambda_{ij,t}$ represents the portfolio weights of EME currency i, subject to the following conditions:

$$\lambda_{ij,t} = \begin{cases} 0 & \text{if} \quad \lambda_{ij,t} < 0 \\ \lambda_{ij,t} & \text{if} \quad 0 \leq \lambda_{ij,t} \leq 1 \\ 1 & \text{if} \quad \lambda_{ij,t} > 1 \end{cases} \tag{3.13}$$

The portfolio weight of US dollar appreciation j is given by $1 - \lambda_{ij,t}$. Furthermore, this study investigates the stability of the hedge ratio and portfolio weights over time.

3.4.3 Cross Quantilogram (CQ)

The limitation of the DCC-GARCH model is that it does not show the directional predictability from one variable to another. Our main interest in this study is to investigate the directional predictability of US dollar appreciation on the currency depreciation of EMEs. Therefore, we adopt the Cross-Quantilogram (CQ) framework proposed by Han et al. (2016), which captures serial dependence between two time series at different conditional quintile levels. The following section describes CQ.

Let us consider two stationary time series: y_t and x_t. We assume that $y_t = (y_{1t}, y_{2t})' \in \mathbb{R}^2$ and $x_t = (x_{1t}, x_{2t}) \in \mathbb{R}^{d1} \times \mathbb{R}^{d2}$, where $x_{st} = [x_{st}^{(1)}, ..., x_{st}^{(ds)}]' \in \mathbb{R}^{d_s}$ with $d_s \in \mathbb{N}$ for $s = 1, 2$. The conditional distribution of y_{st} given x_{st} can be written as $F_{y_s|x_s}(.|x_{st})$

and the density function of the conditional distribution can be written as $f_{y_s|x_s}(.|x_{st})$. The conditional quintile distribution is expressed as follows:

$$q_{s,t(\tau_s)} = \inf\{\sqsubseteq : F_{y_s|x_s}(x_{st}) \geq \tau_s\}, \qquad \tau_s \in (0,1). \tag{3.14}$$

To measure the serial dependency between two events $\{y_{1t} \leq q_{1,t}(\tau_1)$ and $\{y_{2,t-k} \leq q_{1,t}(\tau_1)$ for an arbitrary pair of $\tau = (\tau_1, \tau_2)$ and for an integer k, we first define the quantile-hit process as:

$$1[y_{st} \leq q_{s,t}(.)], \quad s = 1, 2. \tag{3.15}$$

Then, we measure the cross-quantilogram, which is defined as the cross-correlation between quantile-hit processes:

$$\rho_\tau(k) = \frac{E\left[\psi_{\tau_1}(y_{1t} - q_{1,t}(\tau_2))\psi_{\tau_2}(y_{2,t-k} - q_{2,t-k}(\tau_1))\right]}{\sqrt{E\left[\psi_{\tau_1}^2(y_{1t} - q_{1,t}(\tau_2))\right]}\sqrt{E\left[\psi_{\tau_2}^2(y_{2,t-k} - q_{2,t-k}(\tau_2))\right]}} \tag{3.16}$$

Here, k represents the number of lead-lag periods to time t, and $\psi_a(u) \equiv 1[u < 0] - a$ denotes the quantile-hit process. Our main aim in this section is to examine the dynamics of the currency depreciation y_t based on its previous level (y_{t-k}) and the quantiles of the currency depreciation when the information set is given, especially when US dollar appreciation (x_t) is given. In other words, we examine the dynamics of the correlation between current and past local currency depreciation (y_t, y_{t-k}) of selected EMEs, considering the quantiles of depreciation when the quantiles of US currency appreciation are given. Therefore, the above equation not only presents the dynamic correlation between the present and past local currency depreciation of selected EMEs but also provides an opportunity to examine whether level quantiles of local currency depreciation and US currency depreciation affect the correlation between y_t and y_{t-k}. In this study, we consider 1, 5, 22, and 66 lagged days for k, where 5, 22, and 66 represent a week, month, and three-month lagged period, since our daily series contains working days of the week, not weekends.

The CQ captures serial dependency between the two series at different quintile levels and identifies the presence of predictable directionality between y_t and x_t, with $\rho_\tau(k) = 0$ indicating no cross-dependence or directional predictability and $\rho_\tau(k) \neq 0$ suggesting its presence.

To formally test the existence of directional predictability from x_t to y_t, we set up the following null and alternative hypotheses (H_0 & H_1): H_0: $\rho_\tau(1) = ... = \rho_\tau(p)$ (no directional predictability) and H_1: $\rho_\tau(k) \neq 0$ for some $k \in \{1, ..., p\}$ (existence of directional predictability). For hypothesis testing, Han et al. (2016) recommend using the Box-Ljung test statistic, given by:

$$\hat{Q}_{\tau}^{(p)} \equiv T(T+2) \sum_{k=1}^{p} \frac{\hat{\rho}_{\tau}^{2}(k)}{(T-k)} \tag{3.17}$$

where T denotes the sample period.

Since the CQ approach deals with stationary series, we test the stationarity of each series using both the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and the Phillips-Perron (PP) test (Phillips and Perron, 1988). Both test results are presented in Table 3.1, showing that all the return series are stationary at the level.

3.5 Results

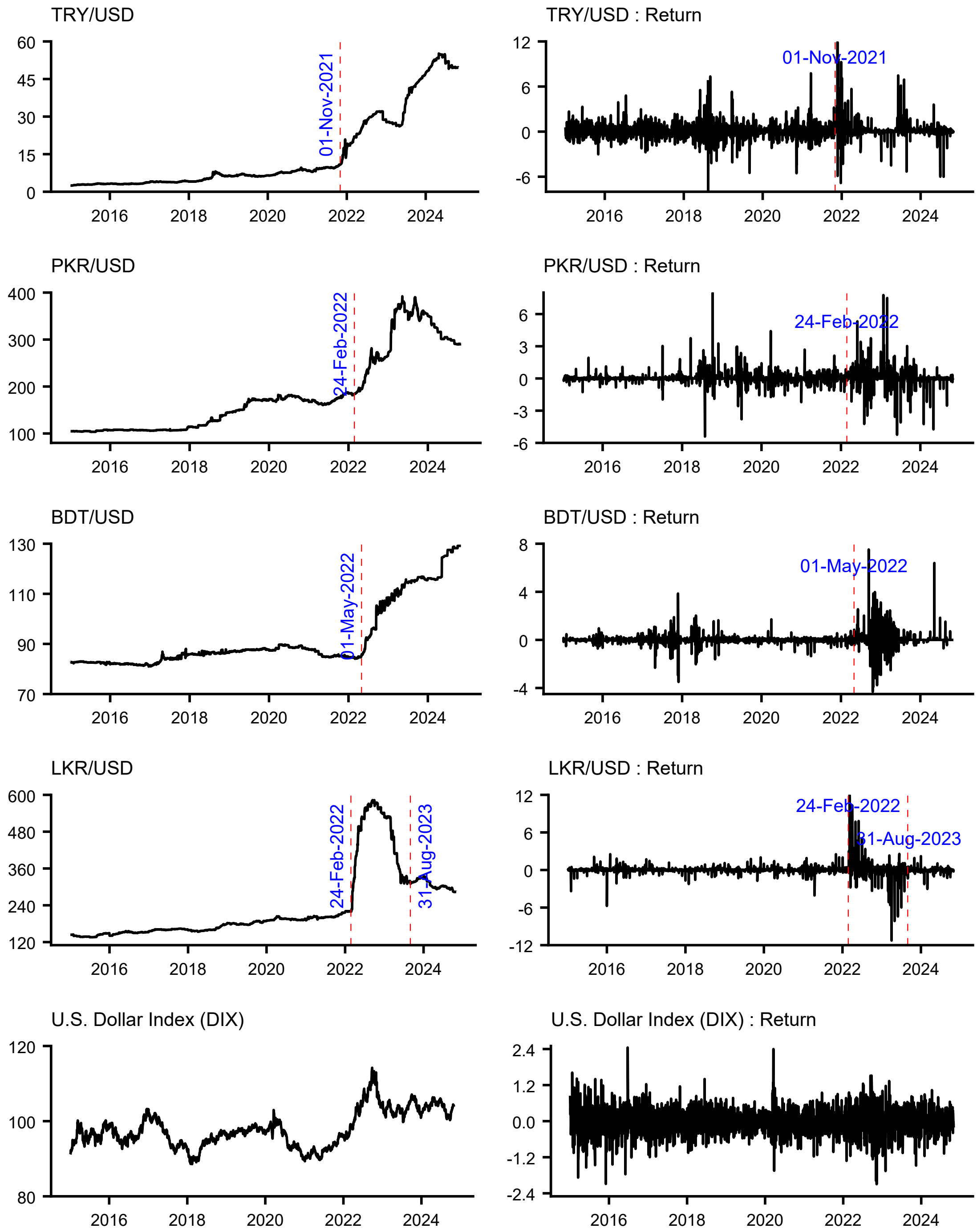
3.5.1 Preliminary Analysis

Figure 3.1 displays the DIX and exchange rates of TRY, PKR, BDT, and LKR against the US dollar. The selected EME currency rates depreciate over time against the US dollar, as shown by the increasing trend (see the first column of Figure 3.1). However, the depreciation accelerates significantly after the COVID-19 pandemic. The depreciation spikes—in other words, the currency crises—begin on November 1, 2021, in Turkey; February 24, 2022 (the start of the Ukraine-Russia war), in Pakistan and Sri Lanka; and May 1, 2022, in Bangladesh. Furthermore, the EME exchange rates appear to be more volatile during their respective currency crises (see the second column of Figure 3.1).

We transform each series into a returns series using the standard formula given in (3.2) and display their summary statistics in Table 3.1. Since we consider the local currency values of TRY, PKR, BDT, and LKR per one US dollar, their returns can be interpreted as depreciation. Similarly, the returns of DIX can be considered appreciation, as it is an index against other major currencies. The daily mean return of DIX is -0.006%, which indicates that the US dollar depreciates by 0.006% per day. The daily mean returns for TRY, PKR, BDT, and LKR are positive at 0.12%, 0.04%, 0.02%, and 0.03%, respectively, representing their daily depreciation rates. Notably, TRY depreciates more compared to PKR, BDT, and LKR.

In Table 3.1, the kurtosis statistics indicate the presence of heavier tails and a sharper peak in the distribution of TRY, PKR, BDT, and LKR but not for DIX. The Jarque-

Figure 3.1: Real exchange rate in local currency against US dollar



Bera test results provide no evidence of a normal distribution for any of the series. The Ljung-Box Q and Q^2 statistics demonstrate the presence of serial correlation in the returns and squared returns series, respectively. The ARCH-LM results confirm heteroskedasticity in the variance of each series. Furthermore, no statistical evidence of a unit root is found in any series based on both the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) stationarity tests.

Table 3.1: Summary Statistics on percentage returns of exchange rate

	Mean (%)	SD	Skew.	Kurt.	Jarq.	ADF[1]	PP	Q(5)	$Q^2(5)$	ARCH-LM[2]
TRY	0.117	1.242	-0.287	46.2	135932***	-13.0***	-2234***	50***	475***	244***
PKR	0.040	0.646	1.866	38.8	61203***	-13.0***	-2671***	40***	82***	69***
BDT	0.017	0.463	2.512	63.3	265695***	-15.5***	-2767***	164***	116***	71***
LKR	0.027	0.786	2.044	89.0	377780***	-10.5***	-3213***	160***	199***	148***
DIX	-0.006	0.430	-0.101	2.05	310***	-13.9***	-2264***	19**	278***	135***

Note: *** denotes a 1% significant level. We use five lags for the Ljung-Box and ARCH-LM test statistics, as the data consists of daily weekday series. For the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) unit root tests, we select a model without drift and trend.

3.5.2 Dynamic Conditional Correlation

Table 3.2 shows the combined results of univariate GARCH and DCC-GARCH models. We first explain the results of the univariate GARCH model. The conditional mean for each model, represented by the constant term of the UGARCH model, is close to zero and statistically insignificant, suggesting no strong mean trend in the return series across all study variables. The long-run variance (ω) is positive in all cases, aligning with the univariate GARCH model assumption, and is statistically significant for PKR and BDT.

In the table, α and β represent the effects of past shocks and past conditional volatility, respectively, and the estimates are statistically significant at the 1% level. This indicates that the conditional volatility of each series depends on previous shocks and previous conditional volatility. The sum of $\alpha + \beta$ is less than one, which demonstrates the persistence of volatility shocks in the conditional volatility. The parameter of the generalised error distribution in the univariate GARCH model estimation, denoted as (ϕ), is smaller and statistically significant for each series, which confirms the existence of heavy tails in their error distribution. All univariate GARCH results are consistent with Kočenda and Moravcová (2019).

We now examine the primary diagnostic tests for the univariate GARCH model estimation for each exchange rate. The Q and Q^2 test statistics (Ljung-Box portmanteau tests) indicate the absence of serial correlation in the univariate GARCH standardised error and their squared terms. Additionally, the ARCH-LM test confirms that the univariate standardised residuals do not exhibit heteroskedasticity. Consequently, the estimated results of the univariate GARCH model are considered robust and suitable for interpretation.

One of the objectives of this study is to examine how the appreciation of the US dollar and the depreciation of EME currencies are correlated over time. The results of the DCC-GARCH model, presented below the univariate GARCH results in

Table 3.2: Dynamic conditional correlation between US dollar appreciation and currency depreciation in emerging and developing countries

Statistics	TRY	PKR	BDT	LKR
(a) UGARCH Mean Model				
Constant	0.0000	-0.00000	-0.0000	0.0000
	(0.0000)	(-0.0001)	(0.0000)	(0.0000)
(b) UGARCH Variance Model				
ω	0.0001	0.0013***	0.0001**	0.0001
	(0.1880)	(4.3116)	(2.5478)	(0.9115)
α	0.0720***	0.0484***	0.0649***	0.0607***
	(23.60)	(10.966)	(6.1054)	(16.335)
β	0.9014***	0.9487***	0.9215***	0.9279***
	(228.0)	(289.08)	(131.27)	(232.16)
ϕ	0.2500***	0.2405***	0.7158***	0.1473***
	(79.09)	(41.13)	(29.695)	(42.975)
Q(5)	4.453	4.848	1.276	4.708
	[0.2027]	[0.1657]	[0.9997]	[0.1780]
Q2(5)	0.0284	0.3530	0.0097	0.2822
	[0.9999]	[0.9778]	[0.9999]	[0.9855]
ARCH LM	0.0249	0.494826	0.0104	0.5875
	[0.9982]	[0.8852]	[0.9995]	[0.8575]
(c) DCC-GARCH model				
$\bar{R}$	0.1660	0.0524	0.0599	0.0237
DCC-α	0.0088	0.0016	0.0035	0.0031
	(1.0379)	(0.6558)	(1.5538)	(0.0000)
DCC-β	0.9857***	0.9900***	0.9887***	0.9803***
	(58.28)	(78.04)	(243.15)	(15.939)
DCC-MVT	4.7780***	4.0000***	4.0000***	-
	(24.119)	(3.0714)	(22.155)	-
Log-like.	-4296.9	-2267.5	-605.97	-4187.7

Note: Table 3.2, each return series of EME currencies against the US dollar (TRY, PKR, BDT and LKR) is paired with the return series of the US dollar index (DIX) to estimate the DCC-GARCH model. The generalised error distribution (GED) and multivariate t-distributions are applied to the univariate GARCH and DCC-GARCH model estimation, respectively, except for the LKR-DIX combination, where a multivariate normal distribution improves the estimation based on the log-likelihood and AIC values. The t-statistics and p-values are reported in () and [], respectively. (*), (**), and (***) indicate 10%, 5%, and 1% significance levels, respectively.

Table 3.2, explore this relationship. The mean of the time-varying conditional correlation, denoted as $\bar{R}$ in Table 3.2, is positive for all pairs in this study. This finding indicates that the appreciation of the US dollar is positively correlated with the depreciation of the exchange rates of TRY, PKR, BDT, and LKR, aligning with Obstfeld and Zhou (2023). Moreover, the positive correlation is higher between DIX and TRY than in the other cases.

In Table 3.2, the DCC-α is less than 0.01 and statistically insignificant for all cases.

This indicates that the conditional correlation between US dollar appreciation and depreciation of each EME currency is not strongly influenced by new shocks. In contrast, the DCC-β is close to 0.99 and statistically significant, indicating that the conditional correlation primarily depends on past history. The results are consistent with the study of Kočenda and Moravcová (2019).

Figure 3.2: Dynamic conditional correlation between US currency appreciation and local currency depreciation in selected

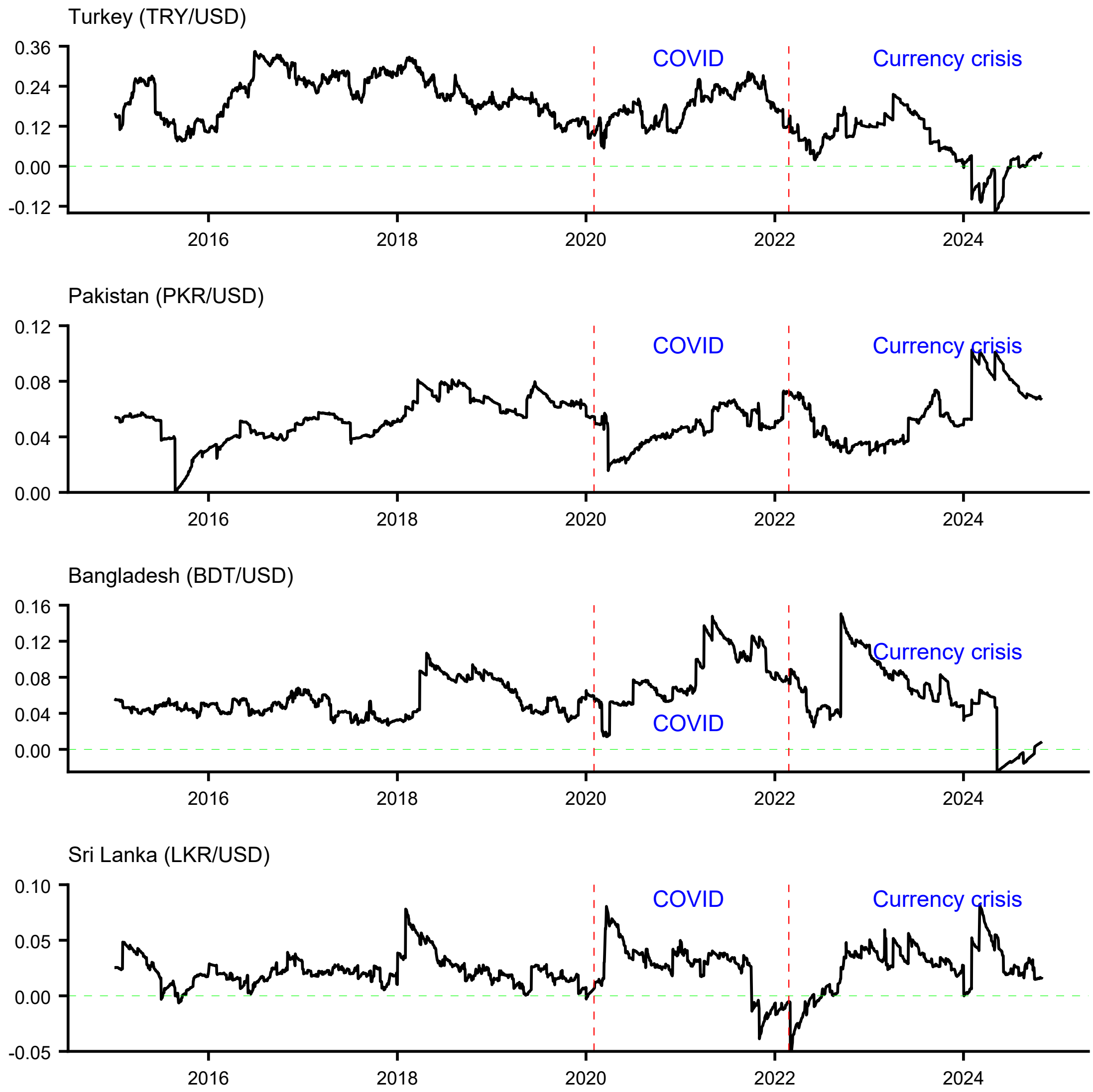


Figure 3.2 displays the dynamic conditional correlation between the appreciation of the U.S. dollar and the depreciation of TRY, PKR, BDT and LKR over time. We observe a time-varying pattern in the conditional correlations, consistent with previous studies (Devereux and Lane, 2003; Kočenda and Moravcová, 2019; Meng and Huang, 2019). During the COVID-19 pandemic, the conditional correlation appears to be lower for the PKR-DIX but higher for the other pairs. In the case of a currency crisis, the TRY

shows a lower dynamic conditional correlation compared to other time periods. In the South Asian region, Pakistan and Sri Lanka exhibit an increasing trend in dynamic conditional correlation, whereas Bangladesh shows a decreasing trend.

Table 3.3: Dynamic conditional correlation between the most depreciated currencies and US currency appreciation

Statistics	TRY	PKR	BDT	LKR
Constant	0.0016***	0.0004***	0.0004***	0.0003***
	(2.952)	(2.784)	(2.673)	(2.827)
ρ_1	0.9921***	0.9928***	0.9910****	0.9833***
	(419.3)	(412.3)	(376.1)	(273.8)
$D_{1,t}$	0.0000	-0.0000	0.0004*	0.0002
	(0.093)	(-0.359)	(1.698)	(1.200)
$D_{2,t}$	-0.0013**	0.0000	-0.0000	0.0001
	(-2.565)	(0.174)	(-0.360)	(0.946)
Q(5)	0.3087	2.4043	0.7483	2.0064
	[0.9975]	[0.7908]	[0.9802]	[0.8483]
ARCH(5)	0.4679	0.0718	0.0582	0.5647
	[0.9933]	[0.9999]	[0.9999]	[0.9896]

Note: Table 3.3 presents the results estimated using the approach of Chiang et al. (2007). $D_{1,t}$ and $D_{2,t}$ are the dummy variables representing the COVID-19 pandemic and currency crisis periods, respectively. We define the COVID-19 pandemic period as spanning from January 1, 2020, to October 31, 2021. The starting points of the currency crisis are considered as follows: November 1, 2021, for Turkey; February 24, 2022, for Pakistan and Sri Lanka; and May 1, 2022, for Bangladesh (see Figure 3.1 for details). Q(5) and ARCH(5) present the test results for serial correlation (Ljung-Box test) and heteroskedasticity (Engle's ARCH LM test), respectively. The t-statistics and p-values are reported in parentheses () and brackets [], respectively. Significance levels are indicated as (*), (**), and (***) for 10%, 5%, and 1%, respectively.

However, we test whether the conditional correlation differs significantly during the COVID-19 pandemic and the currency crisis, following the approach of Chiang et al. (2007). The results are presented in Table 3.3. We find that the dynamic conditional correlation for BDT is significantly higher during the COVID-19 pandemic than in other periods, while no significant differences are observed for TRY, PKR, and LKR. Further, the results show that during the currency crisis period, the dynamic conditional correlation for TRY is significantly lower compared to other periods. In contrast, no statistically significant differences are found for PKR, BDT, and LKR.

In the next stage, we measure the time-varying hedge ratio as specified in (3.11) and calculate the average hedge ratio for each period: pre-COVID, COVID-19, and the currency crisis period. The ratios are stable during the COVID-19 and currency crisis periods compared to the pre-COVID period. The average time-varying hedge ratio of TRY against DIX appreciation is 0.434 before the COVID-19 pandemic. The ratio decreased to 0.337 during the COVID-19 pandemic and again fell to 0.24 during the currency crisis or post-COVID period. However, the hedge ratios for PAK, BDT, and LKR were 0.068, 0.030, and 0.016, respectively, before the COVID-19 pandemic, and there were no significant changes during the COVID-19 pandemic. In contrast, the hedge ratios dramatically increased during the currency crisis period compared with the previous periods.

Table 3.4: Hedge ratio and portfolio weight of the US dollar on EME currencies

	pre-COVID				COVID				Currency Crisis			
	Mean	Std.	Min	Max	Mean	Std.	Min	Max	Mean	Std.	Min	Max
(a) Hedge ratio												
TRY/DIX	0.434	0.315	0.079	2.820	0.337	0.207	0.066	1.290	0.242	0.464	-0.344	2.686
PKR/DIX	0.068	0.071	0.000	0.339	0.054	0.017	0.023	0.092	0.102	0.050	0.027	0.288
BDT/DIX	0.030	0.312	0.004	0.201	0.033	0.023	0.003	0.133	0.068	0.096	-0.108	0.565
LKR/DIX	0.016	0.014	-0.006	0.109	0.021	0.027	-0.073	0.108	0.041	0.077	-0.260	0.298
(a) Portfolio weight												
TRY/DIX	0.235	0.165	-0.019	0.649	0.337	0.185	-0.007	0.821	0.381	0.296	-0.015	0.972
PKR/DIX	0.563	0.281	0.024	0.922	0.432	0.099	0.177	0.722	0.278	0.182	0.043	0.714
BDT/DIX	0.793	0.227	0.064	0.997	0.879	0.089	0.512	0.980	0.568	0.302	0.030	0.987
LKR/DIX	0.679	0.964	0.090	0.964	0.604	0.221	0.098	0.952	0.226	0.242	0.020	0.800

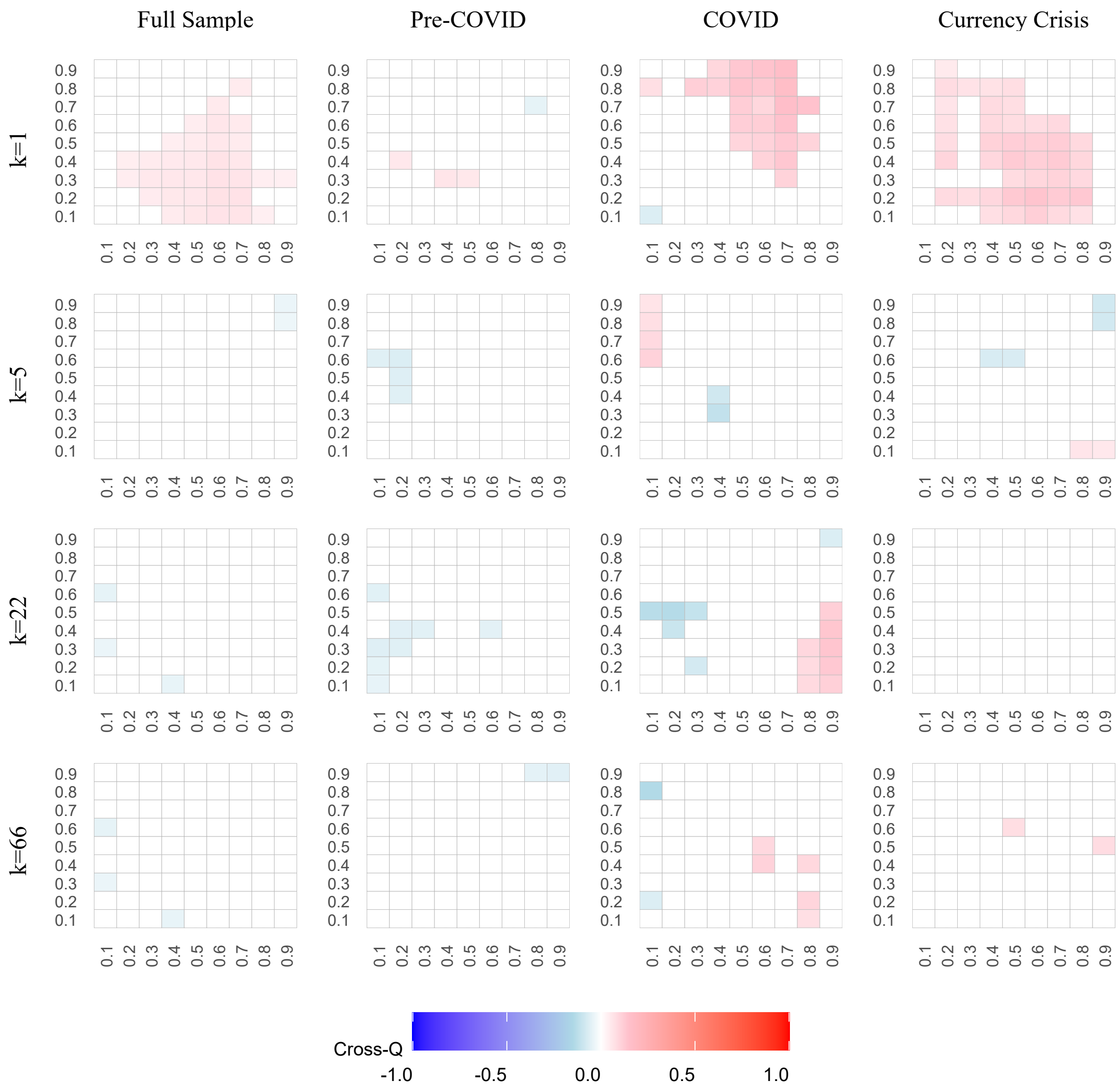
Note: We first compute the daily hedge ratio and the portfolio weight of the US dollar appreciation on EME currency depreciation. Then, we find the averages for pre-COVID, COVID and currency crisis periods. The pre-COVID period spans from January 1, 2015, to January 31, 2020. The starting points of the currency crisis are considered as follows: November 1, 2021, for Turkey; February 24, 2022, for Pakistan and Sri Lanka; and May 1, 2022, for Bangladesh (see Figure 3.1 for details). Furthermore, we define the COVID period as spanning from February 1, 2020, until the day before the currency crisis began in each EME.

Table 3.4 also presents the portfolio weight of the dollar appreciation index on the local currencies of TRY, PKR, BDT, and LKR. The portfolio weight for TRY increased during the COVID-19 pandemic and currency crisis in Turkey compared to the pre-COVID period. In contrast, the portfolio weights for PKR and LKR declined during these periods. Specifically, the portfolio weight for TRY was 0.235 in the pre-COVID period, rising to 0.337 during COVID and further to 0.381 during the currency crisis. In contrast, the portfolio weights for PKR and LKR, which stood at 0.563 and 0.679, respectively, in the pre-COVID period, fell to 0.432 and 0.604 during COVID, then declined further to 0.278 and 0.226 during the currency crisis. However, Bangladesh exhibited a different trend. The portfolio weight for BDT increased from 0.793 in the pre-COVID period to 0.879 during the COVID pandemic but later dropped significantly to 0.568 during its currency crisis.

3.5.3 Cross-quantilogram

The results obtained through the DCC-GARCH model capture the dynamic conditional correlation between US currency appreciation and local currency depreciation in the selected EMEs. However, through the Cross-Quantilogram (CQ) analysis, we explore whether US dollar appreciation has predictive power on the

Figure 3.3: Cross-quantilogram for Turkish currency depreciation



Note:: The Cross-quantilogram is measured using (3.16) individually for each sample periods. The statistical significance level (5%) is calculated using the Box-Ljung test, as described in (3.17). In each plot, the vertical and horizontal axes represent the quantiles of the Turkish currency depreciation (TRY) and US dollar appreciation. All insignificant cross-quantilogram correlations between current and past Turkish currency depreciation when the US dollar appreciation is given and in the selected quantiles are set to zero, represented by white. Therefore, the significant CQ correlations demonstrate that US dollar appreciation can have some predictive power on the dynamics of Turkish currency depreciation in the selected quantile probabilities.

correlation between present and past local currency depreciation of a selected EME. To measure the CQ, we employ the trade-weighted Dollar Index (DIX) and the exchange rates of the Turkish Lira (TRY), Pakistani Rupee (PKR), Bangladeshi Taka (BDT), and Sri Lankan Rupee (LKR) against the US dollar. Further, we split our sample period into pre-COVID, COVID, and post-COVID (local currency crises) periods, as well as the full sample period. The selected quantile probabilities (q) are

$(0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9)$ and the chosen lag orders (k) are $1, 5, 22$ and 66, representing day, week, month and three-month lags. The calculated CQ for the selected local currency depreciation when the US dollar appreciation is given are visualised using a heatmap, where the CQ value is set to zero and displayed in white colour when the correlation between present and past local currency depreciation is not statistically significant at the 5% level when the US currency appreciation is given. Therefore, significant CQ values indicate that US currency appreciation has some effect on the movements of local currency depreciation.

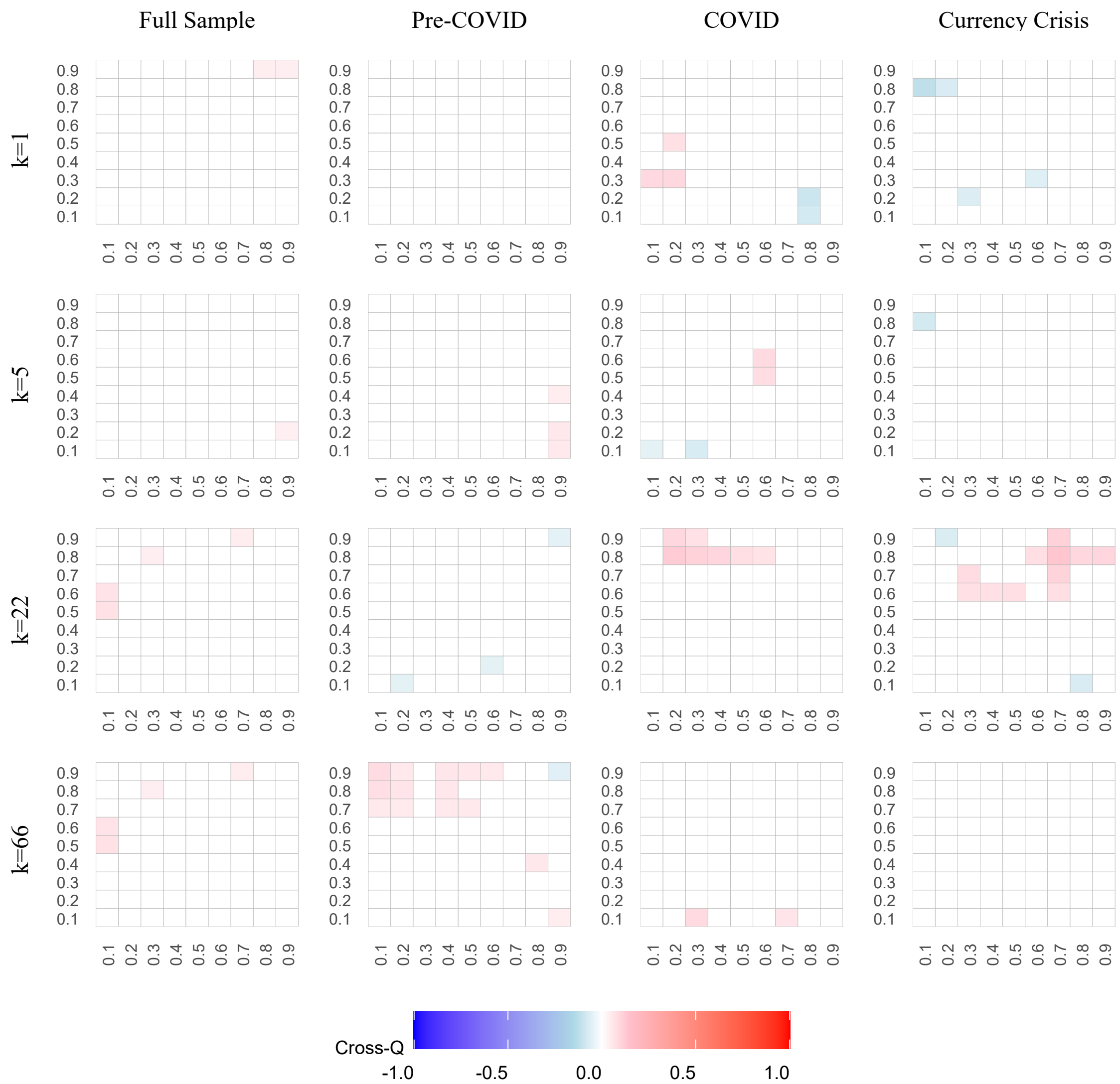
Figure 3.3 illustrates a heatmap of the cross-quantile correlation (CQC) of TRY/USD across various lags ($k = 1, 5, 22, 66$) for different sample periods (Full sample, pre-COVID, COVID, and Turkish currency crisis). The heatmap also represents the directional predictability of TRY/USD currency depreciation dynamics based on US dollar appreciation. The vertical and horizontal axes denote the quantile probabilities for Turkish currency depreciation and the US dollar appreciation, respectively.

The map for the full sample at lag 1 in Figure 3.3 shows that CQ correlation for Turkish currency depreciation is positive and statistically significant when US dollar appreciation occurs. However, in the medium and long term (at lags 5, 22, 66), the CQ correlation is negative when the US dollar appreciates, but only in a few quantiles. These suggest that US dollar appreciation plays an important role in the dynamics of Turkish currency depreciation, and the impact differs across time lags and quantiles.

During the pre-COVID period at lag 1, the CQC is positive at lower and medium quantiles but negative in upper quantiles. At higher order lags, the CQC is negative, particularly a week and a month later. During the COVID-19 pandemic, the CQ correlation is positive at lag order one in many medium and upper quantiles. However, a week, a month and three months later, the CQ correlations are positive and negative depending on the quantile probabilities. When we consider the local currency crisis period, the CQ correlation is positive and highly significant at one-day lag. Still, the correlation is not stronger after a week, and no significant correlation is observed three months later.

The map shown in Figure 3.3 indicates that US dollar appreciation played an important role in shaping the dynamics of Turkish currency depreciation, especially during the COVID-19 pandemic and the local currency crisis period. Although the heat map does not provide the extent to which US dollar appreciation affected Turkish currency depreciation, the map suggests that US dollar appreciation played different roles in the dynamics of Turkish currency depreciation, consistent with the results obtained using the DCC-GARCH model.

Figure 3.4: Cross-quantilogram for Pakistani currency depreciation



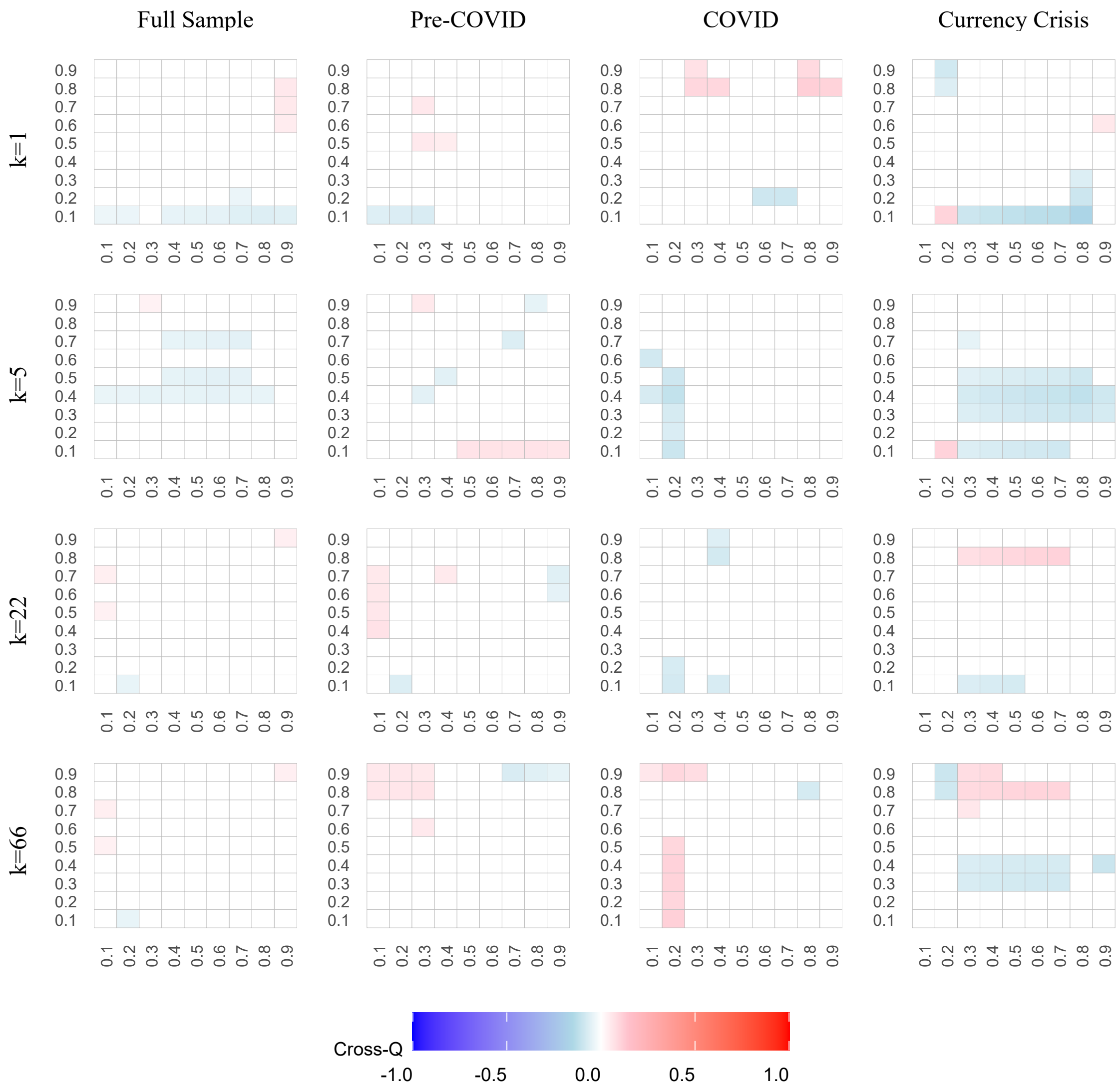
Note: The Cross-quantilogram is measured using (3.16) individually for each sample periods. The statistical significance level (5%) is calculated using the Box-Ljung test, as described in (3.17). In each plot, the vertical and horizontal axes represent the quantiles of the Pakistani currency depreciation (PKR) and US dollar appreciation. All insignificant cross-quantilogram correlations between current and past Pakistani currency depreciation when the US dollar appreciation is given and in the selected quantiles are set to zero, represented by white. Therefore, the significant CQ correlations presented demonstrate that US dollar appreciation can have some predictive power on the dynamics of Pakistani currency depreciation in the selected quantile probability.

We turn our focus to the CQ correlation for Pakistani currency depreciation when the US currency depreciates, as presented in Figure 3.4. The CQ in the heat map shows the CQ correlation between present and past Pakistani currency depreciation when the US dollar appreciates. The full-sample case in Figure 3.4 shows that the

CQ correlation is positive for only a few quantiles across all selected lags. The pre-COVID sample case shows that the CQ correlation is not significant at $k = 1$, but becomes significantly positive after a week, significantly negative after a month, and mixed positive and negative with a dominant positive correlation. However, these are observed only in some quantiles. The COVID-19 sample shows that the CQ correlation is mixed positive and negative in the short-time horizons ($k = 1$ and 5 depending on the quantile probabilities, but turns to positive in the long-term horizons ($k = 22$ and 66). However, we observe the reverse scenario in the case of the currency crisis period. We show that the CO correlation is negative in the short-time horizon and turns to positive in the long-time horizons.

The summary of the results from Figure 3.4 is that the dynamics of Pakistani currency depreciation differ across time when the US currency appreciates. This suggests that, based on the CQ principles, the US dollar is connected to the CQ correlation.

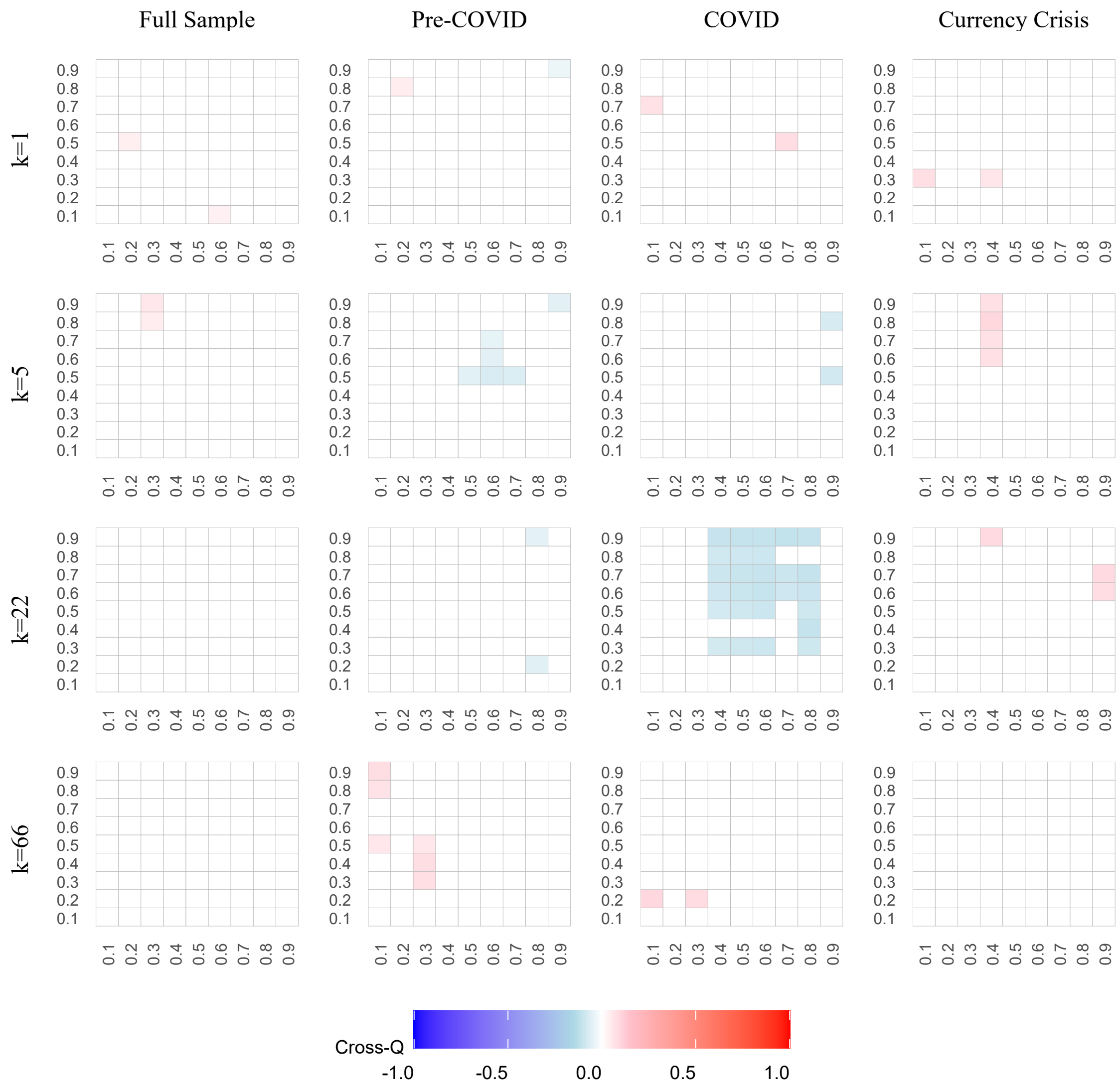
Figure 3.5: Cross-quantilogram for Bangladeshi currency depreciation



Note: The Cross-quantilogram is measured using (3.16) individually for each sample periods. The statistical significance level (5%) is calculated using the Box-Ljung test, as described in (3.17). In each plot, the vertical and horizontal axes represent the quantiles of the Bangladeshi currency depreciation (BDT) and US dollar appreciation. All insignificant cross-quantilogram correlations between current and past Bangladeshi currency depreciation when the US dollar appreciation is given and in the selected quantiles are set to zero, represented by white. Therefore, the significant CQ correlation presented demonstrates that US dollar appreciation can have some predictive power on the dynamics of Bangladeshi currency depreciation in the selected quantile probability.

The CQ correlation for Bangladeshi currency depreciation is presented in Figure 3.5. Overall, unlike the cases of Turkey and Pakistan, during COVID and the currency crisis in Bangladesh, when the US currency appreciates, the CQ correlation between current and past is more strongly negative during the local currency crisis than during the COVID-19 period. The pre-COVID case shows a mix of positive and negative CQ correlations depending on quantiles and lags.

Figure 3.6: Cross-quantilogram for Sri Lankan currency depreciation



Note: The Cross-quantilogram is measured using (3.16) individually for each sample periods. The statistical significance level (5%) is calculated using the Box-Ljung test, as described in (3.17). In each plot, the vertical and horizontal axes represent the quantiles of the Sri Lankan currency depreciation (LKR) and US dollar appreciation. All insignificant cross-quantilogram correlations between current and past Sri Lankan currency depreciation when the US dollar appreciation is given and in the selected quantiles are set to zero, represented by white. Therefore, the significant CQ correlations demonstrate that US dollar appreciation can have some predictive power on the dynamics of Sri Lankan currency depreciation in the selected quantile probabilities.

Figure 3.6 presents the CQ correlation between the present and the past Sri Lankan currency depreciation. The full sample shows that the CQ correlation is positive for a few quantiles and in the short horizon, but not significant in the long horizons, especially after a month and three months. However, the COVID-19 sample case shows that the CQ is strongly negative, especially at lag 22, but the currency crisis case shows that the CQ correlation is positive at lag 1, 5 and 22, but only in some quantiles. Further, we observe no significant CQ correlation in the long horizons, especially after three months.

Overall, the aim of using CQ analysis is to explore the dynamics of local currency depreciation during the COVID-19 pandemic and local currency crisis periods when the US dollar appreciates. The CQ analysis shows that the CQ correlation between present and past local currency depreciation in the selected country varies over time, especially during the COVID-19 pandemic and currency crisis, and is strongly correlated with US dollar appreciation. These results are consistent with previous studies such as Alin Marius Andrieş and Tiwari (2016) and Tamakoshi and Hamori (2014). The strong connection between the dynamics of local currency depreciation and US dollar appreciation is also aligned with Obstfeld and Zhou (2023), which shows that strengthening of the US dollar has a more adverse effect on output and financial markets in emerging market economies.

These findings can be generalised to other similar emerging market economies. However, the dynamics of local currency depreciation can differ from country to country based on each country's macroeconomic characteristics. Therefore, further investigation is needed to incorporate various macroeconomic factors, extending this analysis to include other emerging market economies.

3.6 Conclusion

The results from the univariate GARCH estimation show that the conditional volatility of currency depreciation of the Turkish Lira, Pakistani Rupee, Bangladeshi Taka, and Sri Lankan Rupee against the US dollar depends on their own market shocks and past conditional volatility. Meanwhile, the DCC-GARCH results indicate that depreciation of these currencies is positively correlated with US dollar appreciation over time. Notably, compared to the pre-COVID-19 period, the correlation was significantly higher for Bangladesh during the pandemic, while it was significantly lower for Turkey during its currency crisis. We find no evidence of significant changes in correlation for the other cases during COVID-19 or their respective local currency crises.

Further, we find that the hedge ratio of the Turkish Lira against the US dollar index declines over time, particularly during the COVID-19 pandemic and Turkey's local currency crisis. However, for the Pakistani Rupee, Bangladeshi Taka, and Sri Lankan Rupee against the US dollar, it remains smaller and shows no significant changes during the COVID-19 pandemic period. In contrast, it is double during the currency crises compared to the COVID-19 period in those countries.

The CQ analysis shows that the CQ correlation between present and past local currency depreciation in the selected country varies over time, especially during the COVID-19 pandemic and currency crisis, and has a strong correlation with US dollar appreciation.

Chapter 4

Monetary Policy Shocks on Clean and Brown Energy Stock Markets

Abstract

This study investigates the responses of clean and brown energy stock markets to US monetary policy shocks using Structural Vector Autoregressive (SVAR) and Local Projections models with monthly series data from November 2005 to March 2025. Interestingly, we find that a shock in short-term monetary policy rates has a statistically significant positive instant effect on both clean and brown energy stock markets. In contrast, a shock in long-term monetary policy has negative effects on both markets. Noticeably, the shock in long-term monetary policy has a stronger and statistically significant negative effect on the clean energy market than on the brown energy market. This underlines that higher upfront costs for energy transitions might induce the long-term interest rate to have a more adverse effect on clean energy markets. The findings in this study have significant implications for policymakers striving to navigate energy transitions through financial market dynamics via monetary policy.

Keywords:
Monetary Policy, Clean Energy, Renewable Energy, Short and Long-run Interest Rates, Brown Energy, Fossil Fuels, Stock Markets, and ESG assets

4.1 Introduction

The demand for the energy transition from fossil fuels (brown energy) to clean energy has increased rapidly in recent years, primarily due to global warming. Notably, global clean energy investment surged from US$ 0.565 trillion in 2019 to US$ 2.1 trillion in 2024 (BloombergNEF, 2025). Despite this, the world requires an average of US$5.6 trillion in clean energy investment yearly from 2025 to 2030 to meet net-zero emissions by 2050 (BloombergNEF, 2025). This signals that future demand for clean energy is expected to accelerate in the upcoming years. Hence, the energy shift from brown to clean energy has raised concerns about how financial markets respond to macroeconomic uncertainty, especially monetary policy.

Extensive empirical studies explore the dynamics of monetary policy on financial markets. The monetary policy shock harms the stock markets (Beckers and Bernoth, 2024; Thorbecke, 1997; Maio, 2013; Bernanke and Kuttner, 2005). For instance, stock returns fall when a contractionary monetary policy is imposed (Beckers and Bernoth, 2024), while stock returns increase when an expansionary monetary policy is imposed (Thorbecke, 1997). However, financially limited markets are more vulnerable to a monetary policy shock compared to the financially wealthier markets (Maio, 2013). Furthermore, the responses of the financial markets to the monetary policy shocks vary over time (Paul, 2020). Limited studies focus on the monetary policy shock with clean and green energy financial assets (Bauer et al., 2025; Döttling and Lam, 2025; Havrylchyk and Pourabbasvafa, 2025; Patozi, 2023). The intensity of carbon emissions appears to reinforce the transmission of monetary policy in the United States, whereas no comparable effect is evident within the euro area (Havrylchyk and Pourabbasvafa, 2025). However, Bauer et al. (2025) elucidate that European Central Bank policy surprises have a stronger impact on carbon-intensive equity firms than on green equity firms in Europe.

This study is similar to the recent studies of Bauer et al. (2025), Döttling and Lam (2025), Havrylchyk and Pourabbasvafa (2025) and Patozi (2023). However, our study differs from those studies mainly in the following three perspectives. First, they utilise a panel regression model using firm-level equity data. But we apply a Structural Vector Autoregressive (SVAR) and Local Projections (LPs) using distinguished market-level stock indices for clean and brown energies. The SVAR is widely used in the macroeconomic literature; many empirical studies have utilised it to elucidate the effect of the monetary policy shock on stock market returns (for instance, Thorbecke, 1997; Bjørnland and Leitemo, 2009). Second, the empirical studies include a variable in their panel regression to estimate the effect of monetary policy transmission on clean and brown energy. The variable is obtained by multiplying the following two variables: (i) monetary policy shock and (ii) carbon emission (or ESG score) of the equity firms. In contrast, this study obtains separate equity market indices to represent clean and brown energies. It estimates the SVAR model separately for each energy market to explore the heterogeneous effect of monetary transmission. Third, previous papers consider the interest rate changes around the monetary announcements to obtain monetary policy shocks. Instead, the Federal Funds Rate (FFR) is utilised in this study following Thorbecke (1997), Bjørnland and Leitemo (2009) and Beckers and Bernoth (2024). In addition, we replicate the model estimation using the following interest rates instead of the FFR: (i) US Treasury bill three-month rate traded in the secondary markets (TBL), (ii) US Treasury constant three-month rate (TRS), (iii) US Treasury constant one-year rate (TRM) and (iv) US Treasury constant five-year rate (TRL).

Theoretically, the monetary policy shock is expected to harm stock market returns through various channels. An increase in the FFR leads to lower stock returns by raising the discount rate, the risk-free rate, and interest rates. The discounted cash flow model reveals that a rise in the discount rate reduces stock prices by lowering the present value of future cash flows (Fama, 1970). The Capital Asset Pricing Model (Sharpe, 1964) and Fama-French model (Fama and French, 1988) demonstrate that an increase in the risk-free rate raises the cost of capital and reduces returns on risky assets. Blanchard (1981) extends the IS-LM model and shows the negative effect of a monetary policy shock on stock market returns through the cost of capital channel. For instance, expansionary monetary policy raises stock returns by lowering the cost of capital through a reduction in real interest rates. Hence, based on the mainstream theoretical frameworks, the stock returns for clean and brown energy are expected to react negatively to a monetary policy shock.

Further, the heterogeneous effects of monetary policy on clean and brown energy stock markets can be argued from the two different perspectives: cost of capital and ESG concerns. Through the cost-of-capital channel, a monetary policy shock is expected to have a stronger effect on clean energy markets due to higher upfront costs of the energy transition. From an ESG perspective, the brown energy stock market is expected to be more vulnerable to monetary policy shocks. The theoretical model of Pástor et al. (2021) shows that green assets have lower expected returns at the equilibrium level. Hence, if investors are willing to accept lower returns for clean assets, the clean energy stock market can be assumed to be less reactive to monetary policy shocks than the brown energy markets. An empirical study by Feldhütter et al. (2024) finds that investors are willing to accept a 1–2 bps lower return for green assets to care for the environment. However, the 1- 2 bps difference is not significant. Therefore, this study expects clean energy markets to be more reactive than brown energy markets, given the massive upfront costs of the clean energy transition.

This study finds that the short-term monetary policy shock has positive and significant contemporaneous effects on clean and brown energy stock markets. This is the opposite of the theoretical expectation and the previous empirical findings (see, for example, Thorbecke, 1997; Christiano et al., 2005; Bjørnland and Leitemo, 2009; Paul, 2020; Beckers and Bernoth, 2024). However, the significant positive response supports the study of Jarociński and Karadi (2020), which shows that the central bank's information shock can bias the monetary policy transmission. We account for a negative immediate response of both clean and brown energy stock markets to an impulse in the long-term monetary policy shock, as consistent with previous studies (see, for example, Thorbecke, 1997; Christiano et al., 2005; Bjørnland and Leitemo, 2009; Paul, 2020; Beckers and Bernoth, 2024). The main finding of this study is that an impulse in short- and long-run monetary policies has stronger effects on clean energy markets than on brown energy markets. Even though this is inconsistent with recent studies using firm-level equity data (Bauer et al., 2025; Döttling and Lam, 2025; Havrylchyk and Pourabbasvafa, 2025; Patozi, 2023), this meets our theoretical expectations and the argument of Maio (2013), which accounts that financially limited markets are more sensitive to monetary policy than wealthier markets. In our study, clean energy markets are financially limited markets compared to the brown energy markets.

This study has several notable contributions to the existing literature. First, to the best of my knowledge, no prior studies have examined the monetary policy transmission on clean and brown energy markets using market-level indices as described earlier. This study fills this gap. Second, findings in this study also contribute to the growing literature on ESG since clean and brown energies represent ESG and non-ESG assets, respectively. Third, we find a positive effect of monetary policy shock, which supports the study of Jarociński and Karadi (2020) even though it contradicts other empirical studies. This positive response could encourage future researchers to investigate monetary policy transmission on stock markets further. Fourth, this study selects monetary measures to represent both the short run and the long run and investigates them for each type of stock market. This strengthens the literature on the effects of short- and long-run monetary policy changes on financial markets. Finally, our study provides fresh evidence of monetary transmission in stock markets using an SVAR model with monthly data from November 2005 to March 2025. Based on the availability, the study period in previous SVAR studies lies around 1960 to 2010, except in Beckers and Bernoth (2024) (see, for example, Thorbecke, 1997; Bjørnland and Leitemo, 2009; Paul, 2020; Aastveit et al., 2023; Galí and Gambetti, 2015; Gorodnichenko and Weber, 2016). However, Beckers and Bernoth (2024) employs quarterly data from 1962 to 2018 and sign restrictions. Instead, our study utilises monthly data and recursive ordering to identify monetary policy shocks.

The structure of our study is organised as follows. Section 4.2 provides a comprehensive review of previous studies relevant to our analysis. Section 4.3 describes the variables and data sources. Section 4.4 outlines the models utilised in this study: the simple regression model, SVAR model, identification strategies, and the Local projections (LPs) model. Section 4.5 presents the empirical results from the simple model and SVAR model and a discussion of the results. Section 4.6 displays the results from the LPs as a robustness check of the findings from the SVAR model. Finally, Section 4.7 concludes our study.

4.2 Literature Review

This section reviews existing research on the relationship between stock markets and monetary policy, as well as differences in ESG and non-ESG asset returns.

Empirical research shows that interest rates are key to explaining stock market return variations. Short-term interest rates are particularly relevant to cross-sectional equity risk premia (Maio and Santa-Clara, 2017). An increase in interest rates reduces stock prices (Rigobon and Sack, 2004). In contrast, stock market returns primarily depend on news about expected excess returns rather than on real interest rates (Campbell and Ammer, 1993). Notably, the expected real interest rate exerts a relatively small effect on stock returns (Campbell, 1991).

It is important to explore how stock markets are connected to monetary policy changes, as interest rates are closely aligned with monetary policy. Monetary policy exerts a large effect on ex-ante and ex-post stock market returns (Thorbecke, 1997). In contrast, Patelis (1997) finds that monetary policy has little effect on ex-post stock returns. However, the response of stock markets primarily comes from the effect of unanticipated monetary policy on expected stock returns (Bernanke and Kuttner, 2005; Gorodnichenko and Weber, 2016). Monetary policy changes often come through changes in FFR. The Fed negatively affects stock markets (Bernanke and Kuttner, 2005; Maio, 2013), with a more pronounced impact on financially limited markets than on wealthier ones (Maio, 2013). However, the effect of monetary policy on stock markets varies over time (Paul, 2020).

Monetary policy can be either expansionary or contractionary. Stock prices fall significantly and persistently with contractionary monetary policy (Beckers and Bernoth, 2024), whereas they rise in response to expansionary policy (Thorbecke, 1997). In contrast, Galí and Gambetti (2015) found a persistent rise in stock prices to an exogenous contractionary monetary policy. Furthermore, monetary policy typically affects stock markets rather than being influenced by them; however, Rigobon and Sack (2003) evidenced a significant response of monetary policy to stock markets in the US. However, the response of monetary policy to stock prices is systematic and periodic, especially during recessions and financial instability (Aastveit et al., 2023).

Theoretically, monetary policy affects stock markets by altering the cost of capital. Blanchard (1981) expanded the IS-LM model to illustrate that fiscal and monetary policy changes influence stock markets. It shows that expansionary monetary policy reduces the cost of capital by lowering real interest rates, leading to a stock market boom. Asset pricing models, such as the Capital Asset Pricing Model (CAPM) and the Fama and French (2015) model, define the cost of capital for equity investment by using the risk-free rate as a benchmark. Increases in the risk-free rate raise the cost of capital, leading to detrimental effects on stock markets.

The cost of capital for equity investment is the expected return on equity. Fama and French (2015) The five-factor model indicates that investor tastes determine expected returns. Expected returns for ESG and non-ESG equity investments may vary due to differing investor tastes for each type. Pedersen et al. (2021); Pástor et al. (2021) developed frameworks to estimate the expected return on equity investments incorporating ESG factors. Pástor et al. (2021) model indicates that expected returns are lower for ESG investments compared to non-ESG investments. The model also depicts that ESG investors earn returns below their expectations, whereas non-ESG investors receive returns beyond their expectations. Empirical studies also found lower expected returns on ESG investments compared to non-ESG investments (Feldhütter et al., 2024). Based on the Pástor et al. (2021) model, the difference in expected returns between ESG and non-ESG investments varies according to ESG investors' wealth share and the maximum return they are willing to sacrifice. Consequently, lower expected returns may make ESG assets less responsive to the federal funds rate than non-ESG assets, as interest rates are key to defining the cost of capital for both.

The sustainable energy transition has received increased attention for various reasons, such as global warming and global geopolitical uncertainty, especially the Middle East crisis. The demand for renewable energy has increased dramatically in recent decades compared to earlier. This is a key indicator of sustainable energy transitions (Schmidt et al., 2019). However, clean energy or sustainable transition is vulnerable to rising interest rates. Moving from fossil fuels to sustainable energy has opportunity costs since sustainable energy transitions need capital-intensive investment. In this case, higher interest rates can slow down the energy transition due to increasing cost of capital. Schmidt et al. (2019) finds that interest rates have severe negative effects on the sustainable energy transition since they deteriorate the clean energy sector more than the fossil fuel sector. They derived this finding by comparative analysis of the effect of interest rates on the cost of electricity generation from both renewable sources and fossil fuel sources. They reveal that the cost of electricity generation is much higher for using renewable sources (through large-scale solar energy and onshore wind investments) than using fossil fuels, even with interest. They even argue that fossil fuel electricity costs can be affected by increases in interest rates; therefore, policy strategies should be taken to safeguard the sustainable energy transition against rising interest rates (Schmidt et al., 2019).

Interest rates play a crucial role in investors' decision-making. Investors are not making decisions irrationally, especially in stock market investments, where they consider their expectations, previous market experiences, and past market performance (Cohen and Kudryavtsev, 2012). Investors could prefer sustainable investments over fossil fuels if they are highly motivated by ESG. Some empirical studies using experimental methods provide evidence that investors are ready to forgo returns for investments that promote ESG (Feldhütter et al., 2024; Harasheh et al., 2024). However, the question is to what extent they are ready to forgo returns to support ESG investments. Investors would weigh the opportunity cost of capital against ESG preferences when they need a large amount of capital. As the study of Schmidt et al. (2019) find, rising interest rates can deteriorate ESG or clean energy investment.

In summary, empirical studies demonstrate that the federal funds rate negatively impacts stock market returns, consistent with theoretical models. However, to the best of my knowledge, none of the existing studies has examined interactions between monetary policy and stock markets based on ESG principles. In our study, the clean and the brown energy stock markets can represent the ESG and non-ESG assets, respectively. We expect a negative response in both stock markets to an impulse in the federal funds rate, based on theoretical background on stock markets and monetary policy. However, the clean energy market might show less sensitivity to the changes in the federal funds rate when we incorporate ESG-asset pricing principles. The following sections empirically evaluate the dynamics.

4.3 Data and Variables Description

We examine how monetary policy affects clean and brown energy financial assets. We select the WilderHill Clean Energy Index (WCE), S&P Global Clean Energy Index (GCE) and NASDAQ Clean Edge Green Energy Index (NCE) to represent clean energy stock markets, and S&P 500 Integrated Oil and Gas Index (SPO), Datastream Integrated Oil and Gas Index (DSO) and MSCI Oil and Gas Index (MSO) for brown energy stock market prices. In addition, the S&P 500 composite index and 10 other economic sectoral indices of the S&P 500 are chosen. The 10 economic sectors are commercial services (ECS), real estate (ERE), consumer discretionary (ECD), consumer staples (ECS), financial services (EFS), health care (EHC), information technology (EIT), materials (EMT), utilities(EUL) and industrial sectors (EIS). However, our main interest is in both clean and brown energy stock market indices displayed in Figure 4.1. All the stock market prices are adjusted to consumer prices following Bjørnland and Leitemo (2009). Then, they are transformed into return series using the standard formula given in (4.1), as many empirical studies have utilised it (for instance, Bjørnland and Leitemo, 2009):

$$s_t = log(x_t) - log(x_{t-1}) \tag{4.1}$$

where s_t represents stock market return; $log(x_t)$ and $log(x_{t-1})$ denote the logarithm of stock market price index and its lagged term, respectively. (4.1) reveals that the stock market returns, s_t, are the first difference of the logarithm of stock price index ($log(x_t)$). We employ the above equation to calculate the stock market returns for all selected stock market indices in this study. All the stock returns are multiplied by 100 to make them percentages.

Various monetary measures have been utilised in the empirical literature to identify and explain monetary policy shocks. The Federal Funds Rate (FFR) is one of the most widely used monetary policy measures and has been employed in several studies, including Thorbecke (1997), Bjørnland and Leitemo (2009), and Beckers and Bernoth (2024). This study also selects the FFR as the baseline measure of monetary policy. In addition, we consider alternative monetary policy measures, such as the US Treasury Bill three-month rate (TBL), the US Treasury constant three-month rate (TRS), the US Treasury constant one-year rate (TRM) and the US Treasury five-year yield (TRL). Among these monetary policy measures, the TRL can be regarded as a long-term monetary policy measure. In our model estimation, we employ the monetary policy measures without any transformation because they are already expressed as percentages (see, for example, Bjørnland and Leitemo, 2009).

Figure 4.1: Energy Stock Market Indices

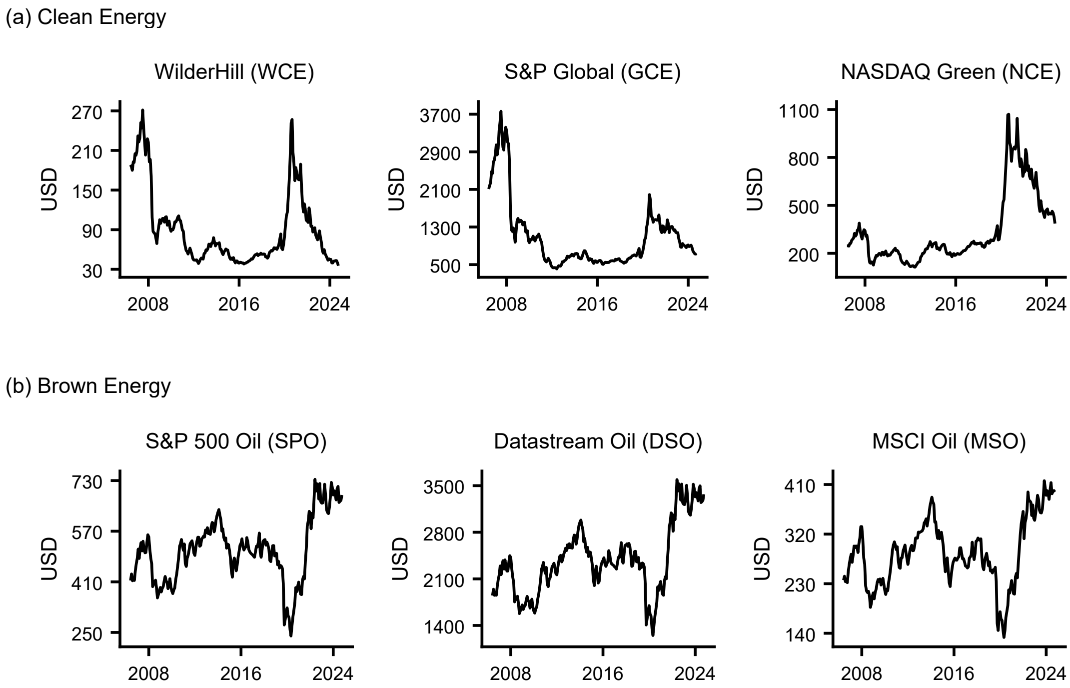
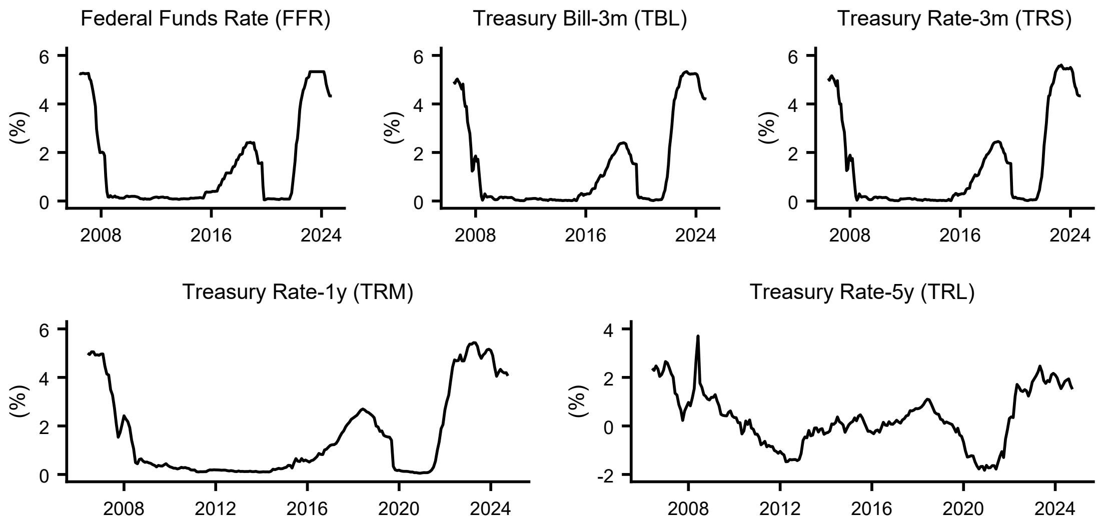


Figure 4.2: U.S. Monetary Policy Measures and Interest Rates



The five monetary policy measures are presented in Figure 4.2, where the FFR, TBL, TRS and TRM exhibit similar movements over time, whereas the TRL follows a somewhat different trend.

To explore the monetary policy transmission on stock market returns, the vast majority of the empirical studies (e.g., Thorbecke, 1997; Bernanke and Kuttner,

Table 4.1: Summary Statistics

Variable	Mean	Median	SD	Min	Max	Skewness	Kurtosis
Clean Energy Stock Market Returns (%)							
WCE	-0.9684	-0.5457	8.9588	-44.3964	22.6403	-0.5498	2.2723
GCE	-0.6876	-0.1571	8.0530	-48.9289	21.4469	-1.1061	5.6653
NCE	-0.0060	0.9495	8.1513	-42.0253	21.6738	-0.7254	3.0664
Brown Energy Stock Market Returns (%)							
SPO	0.0198	0.5692	5.5418	-38.5539	12.2888	-1.6163	9.6303
DSO	0.0643	0.8256	5.4355	-36.0073	11.7835	-1.4500	7.7262
MSO	0.0266	0.4107	5.7062	-38.6132	15.3324	-1.4581	8.7396
Other Stock Market Returns (%)							
S&P 500	0.4288	1.1573	3.8547	-22.1912	11.2973	-2.0064	8.6261
ERE	-0.0298	0.6624	5.7331	-33.7211	19.6705	-1.6749	8.5037
ECS	0.1643	0.6223	4.1874	-18.5535	10.5274	-1.0181	2.6861
ECD	0.5569	1.1690	5.1020	-27.9503	18.0009	-1.3989	5.9987
ECS	0.3409	0.6528	2.7871	-13.0611	6.7090	-1.1041	3.1442
EFS	0.0335	0.4691	5.8660	-30.3906	24.9720	-1.2058	6.5451
EHC	0.4711	1.0166	3.2668	-14.6419	9.2638	-1.2399	3.4087
EIT	0.8995	1.5603	4.6985	-22.5966	13.7224	-1.1847	3.4391
EMT	0.2148	0.8800	5.0242	-33.1629	14.9473	-1.9330	10.0269
EUL	0.1422	0.8067	3.7528	-18.3077	7.9151	-1.3290	4.2207
EIS	0.3581	0.6773	4.8598	-27.5683	17.1755	-1.7454	9.1447
Monetary Measures (%)							
FFR	1.4763	0.3424	1.8685	0.0486	5.3300	1.1106	-0.3298
TBL	1.3887	0.2727	1.8034	0.0114	5.3364	1.1262	-0.2569
TRS	1.4307	0.2757	1.8707	0.0114	5.6059	1.1427	-0.2141
TRM	1.5687	0.5620	1.7549	0.0505	5.4324	0.9985	-0.4973
TRL	0.3131	0.1776	1.1368	-1.8276	3.7095	0.1881	-0.5033
Macroeconomic Variables (%)							
ΔIP	0.2279	1.6094	4.9779	-18.8770	14.9453	-1.4676	3.6156
ΔIF	2.4610	2.1266	1.9205	-1.9782	8.6171	1.0442	1.5224
ΔPP	2.6215	2.1328	4.2406	-6.7086	16.6354	0.7531	0.7228
ΔFR	1.0984	0.5515	5.7103	-20.4657	25.0000	1.5620	6.3843

2005; Bjørnland and Leitemo, 2009; Maio, 2013) control for the following macroeconomic variables: percentage changes in industrial production (ΔIP), inflation rate (ΔIF), percentage changes in producer price (ΔPP), and percentage changes in total Federal Reserves (ΔFR). This study also includes the ΔIP, ΔIF, ΔPP, and ΔFR to investigate the dynamics of the monetary policy shock on clean and brown energy stock market returns. The percentage changes of both industrial production and producer prices are obtained following the method described in Bjørnland and Leitemo (2009). To calculate the percentage changes of the total Federal Reserve, we follow the same method that we apply to calculate the stock market returns described earlier (using (4.1) and multiplying it by 100), as consistent with Thorbecke (1997).

All the data obtained from Datastream (LSEG Data & Analytics) are in monthly format from November 2005 to March 2025. The variables industrial production, producer prices, and inflation rate are obtained monthly. Following Bjørnland and Leitemo (2009), all stock market data and monetary policy measures, including total Federal Reserve, are first obtained daily and then converted into monthly averages, while all other macroeconomic variables are already in monthly averages. All the data pertain to the U.S. economy except WCE and GCE. However, WCE and GCE can be considered to represent the U.S. clean energy market, as dominant U.S. clean energy firms are included in those two market indices. Table 4.1 presents the summary statistics for all the transformed series in this study.

4.4 Methodology

This study applies three different models to explore the effect of monetary policy shocks on clean and brown energy markets: (i) a simple regression model, (ii) an SVAR, and (iii) the LPs.

4.4.1 Simple Model

Following Thorbecke (1997), Bernanke and Kuttner (2005) and Maio (2013), we begin our analysis with a simple model as shown below:

$$s_t = \alpha + \beta \Delta m_t + \varepsilon_t \tag{4.2}$$

where s_t represents returns of the stock market, Δm_t denotes the first difference of a monetary policy measure, and ε_t is the residual of the model. Similarly, α and β are the intercept and slope parameters representing the impact of monetary policy measure on stock market. We estimate the model for each stock market returns with each monetary policy measures given in (4.2). However, this model does not address endogeneity because our study variables are endogenous.

4.4.2 Structural Vector Autoregressive (SVAR) Model

To address the endogeneity of the variables, in the next step we employ the SVAR model following Thorbecke (1997), Bjørnland and Leitemo (2009), and Beckers and Bernoth (2024). initially introduced the SVAR citeSVAR-Sim-1980 in macroeconomic research and can be written as follows:

$$B_0 y_t = B_1 y_{t-1} + ... + B_p y_{t-p} + \omega_t \tag{4.3}$$

where y_t (endogenous variables) and ω_t (structural shocks) are $k \times 1$ column vectors. The structural shocks (ω) are uncorrelated and distributed with zero mean and identity covariance matrix $\Sigma_\omega = I_k$, i.e., $\omega_t \sim (0, \Sigma_\omega)$. In the SVAR, B_i $(i = 0, 1, ...p)$ are $k \times k$ parameter matrices and the B_0 provides the contemporaneous relationship among the endogenous variables y_t.

The prerequisite of the SVAR model is the estimation of the reduced-form VAR model shown as follows:

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + u_t. \tag{4.4}$$

where A_i $(i = 1, ..., p)$ are $k \times k$ reduced form-VAR parameter matrices and u_t are $k \times 1$ vector of reduced form VAR residuals distributed with zero mean and covariance matrix Σ_u, i.e., $u_t \sim (0, \Sigma_u)$. The relationship between the SVAR model in (4.3) and the reduced-form VAR model in (4.4) can be written as follows:

$$y_t = B_0^{-1} B_1 y_{t-1} + ... + B_0^{-1} B_p y_{t-p} + B_0^{-1} \omega_t \tag{4.5}$$

where $B_0^{-1} B_1 = A_1$,...., $B_0^{-1} B_p = A_p$, and $B_0^{-1} \omega_t = u_t$. The matrix B_0^{-1} is called the structural impact multiplier matrix and provides contemporaneous responses of y_t to structural shock ω_t, which is one of our main interests in this study.

This study is also interested in exploring the structural impulse responses of the stock market returns to the monetary policy shocks. The reduced form VAR in (4.5) can be written as a Moving Average (MA) representation of the structural shock as follows:

$$y_t = \Psi_0 B_0^{-1} \omega_t + \Psi_1 B_0^{-1} \omega_{t-1} + \Psi_2 B_0^{-1} \omega_{t-2} + \dots = \sum_{i=0}^{\infty} \Psi_h B_0^{-1} \omega_{t-h}, \tag{4.6}$$

where Ψ_i is a 6×6 matrix and represents the Impulse Response Function (IRF) of our endogenous variables in this study at time horizon $h = (0, 1, 2, \dots \infty)$ to the corresponding reduced-form shocks (u_t). At the same time, $\Psi_i B_0^{-1}$ is a Structural

IRF (SIRF) of the same variables at time horizon $h = (0, 1, 2, \ldots \infty)$ to the structural shocks at time t (ω_t). Notably, SIRF at zero time horizon (at $i = 0$) is the B_0^{-1} since Ψ_0 is an identity matrix. The SIRF for h-period-ahead is:

$$\text{SIRF}(h) = \Theta_h = \Psi_h B_0^{-1}, \quad h = 0, 1, 2, \ldots \tag{4.7}$$

where Θ_h displays the SIRF of the endogenous variables to the structural shocks at horizon $h = 0, 1, 2, \ldots$, where we are interested in the element corresponding to the sixth row and fourth column (Θ_{64}) at each time horizon $h = 0, 1, 2, \ldots$. This element provides the SIRF of the stock market returns (SM_i) to the monetary policy shock (SM_j) at time horizon $h = 0, 1, 2, \ldots$. Notably, when $h = 0$, the element Θ_{64} of Θ_h is the same as the element b_{64} of B_0^{-1}, representing the immediate responses of the stock market returns to an impulse in the monetary policy measure.

4.4.3 Identification

The identification of B_0^{-1} is a crucial step in estimating the SVAR model. In the literature, various identification strategies have been employed to identify monetary policy shocks. Among these, the Cholesky decomposition method has been widely used in empirical studies to examine the impulse responses of stock market returns to monetary policy shocks. Empirical studies by Thorbecke (1997), Patelis (1997) and Maio (2013) are notable examples.

The Cholesky decomposition assumes that B_0^{-1} is a lower triangular matrix. Consequently, the ordering of variables in the VAR system plays a crucial role in identifying the structural shocks. The variables must be arranged according to their degree of exogeneity, with the most exogenous variable placed at the top and the least exogenous variable at the bottom. The remaining variables are ordered according to their relative degree of exogeneity. In the empirical literature, the degree of exogeneity is determined based on economic theory and the assumed relationships among the selected variables.

The long-run restriction is another identification strategy for structural shocks in the SVAR framework, introduced by Blanchard and Quah (1988). This approach assumes that certain structural shocks have no long-run effects on some variables in the system. Unlike the Cholesky decomposition, the long-run restriction is less dependent on the ordering of variables, as the identifying restrictions are based primarily on macroeconomic theory. Bjørnland and Leitemo (2009), for example, employ long-run restrictions to identify monetary policy shocks.

Sign restrictions provide another approach to identifying structural shocks. Unlike the Cholesky decomposition and long-run restrictions, which rely primarily on zero restrictions, the sign restriction approach specifies the expected direction of variables' responses to structural shocks. Beckers and Bernoth (2024) employ an SVAR model with sign restrictions to identify monetary policy shocks. This approach does not require recursive ordering or zero restrictions. Instead, it requires the researcher to specify the theoretically expected signs of the structural responses. For example, economic theory suggests that a contractionary monetary policy shock harms stock market returns. Accordingly, the corresponding response can be restricted to be negative during the identification process.

All of the identification methods discussed above assume that the VAR model has constant error variance. However, stock market returns often exhibit substantial volatility over time. For example, stock markets around the world experienced significantly higher volatility during the Global Financial Crisis and the COVID-19 pandemic. Lütkepohl (2005) and Rigobon (2003) show that structural shocks can also be identified using heteroskedasticity in the error variances. Rigobon and Sack (2003) and Rigobon and Sack (2004) employ heteroskedasticity-based approach to identify monetary policy shocks. Unlike previous methods, this approach does not require ordering, zero restrictions or sign restrictions. Instead, identification relies on changes in the variance of the structural shocks. If there is at least one significant structural break in the variance over time, the structural shocks can be identified.

In this study, we employ the Cholesky decomposition, which is one of the most widely used identification strategies in the SVAR literature. Following the standard literature (Christiano et al., 1999, 2005), we assume that macroeconomic variables do not respond contemporaneously to monetary policy shocks. Accordingly, we adopt a recursive identification scheme by placing the monetary policy variable near the bottom of the ordering, reflecting its relatively lower degree of exogeneity within the VAR system. Consequently, the variables are ordered as shown in (4.8), which is consistent with the specifications adopted by Thorbecke (1997), Patelis (1997), Maio (2013), and Bjørnland and Leitemo (2009).

$$\begin{bmatrix} u_t^{\Delta \mathrm{IP}} \\ u_t^{\Delta \mathrm{IF}} \\ u_t^{\Delta \mathrm{PP}} \\ u_t^{\mathrm{MP}} \\ u_t^{\Delta \mathrm{FR}} \\ u_t^{\mathrm{SM}} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 & 0 & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} & 0 & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} & 0 \\ b_{61} & b_{62} & b_{63} & b_{64} & b_{65} & b_{66} \end{bmatrix} \begin{bmatrix} \omega_t^{\mathrm{ip}} \\ \omega_t^{\mathrm{if}} \\ \omega_t^{\mathrm{pp}} \\ \omega_t^{\mathrm{mp}} \\ \omega_t^{\mathrm{fr}} \\ \omega_t^{\mathrm{sp}} \end{bmatrix} \tag{4.8}$$

Equation (4.8) describes the relationship between the reduced-form residual vector (u_t) and structural shock vector (ω_t), where MP denotes the monetary policy measure and SM denotes stock market returns. The reduced-form residual vector is given by $u_t = (u_t^{\Delta \mathrm{IP}}, u_t^{\Delta \mathrm{IF}}, u_t^{\Delta \mathrm{PP}}, u_t^{\mathrm{MP}}, u_t^{\Delta \mathrm{FR}}, u_t^{\mathrm{SM}})$, while the corresponding structural shock vector is $\omega_t = (\omega_t^{\mathrm{ip}}, \omega_t^{\mathrm{if}}, \omega_t^{\mathrm{pp}}, \omega_t^{\mathrm{mp}}, \omega_t^{\mathrm{fr}}, \omega_t^{\mathrm{sp}})$ where both vectors are (6×1).

In the literature, ω_t^{mp} and ω_t^{sp} are referred to as the monetary policy shock and the stock price shock, respectively (see, for example, Bjørnland and Leitemo, 2009). The primary focus of this study is the element b_{64} of B_0^{-1} presented in (4.8), which captures the contemporaneous effect of the monetary policy shock (ω_t^{mp}) on stock market returns (u_t^{SM}).

4.4.4 SVAR Model Estimation

The main objective of this study is to examine how clean and brown energy stock markets respond to monetary policy shocks. The variables selected for the SVAR model estimation are ΔIP, ΔIF, ΔPP, ΔPP, ΔFR, MP, and SM. We keep ΔIP, ΔIF, ΔPP, ΔPP, and ΔFR fixed in all SVAR model estimations, while the SM and MP variables are represented using different measures.

This study selects three alternatives for both clean and brown energy stock market returns. Specifically, WCE, GCE, and NCE are selected as measures of clean energy stock market returns, whereas SPO, DSO, and MSO are selected as measures of brown energy stock market returns. In addition, this study employs five alternative monetary policy (MP) measures: the Federal Funds rate (FFR), the three-month Treasury bills rate (TBL), the three-month Treasury rate (TRS), the one-year Treasury rate (TRM) and the five-year Treasury rate (TRL).

In SVAR model estimation, each model specification includes only one stock market return measure and one monetary policy measure. The same model is re-estimated using alternative combinations of stock market return and monetary policy measures while keeping the remaining variables (ΔIP, ΔIF, ΔPP, ΔPP, and ΔFR) unchanged. The purpose of estimating multiple model specifications is to assess the robustness of the findings.

Furthermore, we also consider stock market returns from other economic sectors of the US economy. Specifically, we include the 11 stock market return indices presented in Table 4.1. In this case, we follow the same estimation procedure as that used for the clean and brown energy markets by including one stock market return measure and one monetary policy measure in each SVAR model. The purpose of estimating the

SVAR models using other sectoral stock market returns is to determine whether the responses of clean and brown energy stock markets to monetary policy shocks differ from those of other sectors of the economy.

In summary, this study employs three clean energy stock market measures, three brown energy stock market measures, five monetary policy measures, and 11 stock market return measures representing other sectors of the US economy. Consequently, the analysis consists of a total of 85 model specifications, each combining one stock market return measure with one monetary policy measure.

Several studies have applied panel SVAR models to examine the responses of the heterogeneous stock markets to an impulse. For example, Pedroni (2013) proposed a panel SVAR model that allows for cross-sectional heterogeneity, while Mishra et al. (2014) examined how bank lending interest rates respond to monetary policy shocks using a panel SVAR model based on data of 132 countries. The panel SVAR framework has the advantage of incorporating heterogeneity across markets.

In this study, however, our primary focus is on the clean and brown energy markets in the US and their responses to monetary policy shocks. Therefore, we employ the standard SVAR model separately for clean and brown energy stock markets rather than using a panel SVAR framework. In addition, we estimate separate SVAR models for stock market returns from other sectors of the US economy to facilitate comparison. The analysis of cross-sectional heterogeneity across different sectoral stock markets using a panel SVAR framework is beyond the scope of this study and is left for future research.

4.4.5 Local Projections (LPs)

We shift our focus to LPs introduced by Jordà (2005), which have been more popular in macroeconomic research (Herbst and Johannsen, 2024). The LPs have several advantages as an alternative method to the VAR framework. Jordà (2005) listed the following four advantages of the LPs: (i) Standard regression tools are sufficient for them; (ii) They are more robust even if misspecification exists in the model; (iii) They are easier to apply statistical inferences; (iv) They can be applied to even more complex and flexible models even if they might not be easier in a multivariate context. Montiel Olea and Plagborg-Møller (2021) show that the LPs are simple and more robust even when (i) the data are highly persistent and (ii) time horizons are longer. Therefore, we employ LPs to validate the SVAR results regarding monetary policy transmission in clean and brown energy stock markets. The LPs can be written as follows:

$$y_{t+h} = \alpha^{(h)} + A_1^{h+1} y_{t-1} + A_2^{h+1} y_{t-2} + ... + A_p^{h+1} y_{t-p} + u_{t+h}^h, \quad h = 0, 1, 2, \ldots, n \quad (4.9)$$

where y_t contains the same 6×1 vector of endogenous variables as in the SVAR model estimation; α^h represents 6×1 vector of intercepts; A_i^{h+1} is a 6×6 coefficient matrix at lag order i and monthly horizon $h + 1$; and u_{t+h}^h is a 6×1 residuals vector at time horizons $h = 0, 1, 2, \ldots, n$. Equation (4.9) represents a sequence of n linear regressions, collectively referred to as Local Projections (LPs). Based on Kilian and Kim (2011), parameter matrices A_1^{h+1} in (4.9) can be interpreted as the responses of y at the time horizon $t + h$ to reduced-form shocks at time t (u_t). Jordà (2005) estimates the SIRF for LPs in (4.9) normalising A_1^0 as an identity matrix, and it can be written as:

$$\widehat{\text{SIRF}}(h) = \widehat{A}_1^h B_0^{-1} \quad h = 0, 1, 2, \ldots, n \quad (4.10)$$

where $\widehat{A}_1^h$ is the estimated coefficient matrix from (4.9) for $h = 0, 1, 2, \ldots n$ and B_0^{-1} represents the same impact multiplier matrix obtained in the SVAR framework (for further details, Jordà, 2005). The residuals from LPs may be serially correlated or heteroskedastic, and therefore, Jordà (2005) applies the Newey and West (1987) method to obtain robust standard errors.

4.5 Empirical Results

4.5.1 Responses of Energy Stock Market Returns

We begin with the estimated results of the simple model in (4.2), which ignores the endogeneity issues. The results reported in Table 4.2 show that all the stock market returns, including clean and brown energy stock markets, respond positively to the changes in all short-term policy rates (FFR, TBL, TRS, and TRM). This finding is not aligned with Thorbecke (1997), Bernanke and Kuttner (2005), Maio (2013), Maio and Santa-Clara (2017), and Gorodnichenko and Weber (2016), as they report a negative response of stock market returns to the changes in FFR. However, the table shows that changes in the long-term policy rate (TRL) have a negative effect on all stock market returns, consistent with those previous studies. For instance, Bernanke and Kuttner (2005) shows that a 1% increase in interest rate corresponded to an approximate 0.6% decline in stock market returns. In our study, a 1% rise in TRL reduces the stock market returns by 0.9% to 10% depending on the type of stock market.

Next, we compare the responses of clean and brown energy stock markets based on the simple model results reported in Table 4.2. We find that changes in very short-term monetary policy rates such as FFR, TBL, and TRS tend to increase clean energy stock returns more than brown energy stock returns. For instance, a 1% increase in the FFR raises the stock returns by 10-13% for clean energy markets, 7-9% for brown energy, and 3-10% for all other sectoral stock markets (see Table 4.2). We find that the medium-term monetary policy measure (TRM) increases returns in brown energy stock markets more than in clean energy markets. However, we have not seen any significant differences in either case. In contrast, we find that a rise in the long-term monetary policy rate (TRL) significantly reduces clean energy stock returns but has no significant effect on brown energy stock returns. For evidence, a 1% increase in the TRL reduces clean energy stock returns by approximately 6-10% and brown energy stock returns by less than 1%. This finding is completely inconsistent with Bauer et al. (2025), Döttling and Lam (2025), Havrylchyk and Pourabbasvafa (2025), and Patozi (2023).

Table 4.2: Responses of Stock Returns: Evidence from Simple Model

Stock returns	FFR	TBL	TRS	TRM	TRL
Clean Energy Stock Market Returns					
WCE	10.744	10.199*	9.550*	8.980*	-7.871***
	(1.631)	(1.841)	(1.790)	(1.684)	(-2.323)
GCE	13.013*	10.143*	9.490*	7.013	-9.618***
	(1.952)	(1.940)	(1.886)	(1.436)	(-2.977)
NCE	11.137*	10.927**	10.180**	9.860**	-6.343*
	(1.781)	(2.144)	(2.071)	(2.064)	(-1.836)
Brown Energy Stock Market Returns					
DSO	7.731**	8.844**	8.478**	9.843**	-0.942
	(2.217)	(2.028)	(2.030)	(2.474)	(-0.669)
SPO	8.315**	9.453**	9.064**	10.236**	-1.137
	(2.170)	(2.011)	(2.014)	(2.386)	(-0.775)
MSO	9.298*	8.858*	8.417*	10.864**	-1.212
	(1.950)	(1.703)	(1.687)	(2.414)	(-0.809)
Other Stock Market Returns					
S&P 500	6.092*	6.112*	5.727*	5.226	-3.227*
	(1.735)	(1.823)	(1.768)	(1.541)	(-1.816)
ECS	3.745	3.846	3.585	3.083	-3.550**
	(1.128)	(1.089)	(1.049)	(0.827)	(-2.168)
ERE	8.077	8.077	5.678	3.814	-6.816**
	(1.332)	(1.332)	(1.307)	(0.865)	(-2.623)
ECD	5.267	6.013	5.499	5.249	-4.530*
	(1.140)	(1.562)	(1.471)	(1.359)	(-1.924)
ECS	3.265*	2.328	2.030	1.219	-2.597**
	(1.664)	(1.194)	(1.073)	(0.602)	(-2.549)
EFS	9.957**	9.447**	8.866**	8.590*	-1.629
	(2.066)	(2.172)	(2.105)	(1.909)	(-0.611)
EHC	4.746**	5.011**	4.711**	3.082	-2.856**
	(2.168)	(2.462)	(2.378)	(1.433)	(-2.544)
EIT	6.423*	6.768*	6.429*	5.995	-4.113*
	(1.656)	(1.765)	(1.735)	(1.527)	(-1.963)
EMT	4.726*	6.967	3.828	6.067	-4.911**
	(1.769)	(1.597)	(1.380)	(1.487)	(-2.149)
EUL	4.726*	4.248	3.828	2.528	-3.926***
	(1.769)	(1.507)	(1.380)	(0.875)	(-2.851)
EIS	8.368**	7.294*	6.869*	5.990	-3.505*
	(1.990)	(1.756)	(1.720)	(1.462)	(-1.745

Note: FFR, TBL, TRS, TRM and TRL are the monetary policy measures. This table presents the estimates of β_{ij} in the simple model given in (4.2). The t-statistics displayed in parentheses below each coefficient are adjusted for heteroskedasticity and autocorrelation using the approach of Newey and West (1987). Further, ***, **, and * indicates the significant levels at 1%, 5% and 10%, respectively.

4.5.2 Contemporaneous Responses of Energy Stock Returns

We shift to the results of our main model in this study. Table 4.3 presents contemporaneous responses of each stock market to an impulse in each type of monetary policy measure. We find that the long-term monetary policy (TRL) has a negative immediate effect on all the stock market returns, consistent with Thorbecke, 1997; Bernanke and Kuttner, 2005; Bjørnland and Leitemo, 2009; Maio, 2013; Arias et al., 2019; Beckers and Bernoth, 2024. In contrast, the short-term monetary policy (FFR, TBL, TRS, and TRM) has a positive and statistically significant instant effect on all types of stock markets listed in this study. The significant positive effects are unexpected based on theoretical views and previous empirical studies (see, for example, Thorbecke, 1997; Bernanke and Kuttner, 2005; Bjørnland and Leitemo, 2009; Maio, 2013; Arias et al., 2019; Beckers and Bernoth, 2024). However, Jarociński and Karadi (2020) illustrates the possibility of positive responses of stock markets to monetary policy shocks. The study reveals that stock market returns could rise with an increase in interest rates and fall with interest rate cuts because of central bank information shocks. When a central bank announces monetary policy rates, it also conveys information about its assessment of the economic outlook. This information shock could bias the effect of the monetary policy shock on the macro economy, including stock market returns.

Interestingly, this study finds a correct sign for the effect of long-run monetary policy shocks, but not for the short-run monetary shocks. This finding leads us to argue that the central bank information shock might influence more investors' decision-making when short-run interest rate changes occur. Still, it might not be the case for long-run interest rate changes. This can be justified. In general, investors are more sensitive to long-run interest rates than to short-run interest rates because they are not ready to bear the cost or take risks for long periods. When a change occurs in the short-run interest rate, investors could listen more to the central bank information about future economic activities than to the cost of capital. But when it comes to the long-run interest rate, they might pay more attention to the cost of capital rather than to the central bank information shock. Consequently, it is not surprising to have an incorrect sign for a shock in the short-run monetary policy measure while we find a correct sign for a shock in the long-term monetary policy.

In Table 4.3, our main interest is to explore how the responses of clean and brown energy stock markets differ to a shock in the monetary policy measures. We find that an impulse in very short-term monetary policy rates, especially in FFR, TBL, and TRS, has stronger, significant contemporaneous positive effects on clean energy

Table 4.3: Contemporaneous Responses of Stock Markets: Evidence from SVAR Model

Stock returns	FFR	TBL	TRS	TRM	TRL
Clean Energy Stock Market Returns					
WCE	2.9898***	2.5328***	2.4928***	2.3150***	-1.2583**
	(5.878)	(4.993)	(4.910)	(4.464)	(-2.342)
GCE	2.9113***	2.3238***	2.3583***	1.5608***	-1.9551***
	(6.730)	(5.322)	(5.374)	(3.452)	(-4.228)
NCE	2.7524***	2.6394***	2.5892***	2.3315***	-0.9258*
	(5.821)	(5.643)	(5.533)	(4.905)	(-1.877)
Brown Energy Stock Market Returns					
DSO	1.8131***	1.6530***	1.7212***	1.6860***	-0.4988
	(5.792)	(5.211)	(5.404)	(5.490)	(-1.494)
SPO	1.9334***	1.8115***	1.8747***	1.7356***	-0.5989*
	(6.011)	(5.556)	(5.727)	(5.463)	(-1.743)
MSO	1.9030***	1.511***	1.5587***	1.7479***	-0.4670
	(6.198)	(4.783)	(4.908)	(5.793)	(-1.436)
Other Stock Market Returns					
S&P 500	1.4681***	1.3420***	1.3302***	1.2855***	-0.6704***
	(6.175)	(5.685)	(5.609)	(5.577)	(-2.730)
ECS	1.3446***	0.9399***	0.920***	1.2241***	-0.9549***
	(5.111)	(3.610)	(3.536)	(4.676)	(-3.535)
ERE	1.5751***	1.1401***	1.0612***	1.1401***	-1.6385***
	(4.766)	(3.450)	(3.194)	(3.450)	(-5.196)
ECD	1.4580***	1.1902***	1.1022***	1.4272***	-0.6812**
	(4.528)	(3.785)	(3.495)	(4.538)	(-2.072)
ECS	1.0682***	0.8244***	0.7829***	0.6678***	-0.5831***
	(5.754)	(4.355)	(4.119)	(3.610)	(-3.115)
EFS	1.6788***	1.7702***	1.7429***	1.7790***	-0.3569
	(4.950)	(5.474)	(5.321)	(5.526)	(-1.022)
EHC	1.2619***	1.2114***	1.1894***	0.8742***	-0.5683 ***
	(6.043)	(5.961)	(5.837)	(4.339)	(-2.691)
EIT	1.4193***	1.3621***	1.3836***	1.2043***	-0.9009***
	(4.860)	(4.696)	(4.764)	(4.149)	(-2.969)
EMT	1.7994***	1.4307***	1.4204***	1.2664***	-1.1716***
	(5.805)	(4.654)	(4.594)	(4.193)	(-3.718)
EUL	1.2704***	1.3414***	1.3037***	1.1361***	-0.9384***
	(5.499)	(5.726)	(5.542)	(4.868)	(-4.009)
EIS	1.7459***	1.4214***	1.4267***	1.3513***	-0.7139**
	(6.049)	(4.985)	(4.972)	(4.796)	(-2.399)

Note: FFR, TBL, TRS, TRM and TRL are the monetary policy measures. We select 18 lags for the reduced-form VAR following Plagborg-Møller and Wolf (2021) and Olea et al. (2025). This table shows estimates for the element b_{64} of the B_0^{-1} in (4.5) for each stock market return with each monetary policy measure. The t-statistics are displayed in parentheses below each coefficient. Further, ***, **, and * indicate significant levels at 1%, 5% and 10%, respectively.

markets than on brown energy stock markets. For instance, one standard deviation positive unit shock raises all clean energy stock market returns by over 2.75% and all brown energy markets by just below 1.95%. Further, this study finds that a shock in the long-run monetary policy measure (TRL) has a stronger negative and statistically significant effect on clean energy stock markets than on brown energy stock markets. For evidence, a one-standard-deviation positive unit shock in the TRL leads to lower returns in all brown energy stock markets by below 0.6% and in all clean energy markets by approximately 1%, with GCE recording approximately 2% and being statistically significant at the 1% level. These findings align with our prior beliefs, as discussed earlier. However, they are not consistent with the recent empirical studies (Bauer et al., 2025; Döttling and Lam, 2025; Havrylchyk and Pourabbasvafa, 2025; Patozi, 2023), which record brown energy markets as more sensitive to monetary policy decisions.

Many studies which employ firm-level data reveal that brown energy stock markets are more sensitive to monetary policy shocks than the clean energy stock markets (Bauer et al., 2025; Döttling and Lam, 2025; Havrylchyk and Pourabbasvafa, 2025; Patozi, 2023). These studies control for various firm-level factors such as firm age, leverage, liquidity, profitability and cash flow, dividends per share and market-to-book ratio. Our study employs country-level stock market indices and macroeconomic variables to investigate the sensitivity of stock markets to monetary policy shocks. These macro-level data may not adequately capture heterogeneity across firms. Further, the studies that use micro-level data differentiate clean and brown energy stocks based on their ESG score level. Our study considers separate indices for clean and brown energy stock markets rather than their ESG scores. The clean energy stock index represents the overall performances of the stock companies related to clean energy production and services. Similarly, the brown energy stock index represents the overall performance of the stock companies related to fossil fuel production and services. Therefore, the firm-level heterogeneities and differences in clean and brown energy measurements may lead to inconsistent results when we use micro- and macro-level data.

However, our findings align with the findings of Maio (2013), which demonstrate that financially limited markets are more sensitive to interest rates than wealthier markets. In our study, clean energy markets can be treated as financially limited markets since they are in emerging states and require more capital-intensive investments. Brown energy markets can be treated as wealthier markets since they are already in a mature stage and do not require more capital-intensive investments compared to clean energy markets. Further, our finding that the clean energy market is more sensitive to interest rates can be expected based on theoretical viewpoints as well. Based on the theories related to the cost of capital, we can argue that clean energy markets are more sensitive to interest rates or monetary policy shocks than the brown energy markets since the opportunity cost of capital is higher for clean energy investment than for brown energy investment, as the clean energy transition requires a massive amount of capital compared to the amount required for brown energy investments. This can make the clean energy market more sensitive to monetary policy shocks.

The positive effects of a shock in short-term monetary measures could be due to the central bank information shock, which has been discussed previously. The focus here is on why the positive response is larger for clean energy than for brown energy, which can be explained based on the ESG asset pricing literature. Pástor et al. (2021), Pedersen et al. (2021) and Feldhütter et al. (2024) show that investors are willing to accept lower returns for green assets over brown assets. The ESG nature of financial assets might cause the clean energy market to show a stronger positive response than the brown energy markets.

We now shift our focus to comparing the responses of the clean energy market with all other stock markets in this study, excluding brown energy. In Table 4.3, this study finds that clean energy markets' responses to the short-term monetary policy shock are even higher than those of the S&P 500 composite and other economic sectoral stock markets. For example, a one-standard-deviation shock in TRS leads to rises in clean energy market returns of over 2.3% instantly and in all other stock markets of below 1.6%. In the case of a shock in long-term monetary policy, all other stock market returns react negatively and statistically significantly, whereas EFS lacks statistical significance. Still, we can conclude that the long-term monetary policy shock has a stronger effect on clean energy markets than on all other market returns. In addition, this study notes that long-term monetary shock also has stronger negative effects on other capital-intensive markets. For example, a one-standard-deviation positive unit shock significantly reduces the returns of real estate markets (EER) by 1.64%, which is slightly lower than the effect on global clean energy market returns (GCE).

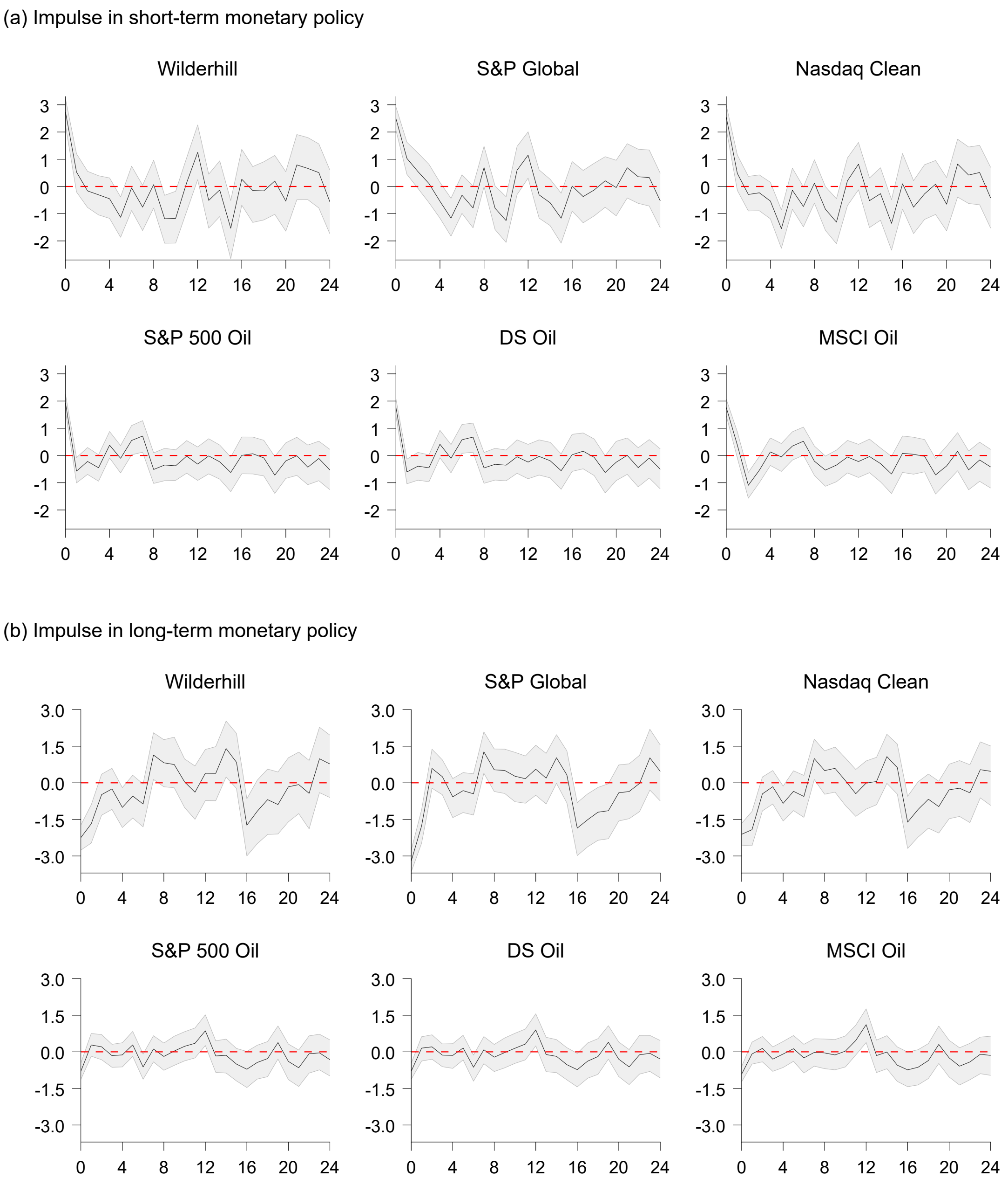
4.5.3 Impulses Responses of Energy Stock Markets

We are also interested in impulse responses of clean and brown energy stock markets to the monetary policy shock over time. Among the four short-term monetary policy measures, we select only TRs, as they yield similar SIRFs for stock market returns. In addition, we use the long-term monetary measure TRL to examine the SIRFs of clean and brown energy stock market returns to shocks in both short-term and long-term monetary policy measures. Figure 4.3 presents the SIRFs of both types of energy markets to impulses in short- and long-term monetary policy rates using the SVAR model. The responses at the zero horizons in Figure 4.3 represent contemporaneous responses discussed earlier. In contrast, subsequent horizons show how each energy stock market reacts over time to a one standard deviation shock in the monetary policy rate at time t (zero horizon). We find that clean energy markets appear to be more responsive than brown energy markets, which is expected given that clean energy markets are generally more capital intensive.

Figure 4.3 shows that an impulse in the short-term monetary policy rate leads to a positive and significant effect on both clean and brown energy markets in the short horizons. The effects turn negative in the long horizons, where clean energy markets often show a significant negative response. The negative response in the long run is consistent with Bjørnland and Leitemo (2009), Galí and Gambetti (2015), Gorodnichenko and Weber (2016) and Beckers and Bernoth (2024). Interestingly, in response to an impulse in the long-term interest rate, brown energy markets tend to show no response over time, while the clean energy market shows more significant responses over time. For instance, the range of the responses is between -1.5% and +1.5% for brown energy but -3% and +3% for the clean energy markets (see Figure 4.3). The response of the clean energy market varies over the time horizons: strong negative responses in the short horizon (approximately 0 to 7 months), positive responses at 8-15 months horizons, and negative responses from approximately the 16th month horizons. The responses of the clean energy market to the long-run monetary policy shock align with Melcangi and Sterk (2024) and Bernanke and Kuttner (2005), which show that the stock market reacts negatively in the short run and positively in the long run to a monetary policy shock. Further, we find evidence of overshooting in the impulse responses shown in Figure 4.3 as consistent with Galí and Gambetti (2015).

It is also interesting to discuss how the energy stock price shocks influence short- and long-run interest rates. Figure 4.4 displays the reaction of monetary policy to an impulse in energy stock prices. In the figure, the response curves start from zero,

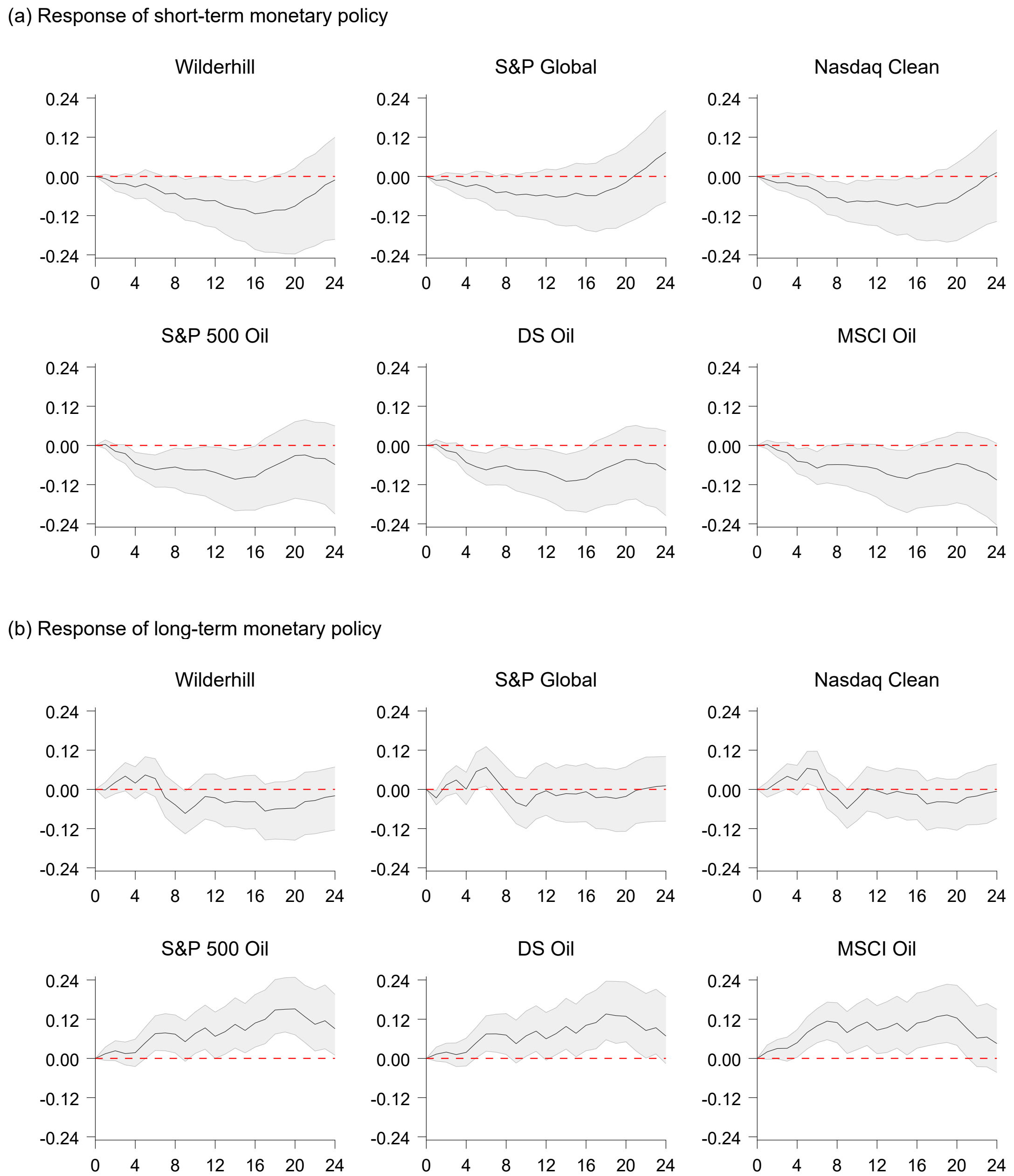
Figure 4.3: IRF of Energy Stock Market Returns to Monetary Policy shock (one standard deviation): Evidence from SVAR



Note: The reduced-form VAR model is estimated with 18 lags, as shorter-lag VARs can produce biased results due to extrapolating from too few correlations in the data (see, for further details, Olea et al., 2025). TRS and TRL are selected to represent the short-run and long-run monetary policy rates, respectively. The confidence bands correspond to the 68% level.

as we impose a zero restriction on the instantaneous effect of the stock price shock on monetary policy, following the studies of Thorbecke (1997), Patelis (1997) and Maio (2013). Interestingly, we find that the stock price shock in both markets has a

Figure 4.4: IRF of Monetary Policy Measure to Energy Stock Markets (one standard deviation shock): Evidence from SVAR



Note: The reduced-form VAR model is estimated with 18 lags, as shorter-lag VARs can produce biased results due to extrapolating from too few correlations in the data (see, for further details, Olea et al., 2025). TRS and TRL are selected to represent the short-run and long-run monetary policy rates, respectively. The confidence bands correspond to the 68% level.

persistent and marginally significant negative effect on the short-term interest rate over the period. This finding is not consistent with (Rigobon and Sack, 2003; Bjørnland and Leitemo, 2009; Arias et al., 2019; Galí and Gambetti, 2015; Aastveit et al., 2023). The long-run interest rate shows asymmetric reactions to the shocks in clean and brown energy stock markets. We find that a brown energy stock price shock leads to a persistent and statistically significant increase in the long-run interest rate over time, consistent with (Rigobon and Sack, 2003; Bjørnland and Leitemo, 2009; Arias et al., 2019; Galí and Gambetti, 2015; Aastveit et al., 2023). In contrast, the reaction of the long-term interest rate to the clean energy stock price shock varies over time. We find that the long-run interest rate reacts positively to the shock in the clean energy stock markets in the short run but tends to be negative in the long run.

Interestingly, clean energy stock price shocks tend to have a negative effect on the long-run interest rate, while brown energy stock price shocks lead to a positive effect. In other words, clean energy stock price shocks increase the likelihood of imposing expansionary monetary policy, while brown energy stock price shocks lead to a contractionary monetary policy. Asymmetric responses in monetary policy decisions can be expected when we consider the ESG nature of assets. An increase in stock prices would induce inflationary pressure on an economy. It could then lead to a contractionary monetary policy, as we observed in the case of long-run interest rates in response to brown energy stock price shocks. At the same time, expansionary monetary policy can also be expected to result from a positive stock price shock if the asset is ESG-aligned and promotes energy transitions to sustainable energy. Further, central banks introduce various schemes to promote green investment, such as lower interest rates for green loans. Therefore, it is not surprising that clean energy stock price shocks tend to lower the long-run interest rate.

4.6 Robustness Check

This study utilises three different market indices to represent clean and brown energy markets individually. We find consistent results individually for clean and brown energy markets even when three different market indices are utilised for each category. However, this study further checks the consistency of the results in the following two ways. First, we re-estimate the SVAR model including Oil Price Returns (OPR) along with the existing variables. Second, this study applies LPs, an alternative method to the SVAR.

First, we re-estimate the impulse responses by adding oil price return in the existing SVAR framework. Many studies which examine the dynamics between monetary policy and stock market returns have not given attention to oil price shocks in their investigations (see, for instance, (Thorbecke (1997), Patelis (1997), Bjørnland and Leitemo (2009), and Maio (2013)). However, Jones and Kaul, 1996; Sadorsky, 1999; Park and Ratti, 2008 find a statistically significant effect of oil price on financial market returns. The effect can be positive or negative depending on the sources of oil price shock: demand-side or supply-side factors. We include the oil price returns in the SVAR to examine the effect of monetary policy shocks on the two energy stock market returns.

Our aim is not to investigate the role of oil price shocks on those stock markets. Instead, we are interested in confirming the consistency of the effect of monetary policy shocks on those two different stock markets that we obtained earlier, even after including the oil price returns in the SVAR system. We still obtain consistent results displayed in Table 4.4 and Figure 4.5 even after including the oil price returns in the existing SVAR. To estimate the results, we place the oil price return at the top in the recursive ordering while keeping other variables below it, as in the order shown in (4.A.4). The reason for placing the oil price return at the top is its exogenous nature in responding contemporaneously to shocks in the other variables in this study. For instance, Burbidge and Harrison (1984); Lippi and Nobili (2012) placed the oil price above the macroeconomic variable to identify the contemporaneous effects of oil price shocks.

Second, we obtain impulse responses using the Local Projections method, and they are displayed in Figure 4.6 and 4.7. We find that impulse responses from LPs and the SVAR models are identical up to the 4th horizon and fairly identical for the rest of the horizons, as consistent with Plagborg-Møller and Wolf (2021), which accounts that the impulse responses from LPs and SVAR are identical for unrestricted lags and close to each other for restricted lags. They also show that even if restricted

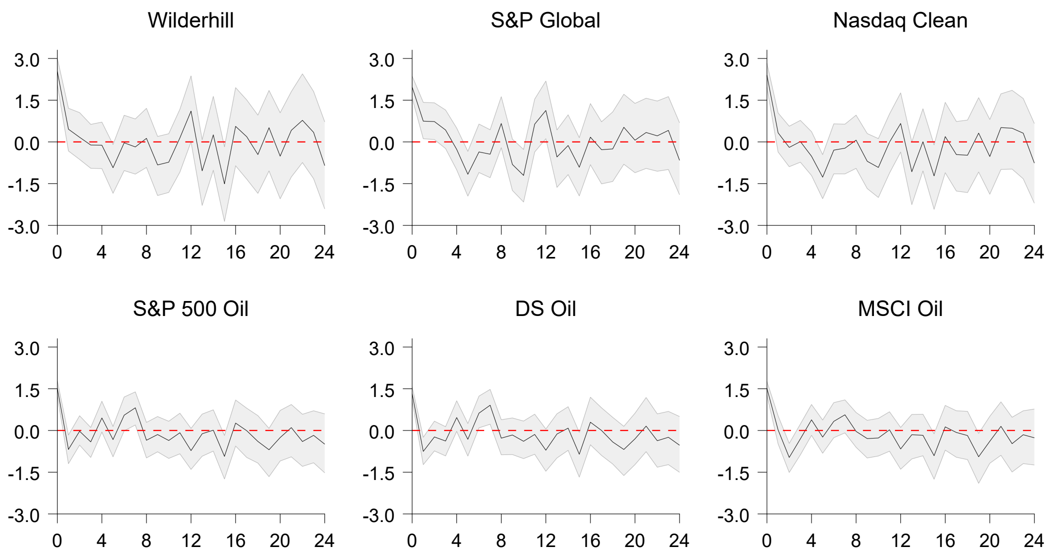
Table 4.4: Contemporaneous Responses of Stock Markets: Evidence from SVAR Model (with oil price returns)

Stock returns	FFR	TBL	TRS	TRM	TRL
Clean Energy Stock Market Returns					
WCE	2.7282***	2.3913***	2.3354***	2.1983***	-1.0216**
	(5.495)	(4.878)	(4.774)	(4.424)	(-1.975)
GCE	2.7509***	2.0538***	2.0580***	1.5185***	-1.5081***
	(6.780)	(5.193)	(5.183)	(3.615)	(-3.543)
NCE	2.6570***	2.5149***	2.4579***	2.2423***	-0.6769
	(5.742)	(5.581)	(5.463)	(4.911)	(-1.417)
Brown Energy Stock Market Returns					
DSO	1.4532***	1.5541***	1.6034***	1.6410***	-0.2878
	(5.305)	(5.930)	(6.028)	(6.072)	(-0.992)
SPO	1.6034***	1.7095***	1.7561***	1.7160***	-0.3720
	(6.028)	(6.237)	(6.318)	(6.072)	(-1.233)
MSO	1.3982***	1.3304***	1.3588***	1.6114***	-0.2211
	(5.544)	(5.245)	(5.305)	(6.361)	(-0.833)
Other Stock Market Returns					
S&P 500	1.3649***	1.2114***	1.1994***	1.1740***	-0.5891***
	(6.035)	(5.631)	(5.562)	(5.534)	(-2.519)
ECS	1.2391***	0.8536***	0.8399***	1.2264***	-0.9399***
	(4.742)	(3.347)	(3.299)	(4.779)	(-3.535)
ERE	1.6105***	1.0470***	0.9983***	0.8486***	-1.6624***
	(4.890)	(3.242)	(3.082)	(2.646)	(-5.296)
ECD	1.4247***	0.9996***	0.9090***	1.2948***	-0.6242*
	(4.472)	(3.304)	(3.003)	(4.259)	(-1.918)
ECS	1.1366***	0.7818***	0.7696***	0.6871***	-0.5850***
	(6.319)	(4.359)	(4.290)	(3.895)	(-3.220)
EFS	1.4747***	1.6367***	1.6038***	1.6594***	-0.2730
	(4.609)	(5.646)	(5.460)	(5.533)	(-0.817)
EHC	1.2652***	1.1613***	1.1499***	0.9041***	-0.4376***
	(6.196)	(6.028)	(5.976)	(4.800)	(-2.097)
EIT	1.3295***	1.1506***	1.1772***	0.9912***	-0.8261***
	(4.7310)	(4.241)	(4.339)	(3.666)	(-2.824)
EMT	1.4916***	1.3173***	1.2847***	1.1858***	-0.9992***
	(5.236)	(4.903)	(4.757)	(4.387)	(-3.446)
EUL	1.3418***	1.3302***	1.2995***	1.1795***	-0.9403***
	(5.905)	(5.721)	(5.567)	(5.096)	(-4.060)
EIS	1.5819***	1.2798***	1.2759***	1.1874***	-0.6758***
	(5.860)	(5.027)	(4.988)	(4.570)	(-2.427)

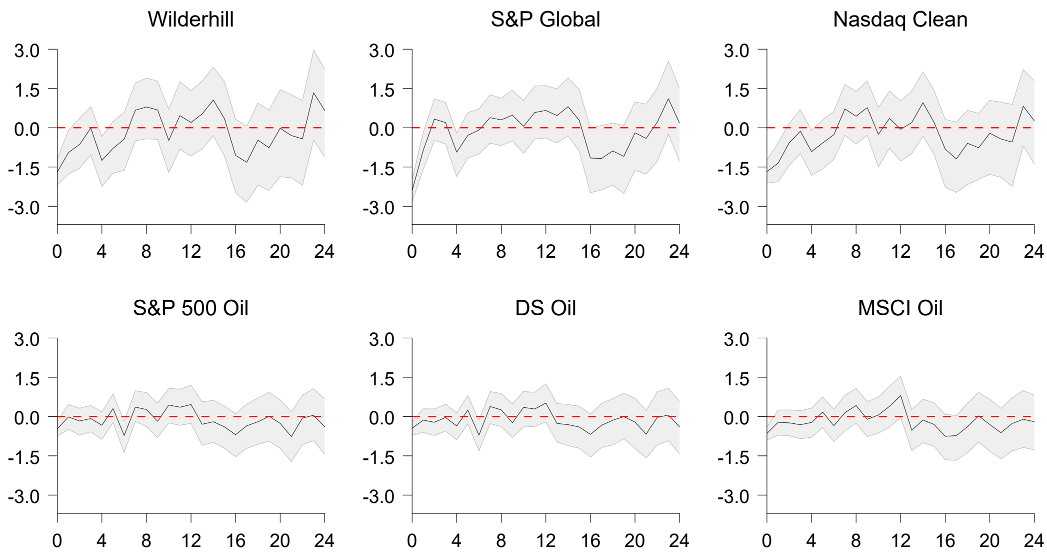
Note: FFR, TBL, TRS, TRM and TRL are the monetary policy measures. We select 18 lags for the reduced-form VAR following Plagborg-Møller and Wolf (2021) and Olea et al. (2025). This table shows contemporaneous responses of corresponding stock market returns to impulses in each monetary policy measure. The t-statistics are displayed in parentheses below each coefficient. Further, ***, **, and * indicate significant levels at 1%, 5% and 10%, respectively.

Figure 4.5: IRF of Energy Stock Markets to Monetary Policy Shock (one standard deviation shock): Evidence from SVAR (with oil price)

(a) Impulse in short-term monetary policy



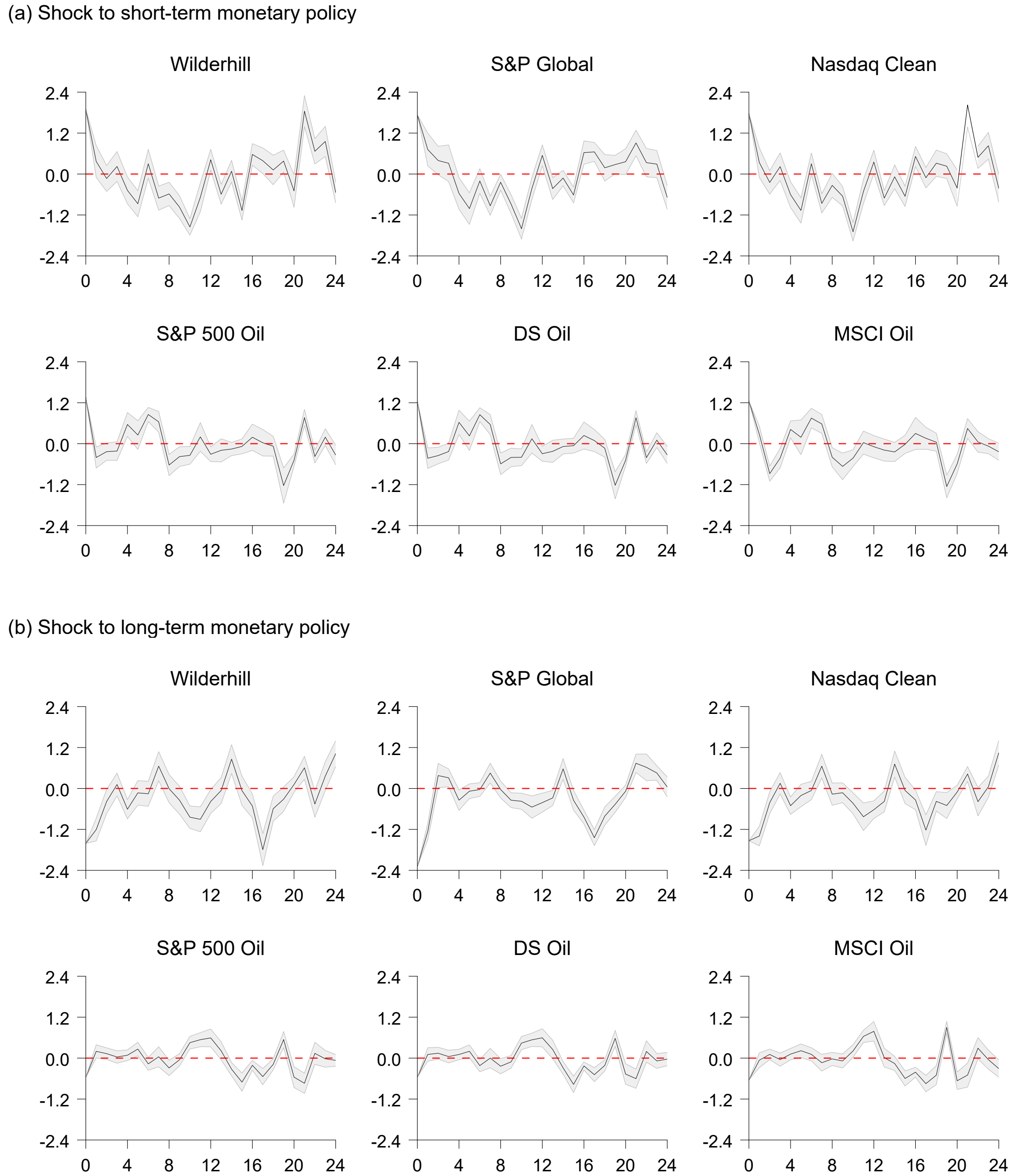
(b) Impulse in long-term monetary policy



Note: The reduced-form VAR model is estimated with 18 lags, as shorter-lag VARs can produce biased results due to extrapolating from too few correlations in the data (see, for further details, Olea et al., 2025). TRS and TRL are selected to represent the short-run and long-run monetary policy rates, respectively. The confidence bands correspond to the 68% level.

lags are chosen, both models provide identical impulse responses up to approximately the 4th truncation horizon. In addition, we notice that the responses from LPs are more statistically significant than the responses from the SVAR model (for instance,

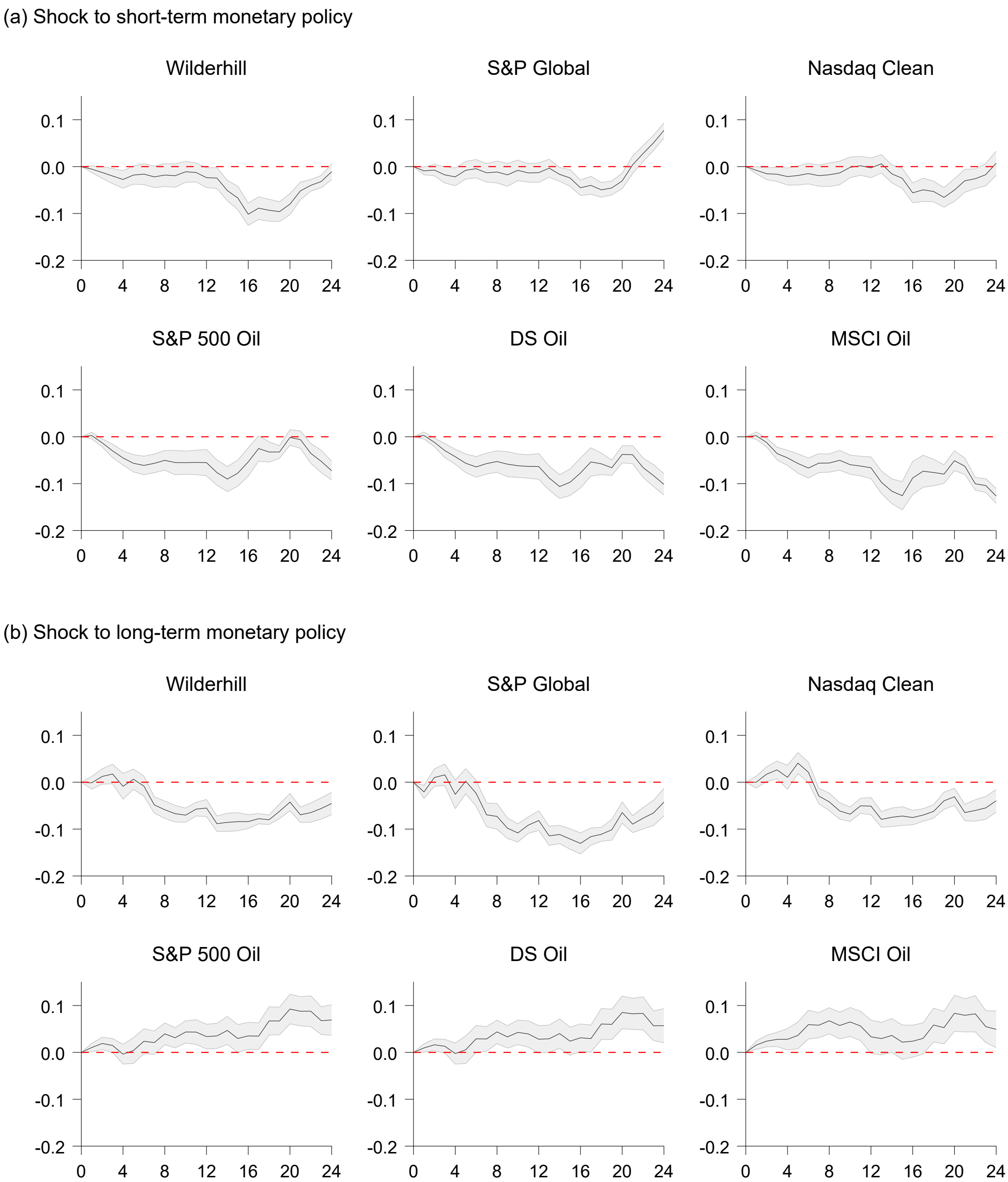
Figure 4.6: IRF of Energy Stock Market Returns to Monetary Policy Shock (one standard deviation shock): Evidence from LPs (with oil price)



Note: LPs are estimated with 18 lags to align with the lag selection in the SVAR model estimation. TRS and TRL are selected to represent the short-run and long-run monetary policy rates, respectively. The confidence bands correspond to the 68% level.

Figure 4.3 and 4.6).

Figure 4.7: IRF of monetary policy measure to energy stock price shock (one standard deviation shock): Evidence from LPs



Note: LPs are estimated with 18 lags to align with the lag selection in the SVAR model estimation. TRS and TRL are selected to represent the short-run and long-run monetary policy rates, respectively. The confidence bands correspond to the 68% level.

4.6.1 Identification via changes in volatility

We also examined the contemporaneous responses of stock market returns to monetary policy shocks using the changes-in-volatility identification approach. Rigobon (2003) develops an identification strategy to address the issue of simultaneity in the contemporaneous relationship among the variables included in the VAR system. Lütkepohl (2005); Lanne and Lütkepohl (2008) show that changes in the volatility of the error variance from a reduced-form VAR model can be exploited to identify monetary policy shocks. The following section explains the SVAR identification approach based on changes in volatility.

Suppose that the reduced-form error covariance matrix in period t is given by

$$\mathbb{E}(u_t u_t') = \begin{cases} \Sigma_1 & \text{for} \quad t \in \mathcal{T}_1, \\ & \vdots \\ \Sigma_M & \text{for} \quad t \in \mathcal{T}_M, \end{cases} \tag{4.11}$$

Within this specified framework, let $\Sigma_m = (\Sigma_1, \Sigma_2, ..., \Sigma_M)$, $\mathcal{T}_m = (\mathcal{T}_1, \mathcal{T}_2, ..., \mathcal{T}_M)$ and $m = (1, 2, ..., M)$. There are M volatility regimes, each assumed to be mutually exclusive. The sets $\mathcal{T}_m$ denote the sample periods corresponding to the different volatility regimes, while Σ_m represents the error covariance matrices associated with each regime. The error covariance matrices can be decomposed as

$$\Sigma_1 = B_0^{-1} B_0^{-1\prime}, \quad \Sigma_m = B_0^{-1} \Lambda_m B_0^{-1\prime} \quad \text{for} \quad m = 2, ..., M. \tag{4.12}$$

In Equation 4.13, the diagonal matrices $\Lambda_m = \text{diag}(\lambda_{1m}, ..., \lambda_{Km})$ capture the changes in volatility relative to the first volatility regime. In this study, we identify a structural break in January 2020, immediately before the COVID-19 pandemic, and therefore consider only two volatility regimes with the single break point. Consequently,

$$\Sigma_1 = B_0^{-1} B_0^{-1\prime}, \quad \Sigma_2 = B_0^{-1} \Lambda_2 B_0^{-1\prime} \tag{4.13}$$

Under this specification, B_0^{-1} is identified without imposing either zero or sign restrictions because the number of unknown parameters equals the number of independent equations provided by the two unique covariance matrices (Σ_1 and Σ_2). The parameters B_0^{-1} and λ_m are estimated by maximizing the log-likelihood function.

Table 4.5 presents the contemporaneous responses of energy stock market returns to monetary policy shocks. Five alternative measures are employed to capture monetary policy shocks. The results once again confirm that clean energy stock market returns are more sensitive to monetary policy shocks than brown energy stock market returns. Furthermore, we find that shocks to the long-term monetary policy measure (TRL, the five-year Treasury yield) have more pronounced negative effects on clean energy stock markets than on brown energy stock markets. This finding suggests that long-term monetary policy changes have more severe effects on more capital-intensive industries than on less capital-intensive industries. These results are consistent with those obtained using the Cholesky identification strategy.

Table 4.5: Contemporaneous Responses of Energy Stock Markets Identified via Heteroskedasticity

Stock returns	FFR	TBL	TRS	TRM	TRL
Clean Energy Stock Market Returns					
WCE	2.3372***	1.5720	1.7163**	1.1611	-1.8180
	(0.295)	(1.956)	(0.7587)	(0.961)	(0.585)
GCE	2.8944***	1.4239	1.6525**	1.3677***	-3.2290***
	(0.155)	(1.274)	(0.618)	(0.483)	(0.516)
NCE	2.0633***	1.5196*	1.7227**	1.1255	-2.8467***
	(0.350)	(0.802)	(0.747)	(0.768)	(0.612)
Brown Energy Stock Market Returns					
DSO	1.6192***	1.2384***	1.1368***	1.4310***	1.8072***
	(0.473)	(0.121)	(0.232)	(0.148)	(0.314)
SPO	1.7026***	1.3535***	1.4366***	1.5155***	0.8729**
	(o.371)	(0.239)	(0.272)	(0.416)	(0.336)
MSO	1.4616***	1.0913***	1.2207*	1.2150***	-0.4247
	(0.463)	(0.267)	(0.694)	(0.394)	(0.284)

Note: FFR, TBL, TRS, TRM and TRL denote the monetary policy measures. We estimate the reduced-form VAR with 12 lags following Plagborg-Møller and Wolf (2021) and Olea et al. (2025). The matrix B_0^{-1} is estimated while allowing for simultaneity; that is, the contemporaneous response matrix is identified without imposing either zero or sign restrictions on B_0^{-1}. Standard errors are reported in parentheses below each coefficient. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

4.7 Conclusion

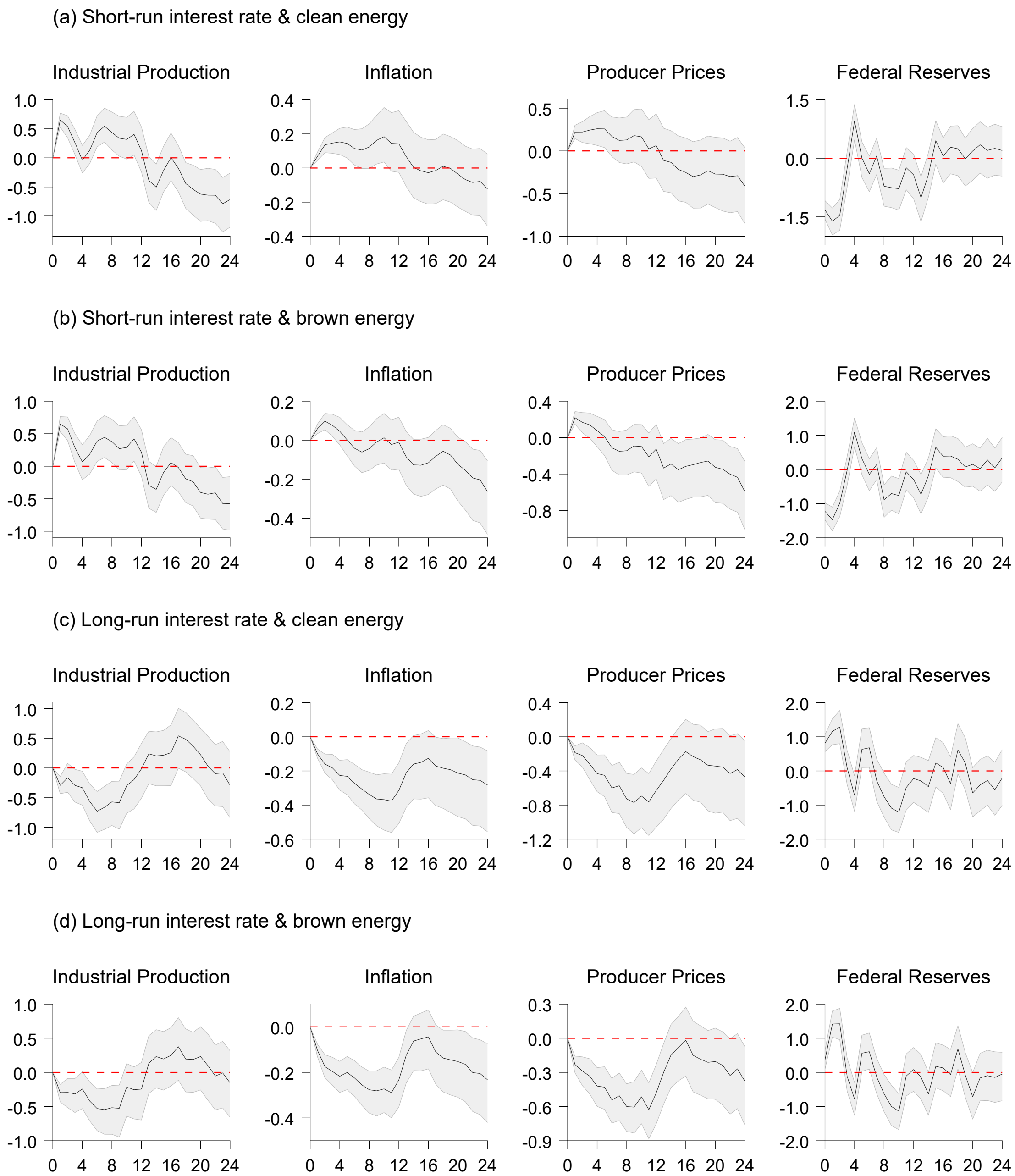
This study investigates the reaction of clean and brown energy stock markets to monetary policy shocks and finds several key findings. First, we find that the short-term monetary policy measure has a statistically significant positive immediate effect on all the stock markets selected in this study, including clean and brown energy markets. In contrast, the long-term monetary policy measure has negative immediate effects on all of them. Second, this study accounts for the fact that the clean energy market has a stronger positive contemporaneous response to a shock in the short-term monetary policy measure and a stronger negative immediate response to a shock in the long-term monetary policy indicator compared to those in brown energy markets. Third, we notice that the clean energy market tends to be more reactive over time horizons than the brown energy markets to a one-time shock in short-run and long-run monetary policy rates. Fourth, this study shows that the reaction of the clean energy market over long horizons turns negative to a one-time shock in the short-run policy rate but turns positive to a one-time shock in the long-run policy rate. In contrast, brown energy markets tend to have no response. Last, interestingly, we find that a clean energy stock price shock leads to a lower long-term interest rate over long horizons. In contrast, a brown energy price shock increases the long-term interest rate persistently and statistically significantly.

The findings of this study offer several key implications for policymakers and investors. As the world moves toward clean energy and away from fossil fuels to mitigate global warming, our study can help policymakers better understand the dynamics of clean and dirty energy markets in response to monetary policy decisions. Such insights could guide policymakers in navigating energy transitions and implementing effective policies to reduce greenhouse gas emissions through financial market activities, which play a crucial role in macroeconomic dynamics. This study also provides implications for investors, as they are more keen to understand immediate and time-delayed reactions of green and brown energy markets to short-term and long-term policy changes to maximise their profit with minimal risk. Further, our study provides a platform for future researchers since we find some inconsistent findings compared to the theoretical expectations on the dynamics between the stock market and monetary policy and support the argument in the study of Jarociński and Karadi (2020).

4.A Appendix

4.A.1 Monetary Shocks on Macroeconomic Variables

Figure 4.8: IRF of Macroeconomic Variables to Monetary Policy Shock (one standard deviation shock)



Note: The reduced-form VAR model is estimated with 18 lags, as shorter-lag VARs can produce biased results due to extrapolating from too few correlations in the data (see, for further details, Olea et al., 2025). TRS and TRL are selected to represent the short-run and long-run monetary policy rates, respectively. The confidence bands correspond to the 68% level.

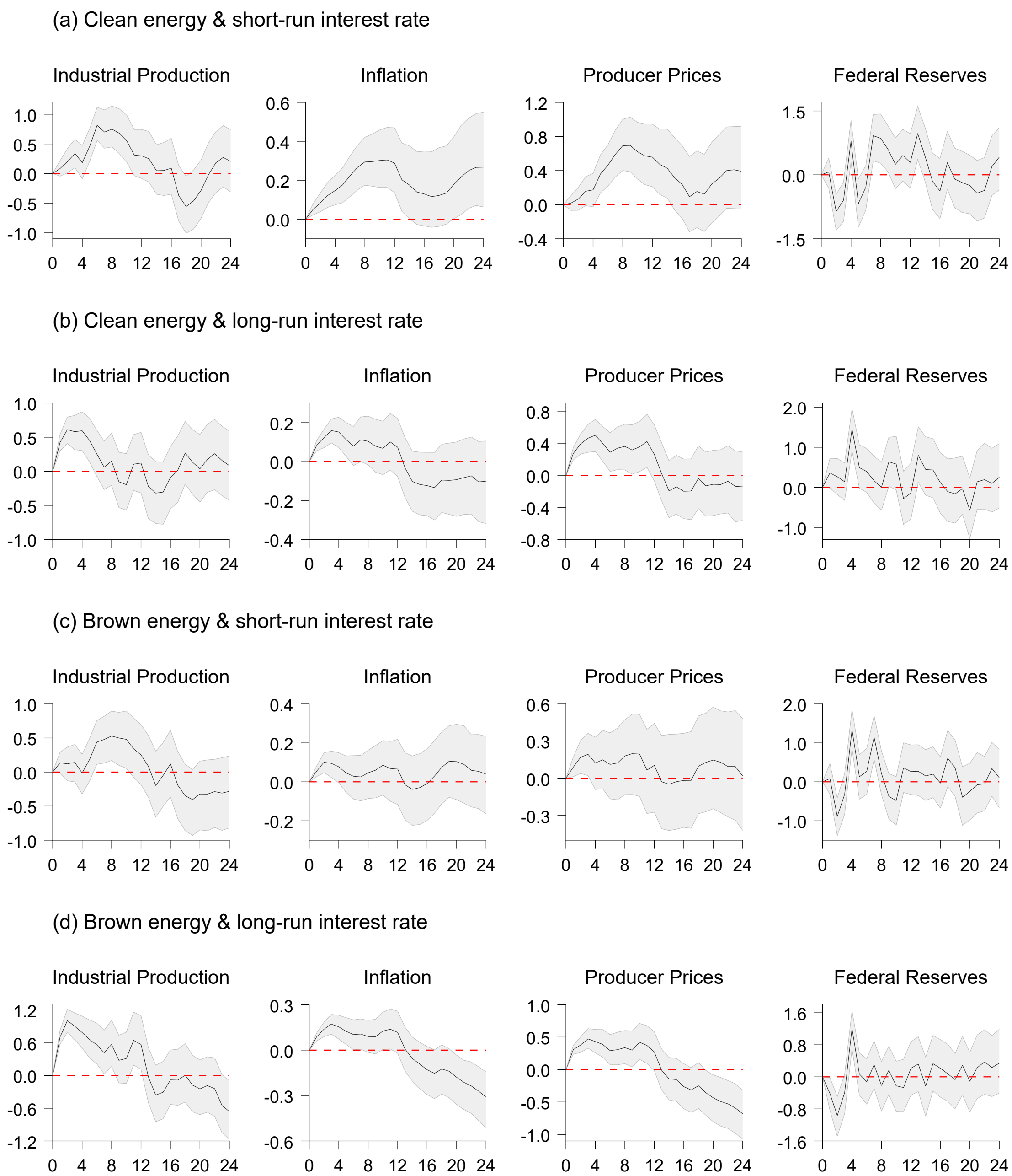
The SVAR estimation also provides the SIRF for the macroeconomic variables to monetary shocks. Figure 4.8 displays the reaction of the macroeconomic variables to monetary shocks. Interestingly, we find that all four macroeconomic variables (industrial production, inflation rate, producer prices, and federal reserves) show asymmetric reactions to shocks in short-run and long-run monetary policy measures, regardless of which type of stock market is selected for the model estimations. This study finds that a shock in the short-term monetary policy rate increases industrial production, inflation, and producer prices in the short horizon and then lowers them in the long horizon, as aligned with Bjørnland and Leitemo (2009). This finding differs when we consider a positive shock in the long-run interest rate. A positive shock in the long-run interest rate significantly lowers industrial output in the short horizon, approximately up to one year, and then tends to raise output. This can be expected theoretically because increases in the long-run interest rate could raise production costs and then lead to lower output. But in the long run, investors can find strategies to overcome these issues, which can lead to a rise in output. However, there is no significant evidence of a long-run rise. Noticeably, a positive shock in the long-run monetary policy rate persistently and significantly lowers the inflation rate and producer prices, which is one of the ultimate objectives of imposing contractionary monetary policy.

It is also interesting to illustrate the effect of monetary policy shocks on the federal reserves. We find that shocks to both short- and long-run monetary policy rates have a significant effect on the federal reserves only in the short horizons, but no effect in the long horizons. However, the effect in the short horizons depends on the type of monetary policy measure, either a short-run or a long-run measure. We find that a positive shock in the short-term monetary policy rate drops instantly and significantly the federal reserve and then makes a quick recovery. In contrast, a positive shock in the long-term monetary policy rate produces a positive and significant immediate effect on the federal reserve, consistent with theoretical expectations, and then the effect gradually becomes negative.

Overall, we understand that the long-term interest rate could be a better monetary policy measure than the short-run interest rate to adjust macroeconomic variables and achieve economic and financial stability, since the responses of macroeconomic variables are consistent with theoretical expectations regarding the dynamics between macroeconomic variables and monetary policy measures.

4.A.2 Energy Stock Price Shocks on Macroeconomic Variables

Figure 4.9: IRF of macroeconomic variables to energy stock price shocks (one standard deviation shock)

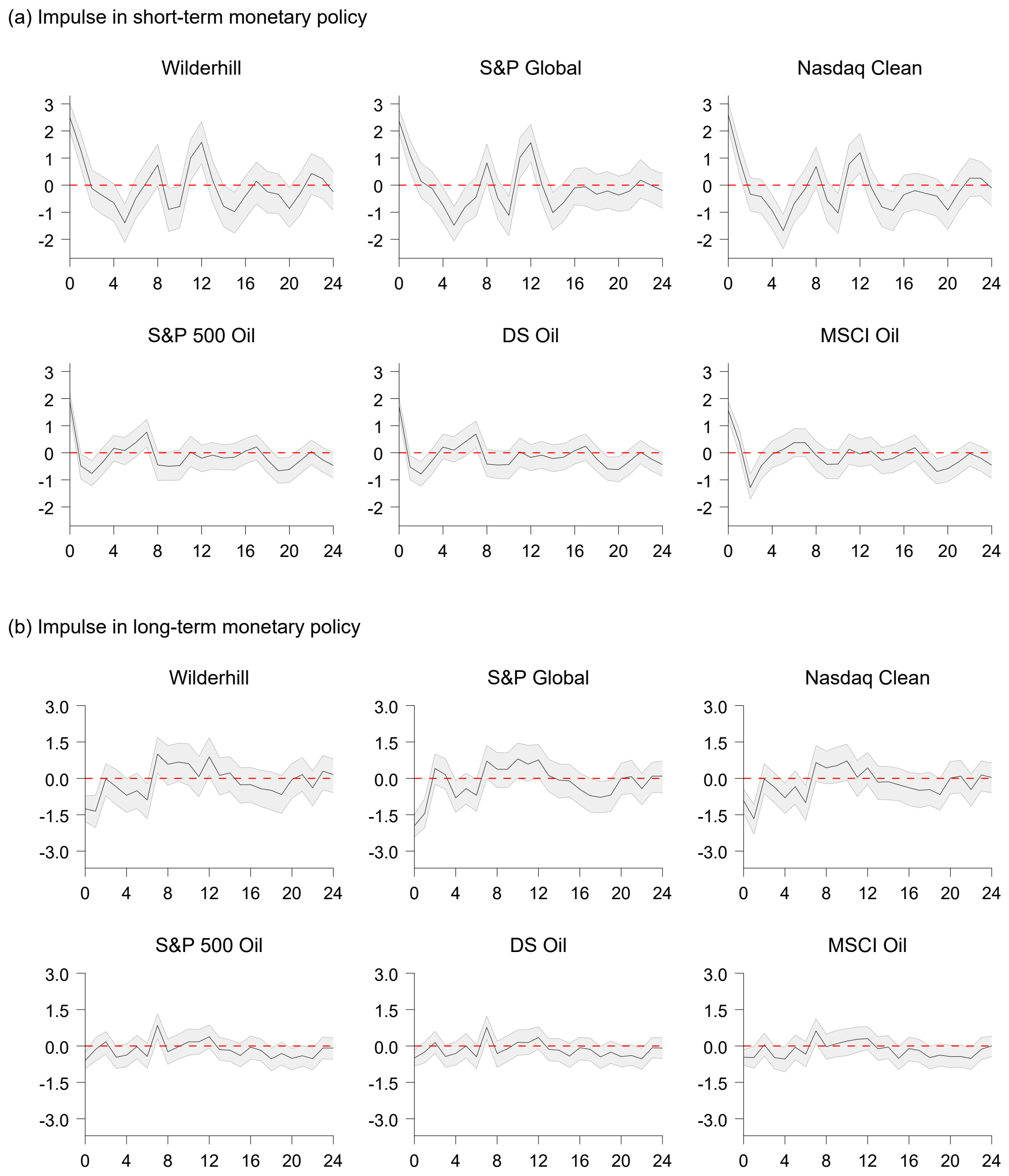


Note: The reduced-form VAR model is estimated with 18 lags, as shorter-lag VARs can produce biased results due to extrapolating from too few correlations in the data (see, for further details, Olea et al., 2025). TRS and TRL are selected to represent the short-run and long-run monetary policy rates, respectively. The confidence bands correspond to the 68% level.

Figure 4.9 presents the responses of the macroeconomic variables to both energy price shocks. The figure shows that both types of energy stock price shocks have similar effects on macroeconomic variables irrespective of monetary policy measures. We find that an energy stock price shock persistently increases industrial output, inflation rate, and producer prices over the time horizons, at least for a year. It is not surprising because theoretically, higher stock prices increase consumer welfare and aggregate demand. As a result, it would lead to an increase in output and prices, as evidenced by Bjørnland and Leitemo (2009). Noticeably, this study accounts for the responses of the Federal Reserve, which appear to be positive in short horizons, consistent with theoretical expectations, and show overshooting over the horizons. It is not surprising because Galí and Gambetti (2015) presents some evidence for the overshooting of financial assets to monetary policy shocks.

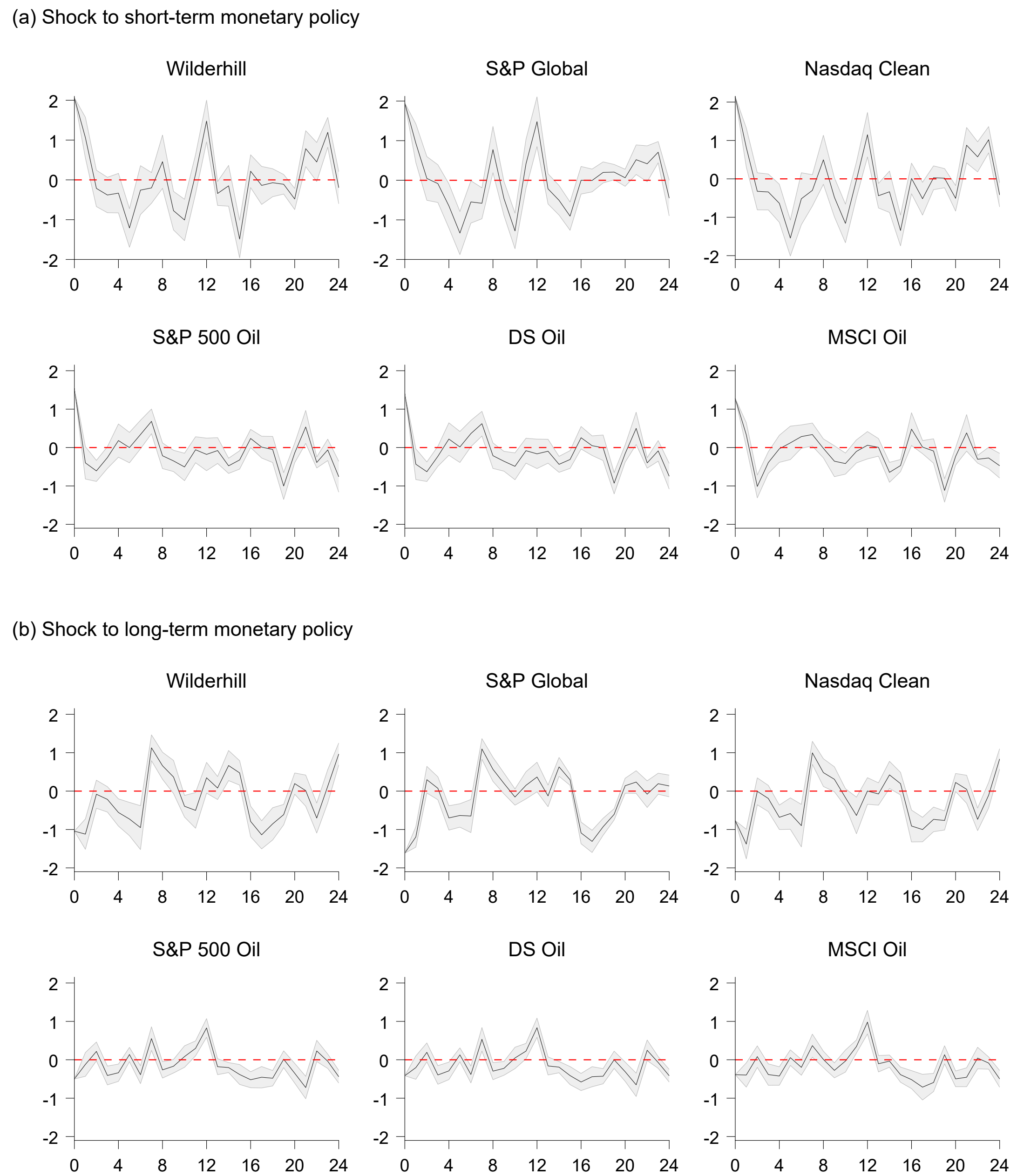
4.A.3 Impulse Responses: SVAR & LPs with Lag=12

Figure 4.10: IRF of energy stock market returns to monetary policy shock (one standard deviation): SVAR at Lag=12



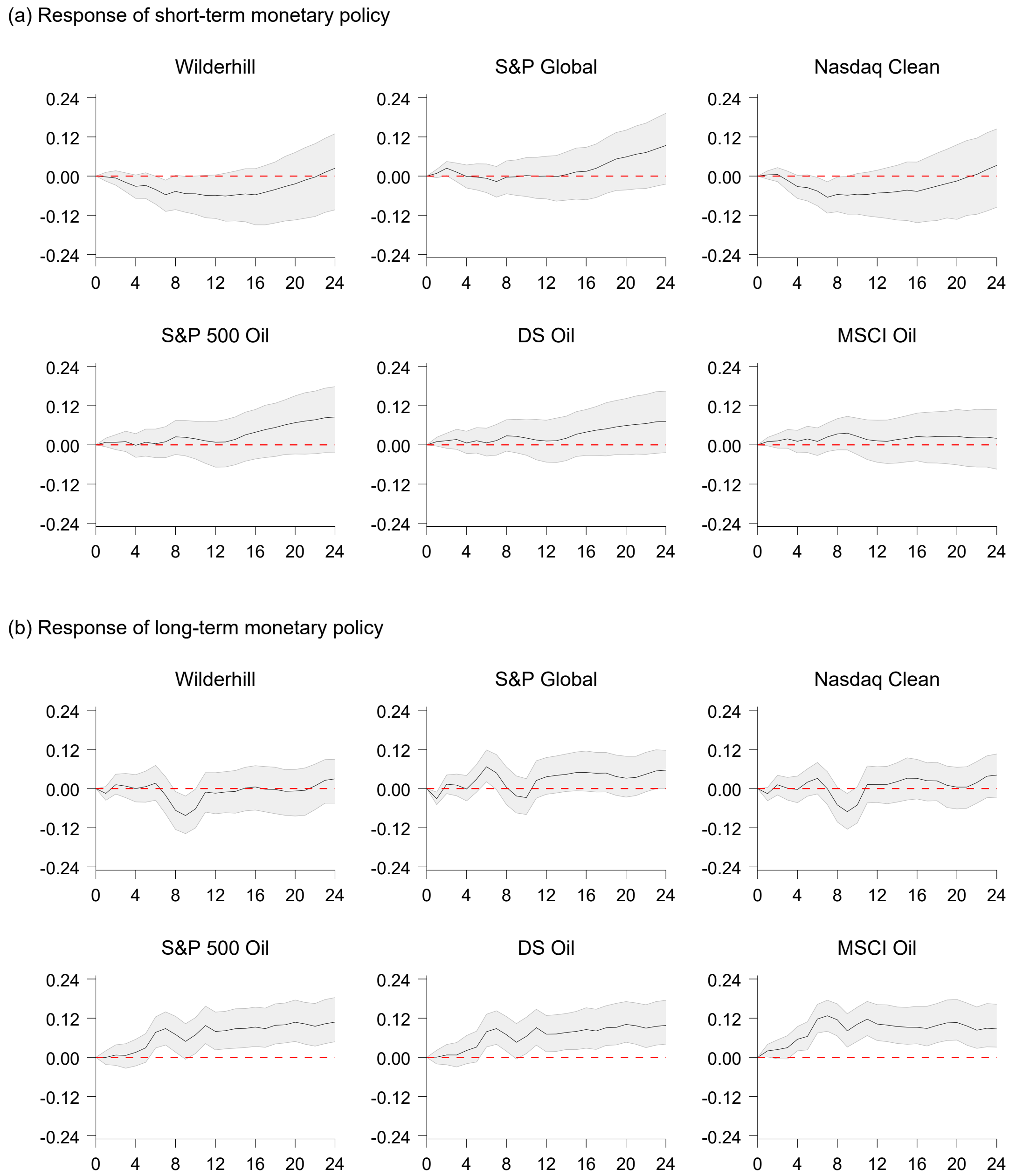
Note: The reduced-form VAR model is estimated with 12 lags. TRS and TRL are selected to represent the short-run and long-run monetary policy rates, respectively. The confidence bands correspond to the 68% level.

Figure 4.11: IRF of energy stock market returns to monetary policy shock (one standard deviation shock) : LPs at Lag=12



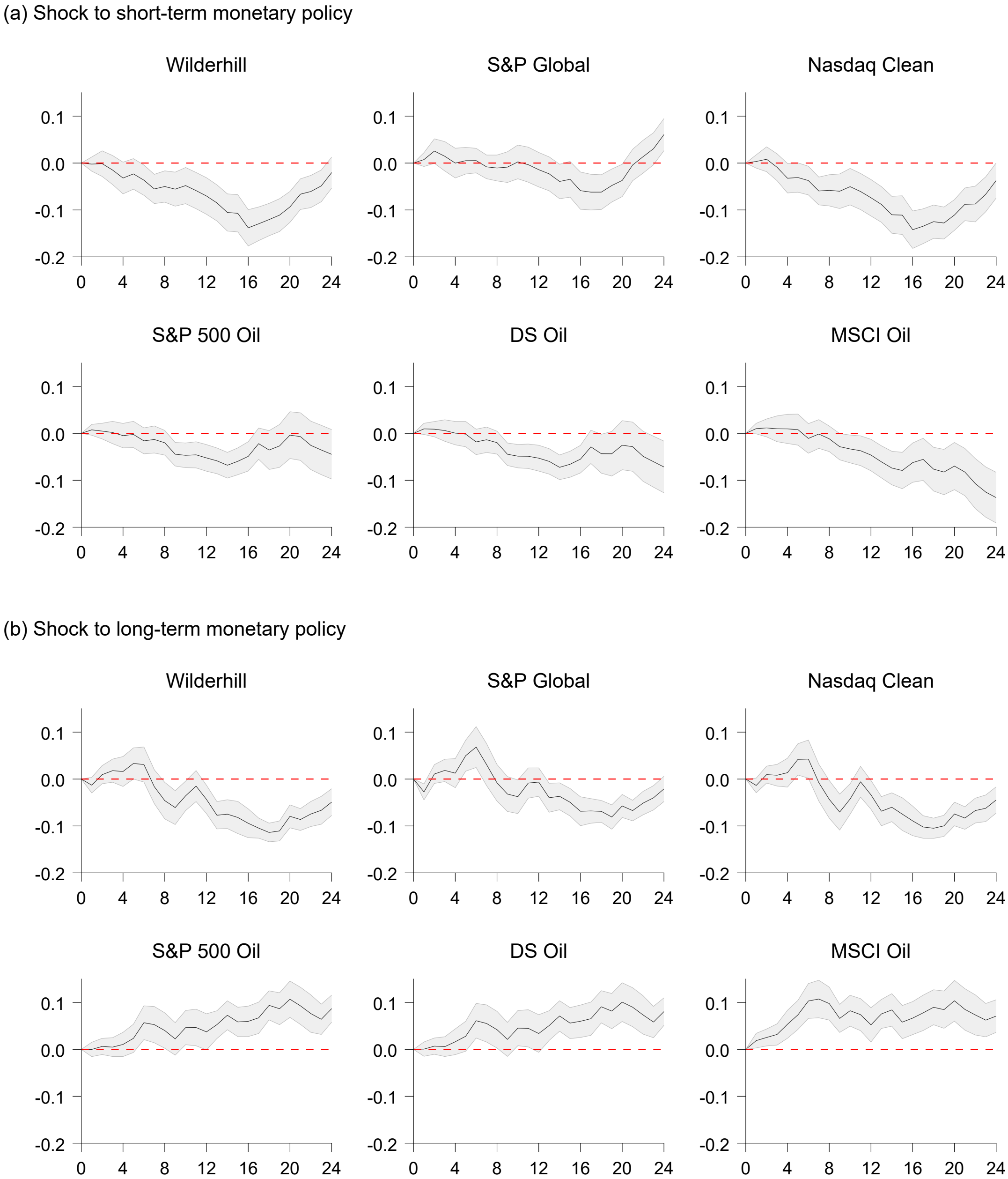
Note: LPs are estimated with 12 lags. TRS and TRL are selected to represent the short-run and long-run monetary policy rates, respectively. The confidence bands correspond to the 68% level.

Figure 4.12: IRF of monetary policy measure to energy stock price shock (one standard deviation): SVAR at Lag=12



Note: The reduced-form VAR model is estimated with 12 lags. TRS and TRL are selected to represent the short-run and long-run monetary policy rates, respectively. The confidence bands correspond to the 68% level.

Figure 4.13: IRF of monetary policy measure to energy stock price shock (one standard deviation shock): LPs at Lag=12



Note: LPs are estimated with 12 lags. TRS and TRL are selected to represent the short-run and long-run monetary policy rates, respectively. The confidence bands correspond to the 68% level.

4.A.4 Recursive Ordering with Oil Price Returns

$$
\begin{bmatrix} u_t^{\mathrm{OPR}} \\ u_t^{\Delta\mathrm{IP}} \\ u_t^{\Delta\mathrm{IF}} \\ u_t^{\Delta\mathrm{PP}} \\ u_t^{\mathrm{MP_j}} \\ u_t^{\Delta\mathrm{FR}} \\ u_t^{\mathrm{SM_i}} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 & 0 & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 & 0 & 0 & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} & 0 & 0 & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & b_{55} & 0 & 0 \\ b_{61} & b_{62} & b_{63} & b_{64} & b_{65} & b_{66} & 0 \\ b_{61} & b_{72} & b_{73} & b_{74} & b_{75} & b_{76} & b_{77} \end{bmatrix} \begin{bmatrix} \omega_t^{\mathrm{opr}} \\ \omega_t^{\mathrm{ip}} \\ \omega_t^{\mathrm{if}} \\ \omega_t^{\mathrm{pp}} \\ \omega_t^{\mathrm{mp_j}} \\ \omega_t^{\mathrm{fr}} \\ \omega_t^{\mathrm{sp_i}} \end{bmatrix} \tag{4.14}
$$

Chapter 5

Conclusion

This thesis examines the dynamics of financial markets—particularly stock and exchange rate markets—in response to US conventional monetary policy measures. It comprises five chapters. Chapter 1 outlines the motivation and provides an overview of the main chapters (Chapters 2–4). Chapter 5 concludes with a synthesis of findings and directions for future research.

Chapter 2 analyses the effects of local and US interest rates on stock market returns in emerging market economies (EMEs) using a univariate GARCH model. The results indicate: (i) local interest rates generally exert negative and significant effects, while US interest rates often have positive and significant effects; (ii) local interest rate changes increase conditional volatility more than US rate changes; (iii) US rate volatility has a stronger influence on stock market volatility than local rate volatility; and (iv) effects vary substantially across EMEs.

Chapter 3 investigates the relationship between US dollar strength and currency depreciation in EMEs using DCC-GARCH and Cross-Quantilogram (CQ). This study provides some key findings. First, the depreciation of the selected currencies is positively correlated with US dollar appreciation over time. Second, the hedge ratio of the Turkish Lira against the US dollar index declines over time, particularly during the COVID-19 pandemic and Turkey's local currency crisis. Third, the hedge ratio for the selected South Asian currencies remains small with no significant changes during the COVID-19 pandemic, but doubled during the local currency crises compared to the COVID-19 period. Finally, the CQ analysis shows that the CQ correlation between present and past local currency depreciation in the selected country varies over time, especially during the COVID-19 pandemic and currency crisis, and has a strong correlation with US dollar appreciation.

Chapter 4 evaluates the impact of US monetary policy shocks on clean and brown energy stock markets. Short-term policy shocks generate an immediate positive effect on both markets, while long-term shocks exert negative effects. The adverse effect is stronger for clean energy stocks, suggesting that high transition costs amplify sensitivity to long-term rates. These results carry important implications for policymakers managing energy transitions through monetary policy.

Finally, the thesis highlights several findings that diverge from theoretical expectations. For example, local interest rates positively affect stock returns in South Korea, and US interest rate changes produce positive and significant effects in markets such as India, China, Hong Kong, Turkey, and Hungary. Moreover, clean and brown energy markets display positive contemporaneous responses to US monetary shocks. While Jarociński and Karadi (2020) offer partial justification, further research is required to explain these outcomes fully.

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