Essays on Financial Risk Modelling

A Thesis Presented in Fulfilment of the Requirements for
the Degree of Doctor of Philosophy in Finance

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Abstract

In today's highly interconnected financial landscape, the risk of shock spillover is a critical factor contributing to increased systemic risk and impacting the global financial stability. Research on spillover effects has gained significant attention from both academics and practitioners. This thesis aims to contribute to this strand of the literature by conducting three studies that employ a variety of connectedness methods to investigate several underexplored issues within the field of financial risk management. These essays delve further into the evolution of these spillover effects during times of extreme financial uncertainty and aim to identify the key drivers of these spillovers. Essay One investigates the high-frequency spillover of volatility shocks across major oil-dependent foreign exchange markets, considering the impact of the oil market's volatility regime. Essay Two examines the return shock spillover between European sectoral credit default swap and the natural gas markets. This investigation is conducted across different quantiles of return distributions, with a special focus on understanding the effects of the ongoing Russian-Ukrainian war on this spillover. Essay Three scrutinizes spillover effects of inflation shocks under normal economic conditions and extreme inflationary conditions between the U.S. and emerging markets. The essay further unveils the determinants of the inflation spillovers among the sample markets.

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List of Abbreviations

VHAR	Vector Heterogeneous Autoregressive
VHAR(Q)	Vector Heterogeneous Autoregressive with measurement errors
VHAR(Q)-DCC-GARCH	Vector Heterogeneous Autoregressive with measurement errors and Dynamic Conditional Correlation
VAR	Vector Autoregression
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
HAR-GARCH	Heterogeneous Autoregressive – Generalized Autoregressive Conditional Heteroskedasticity
TVP-VAR	Time-varying Parameter Vector Autoregression
MS-AR	Markov-Switching Autoregressive
CDS	Credit Default Swap
CPI	Consumer Price Index
EAGLEs	Emerging and Growth-leading Economies
FX	Foreign Exchange
CAD	The Canadian Dollar
MXN	The Mexican Peso
NOK	The Norwegian Krone
EUR	The Euro
GBP	The Pound Sterling
JPY	The Japanese Yen
SGD	The Singapore Dollar
GCI	Generalized connectedness index
BACM	Block aggregation of connectedness index
CSI	Cross-group Spillover Index/ Cross-market Spillover Index
TCI	Total Connectedness Index
TSI	Total Spillover Index
NSI	Net Spillover Index
NPSI/ NPDS	Net Pairwise Spillover Index
DSI	Directional Spillover Index
AUT	Automotive (sectoral CDS)
BNK	Banking (sectoral CDS)
CHM	Chemicals (sectoral CDS)
CM	Construction Materials (sectoral CDS)
IND	Industrials (sectoral CDS)
MAN	Manufacturing (sectoral CDS)
OG	Oil & Gas (sectoral CDS)
TRA	Transportation (sectoral CDS)
UTL	Utilities (sectoral CDS)
EPU	Economic Policy Uncertainty
GFEVD	Generalized forecast error variance decomposition

CHAPTER ONE

Overview of the Thesis

Chapter 1 provides an overview of the thesis. Particularly, the chapter discusses the motivations for exploring the topic of Financial Risk Modelling, with a special focus on several newly developed methodologies used for measuring the risk of spillover. This chapter also outlines the research subjects, the main findings, and contributions of each essay to the existing literature regarding risk interconnectedness among financial markets. The chapter concludes by offering the research outcomes and the structure of the thesis.

1.1 Introduction

The global financial landscape is witnessing a growing interconnectedness among its markets. In this highly integrated environment, financial events or shocks originating in one market can easily propagate across global financial markets. This interconnectedness, while promoting economic growth and transferring knowledge (Gould et al., 2018), also transmits shocks across the system, exacerbating global financial instability. Recent instances of systemic turbulence in the global financial system have been associated with the increasing interconnections and spillover effects of financial markets and institutions. For instance, Diebold and Yilmaz (2012) present evidence of significant increases in volatility spillover from the U.S. stock market to other markets during the 2008-2009 Global Financial Crisis. In another research, these authors document that the total volatility connectedness index of U.S. financial institutions surged to reach its maximum level of 89.2% following Lehman Brothers' declaration of bankruptcy (Diebold and Yilmaz, 2014). The Financial Crisis Inquiry Report highlights that the failure of Lehman Brothers and the impending collapse of the insurance giant American International Group (AIG) in 2008, combined with a tangle of interconnections among financial institutions, led to a seizing up of credit markets. This phenomenon has prompted numerous studies delving into the relationship between financial interconnectedness and financial fragility (Caporale et al., 2006; Gai and Kapadia, 2010; Glasserman and Young, 2016; Battiston and Martinez-Jaramillo, 2018; Martinez-Jaramillo et al., 2019; among others). Further, a large body of empirical research is dedicated to analyzing the dynamics of spillover networks, particularly under crisis periods (Magkonis and Tsopanakis, 2016; Candelon et al., 2012; Wang et al., 2017; Greenwood-Nimmo et al., 2016; among others). These studies have unveiled a noteworthy pattern: the interconnectedness among financial markets becomes more pronounced during periods of high global financial uncertainty. This underscores the critical importance of comprehending the dynamic spillover networks between markets and the potential determinants of these spillover effects. Such understanding is crucial for designing effective risk management strategies as well as adequate policy responses.

In examining the dynamics of interconnectedness, empirical literature explores various measures of spillover effects, including mean spillovers[1] (Theodossiou and Lee, 1993; Billio et al., 2012), volatility spillovers (Bekaert and Harvey, 1997; Ng, 2000; Diebold and Yilmaz, 2012 and 2014; among many others) and tail risk spillovers (Hong et al., 2009; Adams et al., 2014; Hautsch et al., 2015; Härdle et al., 2016; to name a few). The outcomes of these studies can serve as guidance for policymakers and financial institutions in formulating regulatory measures and policies aimed at mitigating systemic risk, ultimately safeguarding the stability of the financial system. Investors can utilize the knowledge of spillover effects to make informed decisions regarding asset allocation, portfolio diversification, hedging strategies, and risk management. Despite much effort devoted to the examination of spillover effects across various financial markets, several unanswered questions persist in the existing literature about spillover networks. These questions revolve around research subjects, methodologies applied, as well as the sort of data used. To fill these research gaps, my thesis explores diverse recently

[1] The term “mean spillover” is used interchangeably with “return spillover” in the literature.

developed econometric methodologies, and employs these techniques to investigate various leftover issues from the literature of volatility spillover and return spillover effects. Unlike existing studies on risk spillover that mostly rely on short-memory process, such as GARCH and VAR model, and low-frequency daily data to estimate volatility, skewness or kurtosis, the first essay in this thesis introduces a new econometric technique based on a long-memory process (Vector Heterogeneous Autoregressive Model). This approach better captures the long-memory characteristics of volatility and other tail risk measures of financial time series. By utilizing high-frequency data, the study accounts for real-time market reactions to news and shocks, thereby achieving more precise measurements and real-time monitoring of spillover effects. Additionally, the remaining two essay in this thesis extend beyond the spillover effect at the conditional means of the distributions to capture spillover at different quantiles. This allows for examinations of how spillover behaviours differ between average shocks and extreme large shocks using diverse advanced econometric techniques. The thesis focuses on topical issues in financial risk management, such as the effect of geopolitical tensions and COVID-19 pandemic-induced crisis on spillover networks among global financial markets.

In particular, the first essay of my thesis applies the multivariate Heterogeneous Autoregressive with measurement errors and Dynamic Conditional Correlation (VHAR(Q)-DCC-GARCH)-based connectedness measures, tailored for high-frequency intraday data, to scrutinize the dynamic realized volatility spillover across major oil-dependent foreign exchange markets, considering the role of the oil market's volatility regime. Notably, the Dynamic Conditional Correlation model (DCC-GARCH) is incorporated in the baseline regression VHAR(Q) to capture the volatility of realized volatility effects. This essay makes a methodological contribution to the literature as it develops a convenient way to compute the generalized connectedness measures (Diebold and Yilmaz, 2012) and the block connectedness matrix (Greenwood-Nimmo et al., 2016) within a modelling framework of VHAR(Q). It is worth noting that the original connectedness approach of Diebold and Yilmaz (2012) and block connectedness of Greenwood-Nimmo et al. (2016) are constructed for a Vector Autoregression (VAR) model, which has a short-memory property. Meanwhile, by using the VHAR(Q)-DCC-GARCH framework, the estimation of volatility spillover in this study can effectively account for both the long-memory property and the measurement errors in the high-frequency measure of volatility.[2] Crucially, this research is the first attempt investigating the effect of the oil market volatility's regime switching on foreign exchange volatility connectedness.

Turning to the issue of return spillover effects, the second essay of my thesis uncovers the return spillover between natural gas and European credit default swap (CDS) markets at the corporate sectoral level, a not-yet-touched topic in the literature. More importantly, this study presents quantitative evidence that supports the intensifying effects of the Russian-Ukrainian war on the return shock spillover among the natural gas and European sectoral CDS markets. The ongoing disruptions in Russian gas supply to Europe, caused by the Russian-Ukrainian conflict, are having severe impacts on European economies. Particularly, European industries, which are heavily reliant on gas as a primary production material, have encountered substantial increases in their production costs. The resultant high production costs pose a threat to corporate profitability and the ability to meet financial obligations. As a result, this study is prompted to investigate the return relationship between the gas market and corporate debt markets, examining how the ongoing conflict influences this relationship. The study begins with examining the significance and the sign of the causal relationship between these markets, using the Granger causality test. Notably, to scrutinize the dynamic return spillover network, this research goes beyond the mean-based connectedness approach to capture the return spillover at extreme quantiles of return distributions by applying quantile-based connectedness

[2] The long memory behavior of volatility is widely documented in the literature (e.g.,Ding, Granger and Engle, 1993; Baillie, 1996; Bollerslev and Mikkelsen, 1996) while the measurement errors in the estimation of volatility using high frequency data are highlighted in Bollerslev et al. (2016, 2018).

framework. As such, the results of my second essay provide evidence supporting that the sign and significance of the causal relationship between European sectoral CDS and gas markets depend on the direction of the causality, and that the extreme large shocks significantly amplify the magnitude of the spillover effects between these markets. This essay further offers the first quantitative evidence of the intensifying effect of the Russian-Ukrainian war on the return shock transmission between gas and sectoral CDS markets. This effect persists for both average shocks and extreme large shock spillovers.

Not all the financial datasets are available on an intraday or daily basis; some, such as the CPI indices, are only reported on a monthly basis. Hence, to deal with the potential loss of observations when computing connectedness measures using low-frequency datasets (e.g., monthly data), the third essay of my thesis utilizes a recently developed TVP-VAR-based connectedness framework, which is specifically designed for handling low-frequency and short datasets (Antonakakis et al., 2020), to gauge the spillover effects in investigating the macro-financial linkages. This econometric tool is then applied to investigate the inflation spillover between the U.S. and the nine emerging and growth-leading economies (EAGLEs), with a special focus on the role of the U.S as a shock exporter or importer in this spillover network. The endeavor of this research extends to the investigation of changes in spillover behavior between the sample economies under extremely inflationary conditions using quantile-based connectedness measures as well as the drivers of this inflation spillover effect.

The following three sections (section 1.2, 1.3, 1.4) present the main findings and contributions of the three essays, respectively. Section 1.5 lists the research outputs of the thesis. The structure of the remainder of the thesis is provided in section 1.6.

1.2 Essay one

The first essay of the thesis examines the dynamics of the high-frequency volatility connectedness across major oil-dependent foreign exchange markets with respect to the effect of the oil market's volatility regime switching. Moreover, the essay provides a portfolio implication based on the main findings of oil-dependent currency connectedness.

Considering the substantial influence of oil price shocks on exchange rates movements in oil-dependent countries, numerous studies have explored the causal relationship between oil prices and exchange rates. For example, in earlier literature, Krugman (1983) endorses the theoretical prediction of significant causal effects from oil prices to exchange rates, based on the terms of trade and the wealth reallocation effect. A later body of empirical work has provided evidence supporting this finding of Krugman (1983), including Coudert et al. (2007), Atem et al. (2015), Ferraro et al. (2015), to name a few. Notably, other scholars, such as Chen and Chen (2007), Lizardo and Mollick (2010), Reboreo (2012), Yang et al. (2017), have investigated the different reactions of oil-importing and oil-exporting currencies to changes in oil prices. That is, the values of oil-exporting currencies tend to appreciate in response to an increase in oil prices, whereas the contrasting reaction is right to oil-importing currencies. Further, the oil-exporting currencies tend to be more susceptible to oil shocks compared to oil-importing currencies. Pertaining to the volatility connectedness between the oil market and foreign exchange (FX) markets, the extant literature reveals a significant volatility linkage between these markets and this interconnectedness tends to strengthen during periods of financial uncertainty (Ding and Vo, 2012; Alam et al., 2019; Jawadi et al., 2016, among others).

Given the documented contrast in reactions of oil-exporting and oil-importing currencies to changes in oil prices, trading in oil-dependent exchange rates frequently attracts interest from FX traders. This is evident in the significant proportion of oil-dependent FX trading, accounting for approximately 73% of global FX trading activity. FX market participants can benefit from portfolio diversification and hedging against oil price risk by engaging in both oil-importing and oil-exporting FX markets. However, this type of FX trading involves a comprehensive understanding of how changes in oil market's volatility regime drive the evolution in volatility connectedness of oil-dependent exchange rates, a leftover issue from the existing literature and a topic of great interest to FX market participants. Such knowledge has become pivotal for FX traders when making decision about asset allocation and risk management strategies for their FX portfolios. As a result, my first essay aims to utilize high-frequency financial returns of seven major oil-dependent FX markets and adopt the VHAR(Q)-DCC-GARCH-based connectedness measures, which is well-suited for intraday data-based measures of connectedness, to investigate realized volatility connectedness across major oil-dependent FX markets under different states of the oil market volatility.

Existing studies often rely on low-frequency data, and employ various types of GARCH model or the vector autoregression (VAR) with the generalized connectedness framework of Diebold and Yilmaz (2012), to model volatility spillovers among diverse financial markets. However, the traditional GARCH and VAR structures are short-memory processes, and so cannot account for the long-memory property – a stylized fact – of the realized volatility. This limitation can introduce a bias in realized volatility estimation. As a result, my first essay develops the long memory process VHAR(Q), introduced by Bollerslev et al. (2018), which can evidently capture the long-memory behavior as well as the time-varying effect of the heteroskedasticity in measurement errors in realized volatility measures, as the underlying function in computing the connectedness measures. The methodological contribution of this study enables the empirical analyses of volatility spillover to overcome the potential biases in parameter estimation caused by long-memory behavior and measurement errors of realized volatility, thereby ensuring more accurate estimates of volatility spillover effects.

Using a sample of seven major free-floating oil-dependent currencies, this study reveals several noteworthy findings as follows. First, the majority of the total volatility connectedness index among the sample oil-dependent currencies stems from the within-group volatility connectedness (e.g., within-oil-exporting-group connectedness or within-oil-importing-group connectedness), while the cross-group connectedness remains relatively low. Second, the cross-group volatility connectedness between these currencies tends to strengthen when the oil market's volatility switches from a low to a high state. These results imply a potential diversification benefit by holding positions in both oil-exporting and oil-importing currencies, but this benefit diminishes when the oil market enters high volatility states. Third, the oil-exporting currencies consistently play the dominant role of shock transmitters in this network connectedness, regardless of different states of the oil market's volatility. The volatility causalities running from the oil-exporting currencies to the oil-importing currencies contribute most to the cross-group volatility connectedness.

Our findings can be explained by the previous results from the research of Ding and Vo (2012), Baruník et al. (2019) and Alam et al. (2019). These authors have documented that the volatility spillover from crude oil to exchange rates increases when the oil market is highly volatile. These resultant increases in FX markets' volatility, driven by the high volatility of the oil market, may propagate quickly across the network of oil-dependent FX markets, resulting in higher FX volatility connectedness. As such, the oil market's switch from a low to a high volatility regime intensifies the connectedness across oil-dependent currencies, reducing diversification benefit of the oil-dependent FX portfolio. These findings hold significant implication for asset allocation when trading oil-dependent currencies following the information of the oil market's volatility regime.

Finally, based on the results of time-varying FX volatility connectedness under different oil regimes, this essay proposes a dynamic oil-regime-dependent FX trading strategy.

This strategy suggests adjusting the weight of the components of an FX portfolio based on the information of the estimated probability of high-oil-volatility regimes to gain greater diversification benefits and mitigate the risk of volatility shock transmission among oil-dependent currencies. The simulated dynamic trading strategy has demonstrated a better performance in term of risk-adjusted return compared to a buy and hold portfolio.

This study makes several contributions to the existing literature. First, it is the first attempt to investigate the effect of the oil market’s volatility regime switching on foreign exchange volatility connectedness. The results yield evidence that a switch in the oil market’s volatility regime is a significant determinant of oil-dependent FX volatility connectedness. Second, this essay offers a convenient way to compute connectedness measures based on the underlying function VHAR(Q)-DCC-GARCH model, which is designed for high-frequency volatility measures. This methodological contribution enhances the accuracy of volatility connectedness estimation in this study by addressing potential biases stemming from long-memory behavior and measurement errors in realized volatility measures. Finally, the suggested oil’s regime-dependent trading strategy in this study allows FX traders to benefit from the understanding of oil’s regime-dependent FX volatility linkages, enabling better risk management of their FX portfolios, and taking most benefits of engaging in both oil-exporting and oil-importing currencies.

1.3 Essay two

The second essay of this thesis aims to examine the causality in return relationship between European sectoral CDS (Credit Default Swap) and natural gas markets at the corporate sectoral level. Specifically, the study scrutinizes the significance and the sign of this bidirectional causal relationship, as well as its dynamic pattern. Importantly, this essay provides quantitative evidence that supports the significant intensifying effects of the Russian-Ukrainian war on the return shock transmission among the sample markets.

The ongoing supply-driven gas crisis in Europe, induced by the Russian-Ukrainian conflict, has adversely impacted European economies, especially those heavily reliant on Russian gas supply. A large body of literature has unveiled the strong interdependence in EU-Russia gas market (Finon et al., 2008; Casier, 2011) and the impacts of disruptions in Russian gas supplies on European economies and financial markets. (Bouwmeester et al., 2017; Di Bella et al., 2022; Lo et al., 2022). In fact, the recent upswing in European gas prices has caused European industries to face higher production cost, diminishing corporate profitability and potential financial difficulties. This, in turn, has severe impacts on the European corporate debt market. Despite the prominent role of gas in industrial production, existing literature on the relationship between energy prices and CDS spreads has mainly focused on the impact of crude oil prices on CDS markets at sovereign level (e.g., Bouri et al., 2017; Bouri et al., 2019; Pavlova et al., 2018; among others) and at sectoral level (Da Fonseca et al., 2016; Lahiani et al., 2016; Balcilar et al., 2020; to name a few). Meanwhile, the research on the relationship between natural gas and corporate debt markets is limited. This study, therefore, aims to fill the void in the literature by investigating the causality in the return relationship between European sectoral CDS markets and natural gas, along with the dynamic pattern of this return connectedness. The research also focuses on the evolution of this relationship during the times of war.

This essay initially proposes two channels to explains the direction and the sign of the causality between European sectoral CDS markets and the natural gas market. The first channel establishes a positive causality running from the natural gas to sectoral CDS markets. Its explanation is related to the changes in the supply side of the gas market, so it is termed *"the supply-side-based channel"*. Meanwhile, the second channel explains the reverse direction of the causality, which runs from the CDS markets to the gas market and suggests a negative causal link from the credit market to the gas market. The explanation of this channel is based on the changes in the demand side of the gas market, and so it is termed *"the demand-side-based channel"*. The inferences drawn from these channels are based on previous literature examining the relationship between the fluctuations of the energy market, credit markets, and the economic indicators (e.g., economic growth, interest rate). This study decomposes the shocks in the CDS markets and the gas market into positive shocks and negative shocks, and begins with conducting the Granger Causality test between these components of shocks. The results of the Granger Causality test support our conjectures regarding the direction and the sign of this causal relationship.

Using daily sectoral five-year CDS index prices of nine European industry sectors, this study investigates the dynamic pattern and determinants of return connectedness between the natural gas and credit markets. This investigation extends beyond average return shock transmission across the sample markets to take into consideration return connectedness at both tails of return distributions, capturing the spillover behavior of extreme large shocks. To do this, the essay employs both the mean-based connectedness framework of Diebold and Yilmaz (2012) and quantile-based connectedness framework of Ando, et al. (2022). The research results reveal several key findings. First, the extreme large positive/ negative shocks significantly intensify the transmission of return shocks between natural gas and sectoral CDS markets, while a symmetrical pattern is observed in return shock transmissions at both tails. Second, the gas market primarily acts as the shock receiver in this network connectedness, especially during extreme events. Third, the return shock connectedness between sectoral CDSs and natural gas exhibits highly volatile fluctuations throughout the research period, regardless of whether the connectedness is measured at the conditional mean or at the tails of return distributions. Finally, using both daily and monthly regression models, this study provides robust evidence of the magnifying effect of the Russian-Ukrainian war on the return shock spillover between European sectoral CDS markets and natural gas, regardless of the shock size.

The second essay contributes significantly to the existing literature in several ways. First, it is the first study to examine the significance and the sign of the Granger causal link between natural gas and CDS markets, a not-yet-touched issue in the literature. Specifically, the findings provide robust evidence supporting that the shocks in natural gas market positively Granger cause the shocks in CDS markets, whereas the opposite direction of this causal relationship is significantly negative. Second, this essay addresses the unanswered question of whether the return connectedness between sectoral CDS markets and the natural gas market changes under conditions of financial uncertainty. The study goes beyond the mean-based return connectedness to capture the connectedness at different quantiles of return distributions. As such, this research endeavors offer the first evidence of significant return shock transmission between credit markets and the gas market, with extreme large shock spillovers being more pronounced than average shock spillovers. Finally, this essay contributes to the growing literature on the effects of Russian-Ukrainian war on global financial markets by quantifying the magnitude of the war effect on return shock transmission among the natural gas and European sectoral CDS markets.

1.4 Essay three

The third essay of the thesis investigates the dynamics and the drivers of the inflation spillovers between the U.S. and nine emerging and growth-leading economies (EAGLEs), especially the spillover behavior under the periods of extremely inflationary conditions. Further, this study reveals how the inflation spillovers between emerging markets and the U.S. depends on the economic characteristics of these emerging countries.

Over the last two years, the world's economies have grappled with periods of extreme inflation. This surge in inflation worldwide can be attributed to various global factors, such as the extensive stimulus packages enacted in response to the COVID-19 pandemic, disruptions in global supply chain caused by pandemic-related restrictions, and the energy crisis triggered by the Russian-Ukrainian conflict. In 2022, the battle of national central banks against hyperinflation has led to questions about the effectiveness of their actions. This has sparked a discussion about whether central banks should consider the impact of international inflation spillover when formulating policies to control domestic inflation rates. As a result, a comprehensive investigation of international inflation spillover has become an issue of great interest to policy makers and regulators. Previous literature on the inflation spillover has predominantly concentrated on developed countries (e.g., Halka and Szafranek, 2016; Jordan, 2016; Tiwari et al., 2019; Wen et al., 2021; Elsayed et al. 2021; Pham and Sala, 2022), while there is limited research on inflation spillover between emerging and developed markets. This essay aims to fill the void in the literature by conducting the first investigation of the dynamics and the drivers of the inflation spillover between the U.S and nine emerging and growing-leading economies (EAGLEs), with a special focus on this inflation spillover under extreme inflationary periods.

Previous studies have documented that the inflation rates can spill over from one country to another through international trade linkage (Tootell, 1998; Bernanke, 2007; Auer and Saure, 2013), commodity prices (Ciccarelli and Mojon, 2010), synchronization of monetary policies (Tiwari et al., 2015), and input linkage (Auer et al., 2019). Another strand of literature has explored the spillover effects of monetary policy shocks in the U.S on emerging markets (Chen et al., 2014; Anaya et al., 2017; and Bräuning and Ivashina, 2020; among others). My study contributes to this strand of literature by examining inflation spillover effect between the U.S and EAGLEs at both conditional mean and tails of the inflation distributions. Particularly, this research focuses on the role of the U.S. in this inflation spillover network, and proposes two channels, “*the money policy*” and “*the consumption channel*”, to explain the role of the U.S. as exporter or importer of inflation shocks to/ from the emerging markets.

Employing the recently developed TVP-VAR-based connectedness framework, designed for low-frequency and short sample data, such as inflation data, this essay presents several findings. First, this essay provides evidence of a moderate spillover effect of average inflation shocks between the U.S. and EAGLEs. The upward trend of inflation spillover among sample markets over the research period reflects increasing economic and monetary integration between the countries. Second, the role of the U.S. in the inflation shock transmission with emerging countries varies between being a net inflation-exporter and inflation-importer over times, but on average, the U.S. acts as a net importer of inflation in the system. Third, this study points out that inflation spillover effects with the U.S. are more pronounced for the emerging markets with higher openness, the net oil-importing emerging markets, and the emerging markets following free-float exchange rate regimes. Fourth, this research extends the analysis to scrutinize the inflation spillover effects of extreme inflation shocks by applying quantile-based connectedness framework. Notably, the results of upper-quantile connectedness show that extremely large positive shocks of inflation significantly strengthen the spillover effects between the U.S. and the EAGLEs. Finally, this essay provides robust evidence that the value of the U.S. dollar, emerging markets’ economic policy uncertainty, and bilateral trade are key determinants of the inflation shock transmission among the system.

The contribution of this essay can be outlined as follows. First, this study is the first attempt to examine the dynamic inflation spillover between the U.S. and the EAGLEs, which has gained critical importance in this increasing inflationary environment. To differentiate itself from previous studies on inflation spillover, this essay adopts a newly developed TVP-VAR-based connectedness approaches, which is suitable for low-frequency and short dataset. This approach overcomes the problem of data loss (Antonakakis et al., 2020) and subjectivity bias in choosing the length of the rolling-window method, as seen in generalized connectedness measures (Diebold and Yilmaz, 2012). Second, the research identifies the role of the U.S. in this spillover network, a question of particular interest to policymakers and regulators in both the U.S. and emerging economies. Third, this study answers the question of whether a highly inflationary environment changes the spillover behavior between the U.S. and emerging markets, an issue leftover in the literature and of significant concern to policymakers. Finally, these research endeavours provide a first comprehensive understanding of how the inflation spillover effects between the U.S and emerging countries depend on the economic characteristics of these countries.

1.5 Research outputs from the thesis

Essay one titled *"High-Frequency Volatility Connectedness across Foreign Exchange Markets: The Role of Oil Market's Volatility Regime"*, will be submitted to a journal. This paper has been presented at the 26th Annual (2022) New Zealand Finance Colloquium and the seminar at School of Economics and Finance, Massey University (2021).

Essay two titled *"The Nexus between European Sectoral Credit Default Swap and Natural Gas Markets: The Russian-Ukrainian War Effect"*, will be submitted to a journal.

Essay three titled *"Does the U.S. Export Inflation? Evidence from the Dynamic Inflation Spillover between the U.S. and the EAGLEs"*, is published in International Review of Economics and Finance.

Nguyen, T. T. T., Pham, S. D., Li, X. M., & Do, H. X. (2024). Does the US export inflation? Evidence from the dynamic inflation spillover between the US and EAGLEs. *International Review of Economics & Finance*, *94*, 103427.

1.6 Structure of the thesis

The remainder of the thesis is organized as follows. The main body of the thesis comprises three essays, each presented in a separate chapter. In chapter 2, the first essay investigates the high-frequency volatility connectedness across major oil-dependent foreign exchange markets, considering the influence of the oil market's volatility regime switching. The second essay on the causal relationship and the dynamic pattern of the return connectedness between European sectoral CDS and natural gas markets is presented in Chapter 3. Chapter 4 presents the third essay, which examines the dynamic pattern and drivers of the inflation spillover between the U.S. and the nine emerging and growth-leading economies (EAGLEs). Finally, chapter 5 concludes the thesis by summarizing the key findings, the implications and the future research areas of each of the three essays.

CHAPTER TWO

High-Frequency Volatility Connectedness across Foreign Exchange Markets: The Role of Oil Market's Volatility Regime

Chapter 2 presents the first essay of the thesis. This essay investigates the dynamic high-frequency volatility connectedness across major oil-dependent foreign exchange markets with respect to the effect of the oil market's volatility regime switching. This investigation is conducted by developing the connectedness measures within a multivariate Heterogeneous Autoregressive model with measurement errors (VHAR(Q)). Further, the portfolio implication based on the main findings of oil-dependent currency connectedness is provided accordingly.

2.1 Introduction

Oil plays a pivotal role as the major energy source for industrial production, exerting growing impacts on global economies, particularly those heavily reliant on crude oil, both as importers and exporters. The increasing oil trade and the inherent volatility of the oil market have put pressure on the trade balance and the balance of payment of oil-exporting and oil-importing countries, which in turn drives their exchange rate fluctuations. Given the significant effect of oil price shocks on exchange rates, it is no surprise that theoretical and empirical literature has extensively studied the relationship between oil prices and exchange rates. Scholars, such as Golub (1983), Krugman (1983), Blomberg and Harris (1995), Amano and van Norden, (1998a, 1998b), Sadorsky (2000), among others, have dedicated considerable efforts to this area of study. Furthermore, there have been a notable focus on understanding how currencies of oil-importing and oil-exporting nations react differently to changes in oil prices, as evidenced by the works of Chen and Chen (2007), Lizardo and Mollick (2010), Reboreo (2012), and Yang et al. (2017).

In theory, Golub (1983) and Krugman (1983) state that a rise in oil price results in wealth transfer impacts and asset reallocations from oil importers to oil exporters. This suggests that the values of oil-exporting currencies may appreciate while oil-importing countries experience the depreciation in the value of their currencies in response to an oil price increase. In empirical studies, Chen and Chen (2007), and Lizardo and Mollick (2010) provide evidence, showing that a higher real oil price leads to a significant appreciation of currencies in net oil-exporting nations. Due to the contrasting reactions of the oil-exporting and oil-importing exchange rates to a change in oil price, it is deemed to be a potential diversification benefit and hedging opportunity against oil price risk by taking positions in both oil-importing and oil-exporting foreign exchange (FX) markets. However, an increase in interconnectedness risk of the oil-dependent currencies caused by shifts in the oil volatility's regime may reduce the FX portfolio diversification benefit. As a result, the effect of oil volatility's regime changes on the interconnectedness among oil-dependent currencies, a leftover issue from the existing studies, should be of interest to FX market participants. Our study aims to fill this void by investigating the high-frequency volatility connectedness among oil-dependent currencies under different states of the oil market volatility. The endeavor of our study would help enhance the performance of the oil-dependent FX portfolios as FX portfolio managers can actively adjust their portfolio allocation based on the knowledge of oil volatility's regime-dependent FX connectedness. This way, they would achieve the most of diversification benefit of the oil-dependent FX portfolio as well as reducing the risk of FX volatility connectedness under different states of the oil market.

To this end, we rely on the sample of seven major free-floating oil-dependent currencies,[3] including three oil-exporting currencies: the Canadian Dollar (CAD), the Mexican

[3] Note, our study relies on the high-frequency measure of volatility (i.e., realized volatility), thereby our sample is restricted to only major free-floating oil-dependent currencies that have consistently been net oil-exporter or net oil-importers during the whole research period.

Peso (MXN), the Norwegian Krone (NOK); and four oil-importing currencies: the Euro (EUR), the Pound Sterling (GBP), the Japanese Yen (JPY) and the Singapore Dollar (SGD). These are the highest liquid oil-dependent exchange rates given the significant trading activity of these currencies accounting for 73% of the global FX daily turnover in 2019.[4] The heavy trading of the sample exchange rates in global FX markets highlights the relevance of our study for investors who seek the diversification and hedging opportunity by maintaining their positions in both oil-exporting and oil-importing FX markets. We investigate the dynamic volatility connectedness between the oil-exporting and oil-importing currencies at both the *individual*- and *group*-currency levels using high-frequency data for the period between January, 4th 2010 and September, 30th 2020. Our study utilizes the multivariate Heterogeneous Autoregressive model with measurement error, known as VHAR(Q) model, to model vector realized variance of sample FX markets. The VHAR(Q) serves as the base modelling framework to derive the generalized connectedness index (GCI, hereafter) of Diebold and Yilmaz (2012) and the block aggregation of connectedness matrix (BACM, hereafter) of Greenwood-Nimmo et al. (2016). Then, we go further to explore whether the spillover effect between oil-exporting and oil-importing currencies is affected by the oil market's regime switching and suggest a dynamic oil's regime-dependent FX trading strategy based on these findings.

Several major studies have used the original VHAR–DCC-GARCH model extended from the univariate HAR-GARCH (Corsi et al., 2008; and Corsi, 2009) to model vector realized volatility and examine high-frequency volatility spillover among financial markets (see, Bubák et al. 2011 and Luo and Ji, 2018). The use of the VHAR model specification has its own advantage compared to the traditional Vector Autoregression (VAR) structure in the sense that the VHAR can conveniently and appropriately capture the long-memory behavior – a stylized fact – of the realized volatility. However, the original VHAR does not address the inconsistency

[4] See, the Triennial Survey of turnover in OTC FX markets by Bank for International Settlements, April 2019.

problem in estimated parameters due to the variation in measurement error in realized volatility estimator (see, Bollerslev et al., 2016, 2018). The remaining measurement error in realized volatility measure is caused by the limitation in the sampling frequency of intraday data. Bollerslev et al. (2018) introduced VHAR(Q) to overcome this issue and can effectively capture the time-varying effect of the heteroskedasticity in measurement errors in realized volatility measures, and hence improving the accuracy of realized volatility estimation. As a result, to ensure that our estimations of the FX connectedness are not biased due to the long-memory behavior as well as the heteroskedasticity in measurement errors of the realized volatility, we develop the connectedness measures within the VHAR(Q)–DCC-GARCH modelling framework to investigate volatility spillover. Notably, following the spirit of the HAR-GARCH model proposed by Corsi et al. (2008), we incorporate the DCC-GARCH into our multivariate baseline framework VHAR(Q) to model the vector residuals obtained from the VHAR(Q), and thus further capturing the volatility clustering property in the residual series.

Regarding the static connectedness analysis, we construct the generalized connectedness index (GCI) and the block aggregation of connectedness matrix (BACM) within a VHAR(Q)–DCC-GARCH framework and provide several significant findings of oil-dependent currency connectedness at both individual-currency and group-currency level. Our block structure is built up by two groups, namely oil-exporting group and oil-importing group. First, we point out that the total connectedness index of the currency system is relatively high at 50.42%, but it mainly caused by the strong linkage between the currencies in the same group (i.e., within-group connectedness). Specifically, the major portion of 71.92% of total connectedness index of the FX system comes from the within-group connectedness while only 28.08% of total connectedness index is attributed to the cross-group volatility connectedness. The latter confirms the potential benefits of diversification by combining oil-exporting and oil-importing currencies in a portfolio. Second, our study provides evidence that the cross-group connectedness is mostly caused by volatility causalities from the oil-exporting currencies to the oil-importing currencies and concentrated in the short-run. This is evidenced by the positive net-group spillover index of oil-exporting group of 6.82%. Further, the realized volatilities of oil-importing currencies are strongly affected by the volatility shock transmission from the oil exporting currencies, mainly MXN and NOK. For example, the average directional pairwise connectedness from MXN to oil-importing currencies is high ranging from the lowest of 11.71% (MXN-GBP) to the highest of 23.53% (MXN-JPY).[5] NOK is also the oil-exporting currency which plays the significant role in transmitting volatility shocks to oil-importing currencies, as evidenced by its strong directional pairwise connectedness of 11.37% (NOK-GBP) and 14.20% (NOK-SGD).[6] The strong connectedness of these pairs is likely to be the most contributors of cross-group volatility connectedness of the currency system and could be explained by the significant bilateral trade balance between these countries/areas.

Turning to the time-varying connectedness analysis, we evaluate the time-varying fluctuations of the connectedness measures among oil-dependent currencies together with the changes in the oil market's regime. First, we provide evidence that the Cross-group Spillover Index (CSI) of the currency system is highly volatile during research period, ranging from the lowest level of around 20% during the low-volatility oil regime to 50% during the high-volatility oil regime. This finding implies that the diversification benefit of an FX portfolio consisting of both oil-exporting and oil-importing currencies significantly declines when the oil market experiences high-volatility times. Second, the time-varying net spillover index of exporting group is overwhelmingly positive during the research period and peaks at high level

[5] Over the last 11 years, the bilateral trade between Japan and Mexico has experienced remarkable growth by 71%. Japan has emerged as the second largest market of agricultural products and seafood exports to Mexico while Mexico is the leading suppliers of meat product to Japan. (See, https://www.gob.mx/se/prensa/mexico-and-japan-promote-results-and-opportunities-of-the-agreement-for-the-strengthening-of-the-economic-partnership)
[6] Norway and the UK are strategic trade partners. Norway exports seafood to the UK and imports many products such as machinery, chemicals, and vehicles from the UK. (See, Norway and the United Kingdom - Norway in the United Kingdom)

of 39%-40% in the high-volatility oil regime, suggesting the dominant role of volatility shock transmitters of oil-exporting group over the research period regardless of different oil regimes.

We further investigate how a change in the oil market's regime determines the measures of connectedness among oil-dependent currencies by regressing the FX connectedness measures on the estimated probability of high-volatility oil regime. First, our results point out that the Cross-group Spillover Index (CSI) increases by 5.348% when the oil market switches from a low-volatility to a high-volatility state. The higher connectedness risk between the oil-dependent currencies due to a shift in the oil market to high-volatility regime may diminish the FX portfolio's diversification benefit. Second, in the increase of cross-group connectedness, MXN and NOK contribute most to propagating the volatility shocks among the system, as evidenced by the largest increases of 11.75% and 20.91% in their "Spillover to others" indexes, respectively, when the oil market enters the highly volatile periods. Meanwhile, the shift of the oil regime has an insignificant impact on the "Spillover to others" indexes of GBP and JPY, implying that these currencies can play the role of volatility stabilizer in the system when the oil market switches to an unstable time. These findings have crucial implications for asset allocation in oil-dependent currency trading following the information of the oil market's regime.

Finally, based on the result of time-varying volatility connectedness between oil-importing and oil-exporting currencies under different oil regimes, we further design a dynamic regime-dependent strategy for a hypothetical FX hedger. This strategy suggests adjusting the FX basket depending on the information of the estimated probability of high-oil-volatility regimes to gain greater diversification benefits and minimize risk of volatility shock transmission among oil-dependent currencies. Particularly, when the oil volatility switches to a high volatility state, the FX portfolio of oil-dependent currencies should be adjusted by reducing the weights of main shock drivers (i.e., oil-exporting currencies) and increasing the weights of shock stabilizers, respectively. By actively reallocating the weights of currencies, we expect to reduce the volatility connectedness of the FX portfolio, hence lowering the portfolio risk. Our simulation results reveal that the dynamic oil's regime-dependent strategy helps the hedger to achieve better performance regarding risk, return and risk-adjusted return. The Sharpe ratio of the dynamic oil-volatility-regime-dependent FX portfolio improves as much as 6.85% compared to a buy-and-hold portfolio.

Our study makes several valuable contributions to the existing literature. First, we extend the extant literature by exploring a not yet touched issue of oil's regime-dependent FX volatility connectedness. While previous studies have mostly focused on the volatility linkage between the oil market and foreign exchange markets, our study turns to scrutinize how the FX volatility connectedness depends on the shifts in oil's volatility regime. Our work offers the empirical evidence that the volatility connectedness across oil-exporting and oil-importing exchange rates significantly strengthens when the oil market switches to a high-volatility time. We also reveal that the oil-exporting currencies consistently act as volatility shock transmitters in the currency system regardless of different oil states. The comprehensive understanding of oil's regime-dependent FX connectedness is important to form an empirical base for FX market participants to decide on their positions in FX markets.

Second, we apply and extend various connectedness measures (i.e., the GCI and the BACM) within the VHAR(Q)–DCC-GARCH system to investigate the time-varying volatility connectedness across oil-dependent currencies at both individual and group-currency analyses. The VHAR(Q)–DCC-GARCH model provides several advantages when estimating vector realized volatility. Specifically, the VHAR(Q) model can successfully replicate the long-memory property of realized volatility (Corsi, 2009) and capture the effects of heteroskedasticity in measurement error in realized volatility (Bollerslev et al., 2018), thereby ensuring the consistency in the realized volatility estimation. Meanwhile, the DCC-GARCH used to model the vector residuals of the VHAR(Q) helps capture the volatility of the volatility effect in vector realized volatility estimation (Corsi et al., 2008). As such, our analyses can deliver better measurement of dynamic volatility connectedness among foreign exchange markets. Further, since the estimated parameters from our baseline VHAR(Q)–DCC-GARCH model are time-varying by the effect of measurement errors, our results of connectedness measures are time-varying without applying the traditional rolling-window approach, hence overcoming the subjectivity bias due to window-length selection.

Finally, our suggested oil's regime-dependent trading strategy has practical implications for FX portfolio management. This dynamic trading strategy allows FX traders to benefit from the knowledge about oil's regime-dependent FX volatility linkages. Portfolio managers who follow the dynamic oil-regime-dependent strategy could better manage their FX portfolio risk as well as benefit from diversification benefit of oil-exporting and oil-importing currencies, hence achieving better risk-adjusted return performance.

The remainder of the study is as follows. Section 2.2 discusses related literature. We describe the methodology in section 2.3. In section 2.4, we present our data collection and preliminary analyses of the data. Section 2.5 provides and discusses the main empirical results as well as the robustness check. Section 2.6 deals with the financial implication of our findings. Section 2.7 concludes.

2.2 Literature review

The extant literature has extensively documented the causal relationship between oil prices and exchange rates. Amano and van Norden (1998a, 1998b) and Golub (1983) provide empirical evidence of the persistent causal effects from oil prices to exchange rates. Other major studies using cointegration approaches and causality tests still detect a unidirectional causal relationship from oil prices and exchange rates. These include Coudert et al. (2007), Lizardo and Mollick (2010), Atems et al. (2015), Ferraro et al. (2015), and Malik and Umar (2019),[7] to name a few. All these findings favor the theoretical prediction of Krugman (1983) based on the terms of trade and the wealth reallocation effect.

However, Zhang et al. (2008), Chen et al. (2010), and Beckmann and Czudaj (2013), among many others, detect a reverse (Granger) causality from exchange rates to oil price fluctuations. These studies document that the depreciation in the U.S. dollar may result in the decline in crude oil prices for foreigners relative to commodity prices, which subsequently boosts the oil price in the U.S. dollar.

Meanwhile, recent studies report the empirical finding of bidirectional causal links between crude oil prices and exchange rates. For instance, Zhang et al. (2016) apply the Granger causality tests and find a bidirectional Granger causality between the oil market and four major oil-dependent FX markets (Canada, Australia, Norway, and Chile). Based on the wavelet approach, Yang et al. (2017) and Reboredo and Rivera-Castro (2013) also support the dynamic bidirectional price spillover across the oil and FX markets.

Further, tail dependence between oil prices and exchange rates is also explored in the literature. Using the copula methodology, Mensi et al. (2017), Reboredo (2012), and Aloui et al. (2013) find that the oil price-exchange rate interdependence in the tails is time-varying and strongly increases during financial uncertainty.

Turning to the volatility connectedness among oil and FX markets, Ding and Vo (2012), Salisu and Mobolaji (2013), and Malik and Umar (2019) employ the GARCH and dynamic correlation models to examine volatility interconnectedness between the oil market and the major oil-dependent currencies but rely on lower-frequency than intraday data. Other studies

[7] In recent works, Malik and Umar (2019) and Atems et al. (2015), further disentangle various components of oil price shocks and identify the dynamic effects of different sources of oil price shocks on the variation in exchange rates. They point out that the shocks to oil demand have notably contributed to the fluctuation in the FX market, especially in financial turmoil, while the oil supply shocks have no significant impact on exchange rate movement.

that use intraday data include Alam et al. (2019) with wavelet analysis, Jawadi et al. (2016) with GARCH analysis, and Baruník et al. (2019) with the use of the generalized spillover index proposed by Diebold and Yilmaz (2012). The findings of these studies indicate that there are significant volatility interactions between the oil and FX markets in both directions and this connectedness tends to have a dramatic increase during periods of financial distress.

More importantly, the extant literature has documented the different effects of oil price changes on oil-exporting and oil-importing exchange rates. Lizardo and Mollick (2010) empirically show that when real oil prices increase, the oil-exporting currencies experience an appreciation in their value and oil-importing currencies may depreciate. Their empirical evidence support the early theoretical analyses of Krugman (1983) and Golub (1983) based on the theory of wealth reallocation. Further, Reboredo (2012) and Yang et al. (2017) reveal that oil-exporting currencies are more connected with oil volatility shocks than oil-importing currencies. The different reactions of oil-importing and oil-exporting currencies to a change in oil price suggest a potential diversification benefit and hedging against oil price risk for FX traders. However, this FX trading activity involves comprehensive understanding of how the volatility connectedness among oil-dependent currencies evolve through different regimes of the oil market, the important issue left over from the literature reviewed above.

This unexplored issue should be of interest to FX market participants when deciding their asset allocation in oil-dependent currencies to hedge against oil price risk and managing the FX volatility spillover risk of their portfolios. Investigating the issue, our study intends to adopt the VHAR(Q)–DCC-GARCH model that can deal with the problems of the heteroskedasticity in measurement error in realized volatility estimator, which differentiates our study from other studies on realized volatility connectedness in terms of research methodology.

The VHAR–DCC-GARCH model has been utilized in several recent papers to model vector realized volatility and hence an appropriate underlying framework to compute connectedness measures between financial assets/markets (e.g., Bubák et al., 2011; Souček and Todorova, 2013; and Luo and Ji, 2018) or to forecast assets' realized volatility (e.g., Chiriac and Voev, 2011; and Čech and Baruník, 2017). For instance, Bubák et al. (2011) employ the VHAR–DCC-GARCH model combined with the connectedness index of Diebold and Yilmaz (2009) to investigate volatility spillover for three Central European currencies. Souček and Todorova (2013) apply the VHAR and dynamic correlation approach in examining realized volatility transmission between crude oil and equity futures markets. Applying the VHAR-DCC/GARCH model, Luo and Ji (2018) examine realized volatility transmission from the U.S. crude oil market to a group of China's agricultural commodities.

However, the VHAR–DCC-GARCH model's estimated parameters can be biased due to the restrictions on the sampling frequency of intraday data used to compute realized volatility. Increasing the sampling frequency from 5-minutes to 1-minute can reduce the measurement errors but may also induce more market microstructure effects (Bollerslev et al., 2016). As a result, the number of intraday data within a trading day should be restricted to balance the costs of measurement errors and market microstructure noise. Since the measurement errors cannot be eradicated in the intraday measure of volatility due to data restriction, the inconsistency problem with estimation remains. None of the above-cited studies have addressed the issue of the presence of varying measurement errors when investigating realized volatility connectedness.

Recently, Bollerslev et al. (2018) propose the so-called VHAR(Q) model to capture the influence of measurement errors in the realized variance estimator. Using this model, one can retain the desirable advantages of the HAR model, while overcoming the inconsistency problem involved in measuring realized variance and modeling volatility spillover. Therefore, we utilize the VHAR(Q)–DCC-GARCH model in the present study. Note, the DCC-GARCH is incorporated to our baseline model to account for the volatility clustering property in residual series obtained from the VHAR(Q) model. Doing so, we offer a convenient approach to facilitate the joint use of the generalized connectedness index (Diebold and Yilmaz, 2012) and the method of block aggregation of the connectedness matrix (Greenwood-Nimmo et al., 2016) within the VHAR(Q)–DCC-GARCH model. This approach enables us to more accurately measure dynamic volatility connectedness between oil-exporting and oil-importing currencies with respect to oil volatility regime-switching.

2.3 Methodologies

2.3.1 The VHAR(Q)-DCC-GARCH framework

We first consider the notion of realized variance (RV) introduced by Andersen and Bollerslev (1998) in estimating volatility of an exchange rate. Realized volatility is calculated from the sum of squared intraday data returns as follows,

$$RV_t = \sum_{i=1}^{M} r_{t,i}^2 \tag{2.1}$$

where $r_{t,i} = \left(\log P_{t-1+i\Delta} - \log P_{t-1+(i-1)\Delta}\right) \times 100\%$, denotes the ith Δ-period intraday log return on the corresponding asset/market within day t; Δ denotes the sampling frequency; and $M \equiv 1/\Delta$ is the number of observations within a trading day. As $M \to \infty$ or $\Delta \to 0$, the RV measure is a consistent estimator for unobservable integrated variance.

The key econometric framework applied in modelling realized volatility series in our study is the VHAR(Q)–DCC-GARCH model, which embraces two elements: VHAR(Q) and DCC-GARCH. The VHAR(Q) model, advanced by Bollerslev et al. (2018) from the univariate Heterogeneous Autoregressive (HAR) model by Corsi (2009), effectively capture the effect of heteroskedasticity in measurement errors in realized volatility measure. The DCC-GARCH is used to model vector residuals resulted from the estimation of the VHAR(Q) to capture the volatility of volatility effect.

The VHAR(Q) is specified below:

$$RV_t = c^{(d)} + \underbrace{\left(\beta^{(d)} \times \iota + \beta_Q^{(d)} RQ_{t-1}^{1/2}\right)}_{\beta_t^{(d)}} \circ RV_{t-1} + \beta^{(w)} RV_{t-1/t-5} + \beta^{(m)} RV_{t-1/t-22} + \varepsilon_t^{(d)} \tag{2.2}$$

The variables and parameters in equation (2.2) are defined as follows. RV_t denotes the $m\times1$ vector of realized volatility with m assets/markets considered. RQ denotes the $m\times1$ vector of realized quarticity, whose element is to be estimated by $\left(M/3\right)\sum_{i=1}^{M} r_{t,i}^4$, and $RQ^{1/2}$ is known as the $m\times1$ vector of asymptotic standard deviations for m assets/markets. $RV_{t\text{-}1}$, $RV_{t\text{-}1/t\text{-}5}$ and $RV_{t\text{-}1/t\text{-}22}$ are the lagged $m\times1$ vectors of average past values of, respectively, daily, weekly and monthly RV_t, given $RV_{t-1|t-k} \equiv \frac{1}{k}\sum_{j=1}^{k} RV_{t-j}$. $\beta^{(d)}$, $\beta_Q^{(d)}$, $\beta^{(w)}$ and $\beta^{(m)}$ are the four $m\times m$ matrixes of parameters to be estimated, ι is the $m\times1$ vector of ones, $c^{(d)}$ is the $m\times1$ vector of intercepts, and $\varepsilon_t^{(d)}$ is the $m\times1$ vector of residuals. The symbol $\circ$ denotes the Hadamard product, allowing the beta coefficients of each regressors to adjust in proportion to the magnitude of their own measurement errors.

The salient feature of VHAR(Q) in Eq. (2.2) lies in its being able to model vector realized variance by incorporating the effect of measurement error into autoregressive parameters. Specifically, the term $\beta_Q^{(d)} RQ_{t-1}^{1/2}$ makes the $m\times1$ vector $\beta_t^{(d)}$ time-varying, to allow for the attenuation effects of measurement errors in the realized variance estimator via the autoregressive parameter $\beta_t^{(d)}$ that also captures the strong persistence of volatility. This way, the estimation of volatility interconnectedness would be more accurate. We expect all the $\beta_Q^{(d)}$ coefficients to be negative: The greater the temporal variation in the measurement error variance (i.e., the higher the value of *RQ*), the less informativeness the lagged *RV* contributes to explaining future *RVs* (i.e., the lower the $\beta_t^{(d)}$ coefficient).

Further, Corsi et al. (2008) propose the HAR-GARCH model to capture the volatility clustering property in the residual series obtained from the univariate HAR model. Following this spirit, in this study we apply the multivariate version of the HAR-GARCH model, the so-called VHAR(Q)-DCC-GARCH model, and thus allow the $\varepsilon_t^{(d)}$ resulted from our VHAR(Q) model to follow the multivariate GARCH process to capture the volatility of volatility effect.[8] The econometric tool used for this purpose is the standard DCC model of Engle (2002). To save space, we include the estimation of the DCC-GARCH model for vector error terms resulted from the VHAR(Q) in Appendix A.2.1.

To sum up, the estimation of our VHAR(Q)–DCC-GARCH model for vector realized volatility involves two steps. In step 1, the autoregressive coefficients ($c^{(d)}$, $\beta_t^{(d)}$, $\beta_Q^{(d)}$, $\beta^{(w)}, \beta^{(m)}$) are estimated from the VHAR(Q) model in Eq. (2.2). In step 2, using the vector error terms resulted from the VHAR(Q) in step 1, the set of parameters of the DCC-GARCH, including ($\omega_i, \alpha_i, \gamma_i |$ i = 1, …, m), is estimated by GARCH(1,1) in Eq. (2.3A) and the correlation coefficients (a,b) are estimated by the DCC model in Eq. (2.5A) of Appendix A.2.1.

2.3.2 Connectedness measures in a VHAR(Q)-DCC-GARCH model

The connectedness index has traditionally been constructed for an underlying VAR process. However, a VAR process does not allow for the high persistence of volatility in estimation. To overcome this shortcoming, we develop the VHAR(Q)–DCC-GARCH process as the underlying function for constructing the generalized connectedness index (Diebold and

[8] Corsi *et al.* (2008) shows that regardless of the transformation of realized variance estimates, the residuals from HAR model exhibit the non-normality distribution and volatility clustering. This is attributed to the variance of realized volatility effects. They also suggest allowing the vector innovation term ε_t obtained from the HAR model to follow GARCH specification to capture the effect of the volatility of volatility for univariate HAR model.

Yilmaz, 2012) and the block aggregation of the connectedness matrix (Greenwood-Nimmo et al., 2016). Since VHAR(Q)–DCC-GARCH can capture the long-memory behavior of volatility and the effect of measurement errors, using the model enhances the quality of volatility connectedness evaluation. To establish the VHAR(Q)–DCC-GARCH process as the underlying function, we propose a ***three-step*** approach as outlined below.

***STEP 1*:** We transform the $m\times 1$ estimated parameter vector $\beta_t^{(d)}$ in Eq. (2.2) into the $m\times m$ diagonal parameter matrix $\beta{'}_t^{(d)}$ as follows:

$$RV_t = c^{(d)} + \beta{'}_t^{(d)} RV_{t-1} + \beta^{(w)} RV_{t-1/t-5} + \beta^{(m)} RV_{t-1/t-22} + \varepsilon_t^{(d)} \tag{2.3}$$

where $\beta{'}_t^{(d)}$ is the time-varying $m\times m$ diagonal matrix with each diagonal element constructed from each element of the $m\times 1$ vector $\beta_t^{(d)}$. As such, Eq. (2.3) is considered analogous to Eq. (2.2).

***STEP 2*:** The transformed VHAR(Q)–DCC-GARCH specification in Eq. (2.3) is rewritten as the restricted VAR(Q)(22)–DCC-GARCH process as in Eq. (2.4):

$$RV_t = c^{(d)} + \Phi_{1,t} RV_{t-1} + \Phi_2 RV_{t-2} + \ldots + \Phi_{22} RV_{t-22} + \varepsilon_t \tag{2.4}$$

$$\varepsilon_t = H_t^{1/2} z_t$$

with ε_t following the DCC-GARCH model to capture the volatility of volatility effect; and H_t being the conditional variance covariance matrix of ε_t estimated by DCC-GARCH model; and $z_t \sim NID(0,I)$; $c^{(d)}$ is the $m\times 1$ intercept vector; Φ_i ($i = 1,\ldots,22$) are the $m\times m$ restricted coefficient matrices satisfying the following conditions,

$$\Phi_{1,t} = \beta{'}_t^{(d)} + \frac{1}{5}\beta^{(w)} + \frac{1}{22}\beta^{(m)} \tag{2.5}$$

$$\Phi_2 = \ldots = \Phi_5 = \frac{1}{5}\beta^{(w)} + \frac{1}{22}\beta^{(m)}$$

$$\Phi_6 = \ldots = \Phi_{22} = \frac{1}{22}\beta^{(m)}$$

and $\beta_t'^{(d)}$, $\beta^{(w)}$ and $\beta^{(m)}$ are estimated using Eq. (2.2) and Eq. (2.3). As mentioned above, the VAR(Q)(22)–DCC-GARCH model in Eq. (2.4) incorporates the restricted parameter matrices obtained from the VHAR(Q) model and the vector error term derived from the VHAR(Q) following the DCC-GARCH model. Evidently, $\beta_t'^{(d)}$ hence $\Phi_{1,t}$ in Eq. (2.5) is time-varying and adjusts to the influence of variations in measurement errors.

STEP 3: Given the stationary VAR(Q)(22)–DCC-GARCH process in Eq. (2.5), we proceed to transform the restricted VAR(Q)(22)–DCC-GARCH into the infinite moving average representation, as depicted in Eq. (2.6). This formulation facilitates the computation of connectedness indexes, following spirit of Diebold and Yilmaz (2012) and Greenwood-Nimmo et al. (2016):

$$RV_t = \sum_{i=1}^{\infty} A_{i,t}\varepsilon_{t-i} \tag{2.6}$$

where the $m\times m$ time-varying coefficient matrices of the moving average $A_{i,t}$ follow a recursion process as $A_{i,t} = \Phi_{1,t}A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with A_0 representing an $m\times m$ identity matrix and $A_{i,t} = 0$ for $i < 0$. Note, the coefficients in the moving average are time-varying due to the effect of measurement error in realized volatility measure on the restricted parameter of the VAR(Q)(22)–DCC-GARCH process.

Using the GCI of Diebold and Yilmaz (2012), the forecast error variance (FEV) decompositions can be constructed from time-varying moving average coefficients ($A_{i,t}$) and conditional variance-covariance matrix of ε_t (H_t) estimated by the DCC-GARCH model. We compute the h-step-ahead error variance decompositions in forecasting x_i as follows:

$$\theta_{ij,t} = \frac{\sigma_{jj,t}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_{h,t} H_t e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_{h,t} H_t A_{h,t}' e_i\right)} \tag{2.7}$$

where H_t is defined above but estimated, σ_{jj} represents the standard deviation of the error term for the jth equation, and e_i denotes the selection vector with a value of one for the ith element and zero otherwise.

Each entry of the variance decomposition matrix is normalized by the row sum as in Eq. (2.8). Subsequently, these normalized entries are utilized in computing the total connectedness index (*TCI*) as in Eq. (2.9).

$$\tilde{\theta}_{ij} = \frac{\theta_{ij}}{\sum_{j=1}^{m} \theta_{ij}} \tag{2.8}$$

$$TCI = \frac{\sum_{i,j=1;i \neq j}^{m} \tilde{\theta}_{ij}}{m} \times 100 \tag{2.9}$$

The directional spillover index received by market i from all other markets j and the directional spillover index transmitted by market i to all other markets j are computed as in Eq. (2.10) and Eq. (2.11), respectively:

$$S_{i.} = \frac{\sum_{j=1;i \neq j}^{m} \tilde{\theta}_{ij}}{m} \times 100 \tag{2.10}$$

$$S_{.i} = \frac{\sum_{j=1;i \neq j}^{m} \tilde{\theta}_{ji}}{m} \times 100 \tag{2.11}$$

By employing VHAR(Q)–DCC-GARCH model as the underlying process for computing connectedness index, we allow the moving average coefficients to vary over time. Thereby, the time-varying volatility spillover is achieved without applying a rolling-window method. Our novel approach thus overcomes the subjectivity bias in window length selection of the rolling-window approach and better measures dynamic volatility spillover.

We further develop the block connectedness analysis of Greenwood-Nimmo et al. (2016) within the VHAR(Q)–DCC-GARCH model. This enhancement enables us to investigate the *group-level* connectedness across two groups of currencies. The results of block connectedness allow us to separate the contribution of *within-group* and *cross-group* spillover to total volatility connectedness as well as evaluate the primary roles of volatility driver and receiver in cross-group spillover (See Appendix A.2.2 for more details of statistical methodology of block connectedness within the VHAR(Q)–DCC-GARCH).

2.3.3 The role of the oil market volatility's regime – Baseline regression models

To investigate how volatility connectedness among the two groups of oil-dependent-FX markets is affected by shifts the oil volatility's regime, we employ the common regime switching model, known as the Markov-Switching Autoregressive (MS-AR) model (Hamilton, 1990).[9] This model allows us to estimate the probability of a *high*-oil-volatility regime p_t of crude oil prices.[10]

Based on the estimated time series of cross-group FX volatility connectedness $CSI^{(h)}$, as in Eq. (2.16A), as well as the estimated time series of "Spillover to others" index (SO) for a given currency, and the estimated probability of *high*-oil-volatility regime p_t, we evaluate the impacts of the oil market volatility's regime on Cross-group Spillover Index (CSI) for the set of sample oil-dependent currencies and the "Spillover to others" index (SO) for a specific currency following the baseline regression models specified as,

$$CSI_{t+1}^{(h)} = \alpha_0 + \alpha_{oil} p_t + \alpha_c Control_t + \omega_{t+1} \tag{2.12}$$

$$SO_{i,t+1}^{(h)} = \gamma_{i,0} + \gamma_{i,oil} p_t + \gamma_{i,c} Control_t + \vartheta_{i,t+1} \tag{2.13}$$

where $Control_t$ is a set of control variables including: (1) the Fed fund rate (*FFR*); (2) the CBOE implied volatility of the S&P 500 index (VIX); (3) the US dollar index (USDX); (4) the geopolitical risk index (GPR) offered by Caldara and Iacoviello (2022). These variables are

[9] See the technical accounts for the MS-AR(1) model in Appendix A.2.3.

[10] Following the extant studies (Bekaert et al., 2015 and Ma et al., 2017), we also consider two regimes, the low- and the high-volatility regime, in modelling the volatility of crude oil futures.

thoroughly selected to ensure that their data are available on a daily frequency basis, and that they have been previously documented or are expected to affect exchange rate returns and exchange rate volatility connectedness. These two first variables represent the effects of Fed's monetary policy and stock market volatility on exchange rate volatility connectedness. Mo et al. (2023) have documented that the Fed Fund Rate has negative impact on exchange rate interconnectedness while stock market volatility exerts positive impact on exchange rate interdependent. The USDX is relative value of the dollar against a basket of six foreign exchange rates, which is documented to significantly affect exchange rate dependences (Xu and Lien, 2022). Salisu et al. (2022) and Duan et al. (2021) provide empirical evidence of the significant impact of the GPR (both recent and historical data of the GPR) oon the exchange rate movement. The main regressor in Eq. (2.12) and Eq. (2.13) is the dummy variable p_t of the estimated probability of *hig*h-volatility oil regime, resulted from the MS-AR model. p_t takes the value of 1 if the estimated probability of high-volatility oil regime is larger than 0.5 and 0 otherwise.

To address the concern about the potential endogeneity issues in the regression analysis, we regressed the CSI on the lagged values of the estimated oil volatility regime and lagged values of a list of control variables. By using lagged values of the explanatory variables as instruments, we aim to eliminate the simultaneity issue, as there is no way that the past value of independent variables can be determined by the current values of dependent variable, thereby addressing the potential simultaneity and hence eliminating endogeneity concerns.

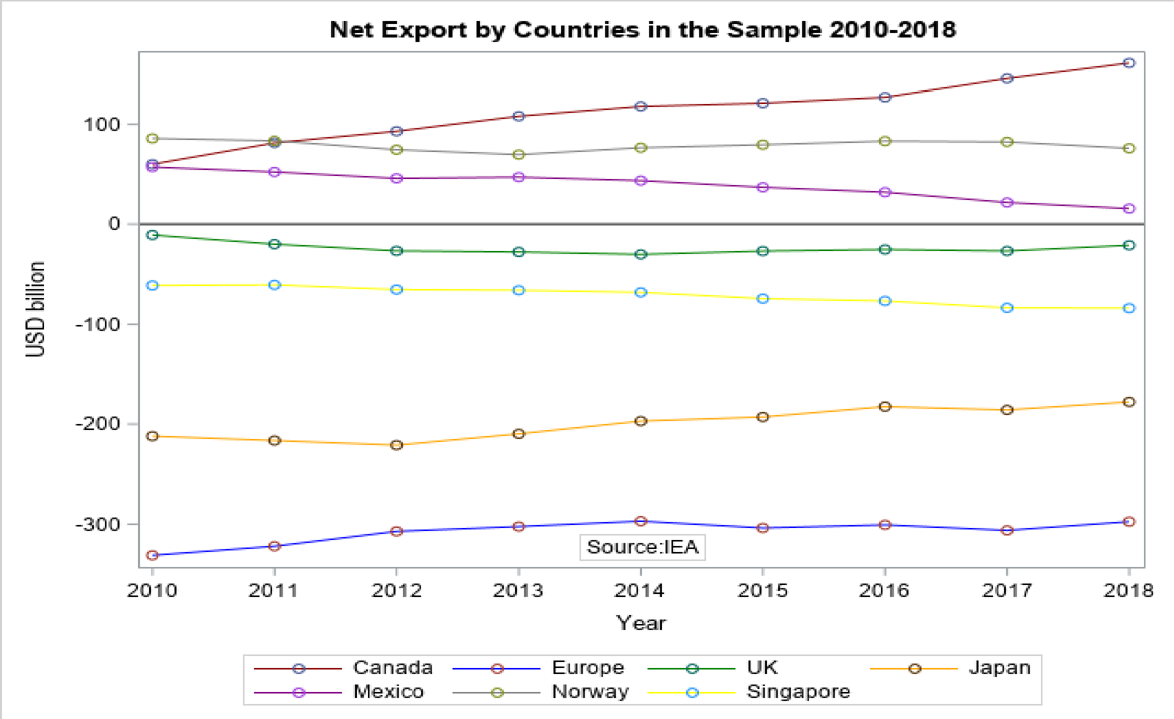
To ensure the consistency of our results concerning the significance and the sign of the relationship between high-volatility oil regime and FX connectedness, we also estimate Eq. (2.12) and Eq. (2.13) with the main regressor being the natural logarithm of the estimated probability of the oil's high-volatility regime obtained from the MS-AR model. These additional results serve to address any concerns that may arise from using the estimated probability of a high-volatility oil regime as a binary variable in our Eq. (2.12) and Eq. (2.13), which may cause a bias in measuring the effect of oil-volatility-regime switching on FX volatility connectedness.

The OLS procedure is adopted to estimate the parameters of the regression models with the *t*-statistics computed using the heteroskedasticity consistent standard errors.

2.4 Data and descriptive statistics

Since our study relies on the intraday measure of volatility (i.e., realized volatility), our choice of sample currencies is restricted to only major *free-floating* oil-dependent exchange rates which have available high-frequency data. Further, the sample currencies are all consistent as oil-exporting or oil-importing exchange rates for the whole research period. This helps our study avoid the changes in the role of oil-exporting or oil importing currencies. After considering these constraints, we select seven major oil-dependent currencies that account for a large portion of 73% of global FX trading in 2019. These include three major free-floating oil-exporting currencies: the Canadian Dollar (CAD), the Mexican Peso (MXN), the Norwegian Krone (NOK), and four primary free-floating oil-importing currencies: the Euro (EUR), the Pound Sterling (GBP), the Japanese Yen (JPY) and the Singapore Dollar (SGD). These seven markets are consistently the major net exporters/importers of oil over our whole sample period based on the figure of net oil-export/import value in USD billion from International Energy Agency (see Figure 2.1). Other major oil importers (i.e., China) or oil exporters (i.e., Middle East countries, Nigeria, Russia) are excluded because of their managed floating exchange rates or pegging currencies to the U.S. dollar.

Figure 2.1 Net oil exports and net oil imports by countries, 2010-2018



Note: The data of net imports by Europe is collected from the annual net imports of 4 major European countries, including Germany, France, Spain, and Italy. Source: IEA Atlas of Energy. Positive numbers show net exports and negative numbers indicate net imports.

We collect the bid and ask quotes of seven major oil-dependent exchange rates against the U.S. dollar from Thomson Reuters Tick History database from 4 January 2010 to 30 Sep 2020. Following the studies of Andersen et al. (2001), we choose the sample frequency of 5-minutes to extract intraday price series to balance the costs of measurement errors and market microstructure noise. Andersen et al. (2001) show that high-frequency measure of risk (i.e., realized volatility) provides a better measure for integrated true latent volatilities, which can capture real-time market reactions and offer a more precise measurement of volatility spillover. This approach allows for real-time monitoring of spillover effects, enabling policymakers and investors to design timely and informed response policies or investing decisions. To avoid modeling explicit weekend effects on trading activity, we exclude the weekend period from Friday 21:00 GMT to Sunday 21:00 GMT, as well as the major holidays (New Year 01 Jan, Christmas day 25 Dec and Easter Monday). A trading day is defined as between 21:00 GMT and 20:59 GMT of the following day. The final sample includes intraday data of 2,188 trading days for the seven sample currencies.

The 5-minute return series are derived by taking the logarithmic difference between the mid-quote prices of each currency. The log mid prices are calculated as the averages of the log bid and ask quotes. Subsequently, these intraday returns are utilized to calculate daily realized variance, daily realized quarticity, weekly realized variance and monthly realized variance.

To investigate the changes in oil's regime, we rely on daily closing price of West Texas Intermediate (WTI) crude oil extracted from DataStream. The WTI is one of the most common benchmarks for the prices of crude oil future.

Table 2.1 reports the summary statistics of daily realized variances of the seven currencies. One can see that MXN (0.6918) and NOK (0.7038) have much higher average realized variances than the remaining currencies, implying stronger volatility in Mexico and Norway FX spot markets. Meanwhile, SGD has the lowest average realized variance (0.1479). In addition, MXN and NOK possess a significantly higher degree of skewness and kurtosis in the distribution of daily realized variance than the other currencies, suggesting their greater fluctuations. The skewness and excess kurtosis statistics of all currencies' realized variances are far above zero, implying that their distributions are non-normal.

Table 2.1 Descriptive statistics

Name	Ticker	Variance							Quarticity		
		Mean	Std. Dev.	Skew	Kurt	LB Q(10)	LB Q(20)	ADF	Mean	Std. Dev.	CV
Canadian Dollar	CAD	0.3197	0.2609	3.90	27.90	5,561.11 ***	8,131.07***	-23.89***	0.000104	0.00121	11.634
Euro	EUR	0.3262	0.2951	4.04	28.46	4,125.98***	6,034.07***	-26.48***	0.000104	0.00103	9.904
Pound Sterling	GBP	0.3307	0.3191	6.19	61.97	4,711.05***	5,431.67***	-21.5***	0.000129	0.00086	6.667
Japanese Yen	JPY	0.3477	0.5574	11.93	204.05	482.17 ***	592.86***	-37.34***	0.000935	0.0217	23.209
Mexican Peso	MXN	0.6918	1.5879	20.35	536.94	1,296.79***	1,555.18***	-33.54***	0.001430	0.0319	22.308
Norwegian Krone	NOK	0.7038	1.3068	20.32	603.11	3,466.90***	3,781.82***	-24.08***	0.002170	0.0586	27.005
Singapore Dollar	SGD	0.1479	0.1293	3.32	18.54	8,157.25***	13,196.18***	-19.41***	0.000017	0.00015	8.824

Note. This table reports the descriptive statistics of daily realized variance and realized quarticity of 7 foreign exchange spot markets. LB Q(10) and LB Q(20) represent the Ljung-Box Q-statistics up to the 10th and 20th order autocorrelation. ADF test represent the augmented Dickey-Fuller unit root test. *** denotes the cases where the null hypothesis of no serial correlation (for LB Q test) and a presence of unit root (for ADF test) is rejected at the 1% significance level. The values of mean and standard deviation of RV and RQ are multiplied by 10^4. CV represents the coefficient of variation of RQ defined by the ratio of the standard deviation of RQ to the mean of RQ.

Table 2.1 also presents the diagnostic test of realized volatility series, including Ljung-Box Q test and the augmented Dickey-Fuller (ADF) test. The Ljung-Box Q statistics for all currencies up to 10 lags and 20 lags indicate significant serial correlation in all the realized variance series. The ADF statistics allow us to decisively reject the null hypothesis that the time series contain a unit root and are non-stationary, implying the stationarity in all cases.

Our study focuses on exploiting the influence of measurement errors to improve the quality of the realized variance measure. Therefore, it is crucial to note that in Table 2.1 the coefficient of variation (CV) of RQ (defined by the ratio of the standard deviation to the mean) are well above one for all the seven currencies. This implies the significant presence of measurement errors in all the realized volatility series. As discussed above, the significant measurement errors in realized volatility caused by the restricted sample frequency of intraday data may induce the inconsistency problem in realized volatility estimation. As such, the evidence supports our selection of the VHAR(Q) model to estimate vector realized volatility.

To examine the presence of the long-memory behavior in the realized volatility of the seven currencies, we construct the auto-correlograms from lag 1 to lag 100 for each currency during two separate sample periods (see Appendix A.2.4). The first is from 2010 to 2014, representing a period of relatively stable oil prices. The second is from 2015 to 2020, encompassing two significant oil price swings in 2015-2016 and in 2020. The figure for the two periods allows us to observe changes in the FX volatility behavior associated with different states in oil volatility. Specifically, the auto-correlograms reveal that in almost all cases, the volatility behavior of currencies changes from long-memory characteristic (hyperbolic slow decay in their auto-correlogram) in the 2010-2014 period to short-memory characteristic in the 2015-2020 period. These changes in the volatility behavior of the seven currencies could be attributed to the significant effects of the underlying economic events and/or oil regime switching.

Our above-provided evidence of significant measurement errors and long-memory behavior in realized volatility highlights the appropriateness of the VHAR(Q) model in this study to account for these properties when modelling vector realized volatility of oil-dependent currencies.

2.5 Empirical results

2.5.1 Regression results of the VHAR(Q)-DCC-GARCH model

Our descriptive statistics and plots of auto correlation function ACF indicate that these currencies' realized volatilities are characterized by long memory and measurement errors, rendering the use of the VHAR(Q) model appropriate. Table 2.2 reports the results of the parameter estimates of the VHAR(Q) model in Eq. (2.2).

The estimation results present the effects of past realized variance components, including short-term (β^d), middle-term (β^w) and long-term components (β^m), on the present realized volatility. The effect of heteroskedasticity in measurement errors in each currency's variance is captured by β_Q^d. As can be seen, the statistical significance of the effect of the past realized variances is observed for all currencies, with a gradual decrease in the influence over the middle- and long-term in almost all cases. Specifically, the past own short-term volatility components (β^d) of five sample currencies (i.e., GBP, JPY, MXN, NOK, and SGD) exert the most substantial impact on their current realized volatility. This indicates that the past short-term realized variances of these currencies are more informative in explaining the variations in their current volatility, compared to the middle- and long-term realized volatility. Notably, among the past own-variance components of exchange rates of three oil-exporters, the middle-term component of CAD and the long-term components of MXN and NOK are insignificant, implying that the current variances of CAD, MXN and NOK are not influenced by their own past longer-term realized volatility components, and only the short-term variance components affect the current volatility of oil-exporting currencies.

Regarding the cross-volatility transmission, there are some worth noting results as follows. First, the present volatility of all currencies in the system are positively affected by the past *short-term* variance component of MXN, as evidenced by the significant short-term coefficients of CAD (0.057), EUR (0.048), GBP (0.088), JPY (0.096), NOK (0.436). This finding is important as it suggests that the volatility transmission from MXN *short-term* variance component to the other oil-importing exchange rates may be the main contributor to the cross-group volatility connectedness among two groups of oil-dependent currencies, and thus the volatility connectedness among two groups is mostly concentrated in short run. Second, the past volatility components of CAD have no significant impact on the current volatility of oil-importing currencies, suggesting that among oil-exporting currencies, CAD contributes least to the cross-group volatility connectedness. Third, among three oil-exporting currencies, NOK is highly affected by the variations in the past realized volatility of oil-importing currencies while there is no such effect on MXN.

Now turn to β_Q^d which captures the effect of the variation in measurement errors on each realized variance. As expected, all the estimates of β_Q^d parameters are negative and statistically significant, except for SGD which is the relatively stable exchange rate with the lowest average realized quarticity as reported. This result is consistent with the above-discussed notion of the VHAR(Q) model that the greater the variation of measurement errors, the less informativeness the past *RV* contributes to estimating the current *RV*. Thus, the effect of heteroskedasticity in measurement errors is efficiently captured by the VHAR(Q) model, thereby enabling us to achieve more reliable estimates of *RV*.

Table 2.2 Regression results of the VHAR(Q) model

	CAD	EUR	GBP	JPY	MXN	NOK	SGD
$\beta^{CAD,d}$	0.351***	0.067	-0.051	0.083	0.483*	0.548***	-0.006
$\beta^{CAD,w}$	0.021	-0.057	-0.092*	0.016	-0.185	-0.438**	-0.027
$\beta^{CAD,m}$	0.475***	0.155**	0.303***	0.003	-0.083	0.224	0.039
$\beta_Q^{CAD,d}$	-149.143***	-27.557	17.762	-38.486	-190.554	-232***	3.346
$\beta^{EUR,d}$	-0.027	0.361***	0.000	-0.118	0.133	-0.84***	-0.008
$\beta^{EUR,w}$	0.230***	0.396***	0.185***	0.253*	0.397	0.732***	0.073***
$\beta^{EUR,m}$	-0.053	0.281***	-0.052	-0.04	-0.729	0.389	0.000
$\beta_Q^{EUR,d}$	-3.957	-83.788**	-14.868	34.349	-90.846	877.32***	24.207*
$\beta^{GBP,d}$	-0.052*	-0.032	0.354***	-0.080	-0.350*	0.497***	-0.022*
$\beta^{GBP,w}$	0.077**	0.014	0.244***	0.005	0.004	-0.152	0.012
$\beta^{GBP,m}$	-0.031	-0.119**	0.261***	0.129	0.397	-0.73***	-0.045**
$\beta_Q^{GBP,d}$	18.184***	16.806	-103.058***	20.253	94.532	-24.099	8.809*
$\beta^{JPY,d}$	0.027	-0.021	-0.046*	0.565***	0.135	-0.229**	-0.015*
$\beta^{JPY,w}$	0.014	0.000	-0.037	0.139**	0.206	-0.064	-0.004
$\beta^{JPY,m}$	0.023	0.030	0.078*	0.183*	-0.184	0.403**	0.031**
$\beta_Q^{JPY,d}$	2.803	6.929	6.955**	-60.7***	0.398	31.957**	4.484***
$\beta^{MXN,d}$	0.057***	0.048***	0.088***	0.096***	0.503***	0.436***	0.023***
$\beta^{MXN,w}$	0.014*	0.010	0.047***	-0.007	0.355***	0.247***	0.006*
$\beta^{MXN,m}$	-0.06***	-0.021	-0.035**	-0.030	0.051	-0.201***	-0.011*
$\beta_Q^{MXN,d}$	-5.577***	-4.77***	-7.099***	-9.79***	-36.9***	-35.442***	-1.81***

$\beta^{NOK,d}$	0.041***	0.022	0.027*	0.022	-0.060	0.532***	0.003
$\beta^{NOK,w}$	-0.017	0.001	0.075***	0.012	-0.061	0.354***	-0.005
$\beta^{NOK,m}$	0.023	-0.026	-0.12***	-0.097**	0.088	-0.005	-0.006
$\beta_Q^{NOK,d}$	-13.207***	-6.231**	-14.700***	-8.091	-7.933	-108.418***	-2.595**
$\beta^{SGD,d}$	-0.092	-0.234**	-0.210**	-0.65***	-0.669	-1.43***	0.376***
$\beta^{SGD,w}$	0.251**	0.059	-0.082	-0.551*	0.398	-0.471	0.356***
$\beta^{SGD,m}$	-0.123	0.069	-0.107	1.175***	0.225	0.323	0.323***
$\beta_Q^{SGD,d}$	49.500	155.522	181.816	820.587	802.042	1500.17	43.482

Note. This table reports the estimated parameters of the VHAR(Q) model for seven foreign exchange rates. ***, ** and * indicate that the estimated parameters are statistically significant at the 1%, 5% and 10% level, respectively. The robust standard errors of the estimates are not represented in this table to conserve space.

Testing the distribution of residuals resulted from VHAR(Q), we plot the changes and autocorrelation function of the residual series and conduct the Ljung-Box Q test.[11] The plot reveals the presence of remaining *volatility clustering* in the residual series, and further supported by the significant serial correlation observed in the Ljung-Box Q test. Thereby, to address this volatility of volatility effect and to ensure the independent identical distribution of vector residuals of the baseline model, we adopt a similar approach as Corsi et al. (2008) by incorporating the DCC-GARCH model (presented in Appendix A.2.1) into the VHAR(Q) model. This approach allows us to effectively model the vector residuals derived from the VHAR(Q) and better capture their underlying dynamics.

The estimate results of variance and correlation equations by the DCC-GARCH model for vector error terms of VHAR(Q) are reported in Table 2.3 Panel A. It shows that the estimates for the ARCH and GARCH effects in each variance equation of each residual series ($\alpha_{i,1}, \gamma_{i,1}$) are all statistically significant. Regarding the result of correlation equation, the estimated parameters (a, b) for the DCC model are significantly different from zero, implying a significant correlation structure among the error terms.[12]

Then, we conduct residual diagnostic tests on squared standardized residual series from the DCC-GARCH estimation, including Li-Mak's (1994) test and Engle's LM test. The Li-Mak's test results in Table 2.3 Panel B indicate no statistically significant autocorrelation in the squared standardized residuals, indicating that the DCC-GARCH model performs well in removing all the autoregressive conditional heteroskedastic effect in the variance of error terms. The results of Engle's LM test also reveal that no remaining ARCH effects in the residuals are observed. Evidently, the successful application of the DCC-GARCH to capture the volatility clustering in residual series effectively eradicates the concern regarding the

[11] The test results are available upon request.
[12] We also consider an asymmetric DCC. The estimated parameter for asymmetry in the correlation structure is insignificant. Thus, we only report the estimated results from the symmetric DCC model. The results of the asymmetric DCC are available upon request.

heteroskedasticity in the variance of error terms from our VHAR(Q) model. As such, the vector error terms of our underlying model VHAR(Q)–DCC-GARCH have no serial autocorrelation and no remaining ARCH effect and thereby supporting the computation of connectedness measures based on the baseline VHAR(Q) – DCC-GARCH model.

Table 2.3 Regression results of DCC-GARCH and diagnostic tests of residuals

Panel A. DCC-GARCH results

	CAD	EUR	GBP	JPY	MXN	NOK	SGD
$\boldsymbol{\alpha_{i,1}}$	0.051***	0.049***	0.053***	0.178**	0.049*	0.055**	0.051***
	(3.21)	(3.83)	(5.05)	(2.37)	(1.21)	(1.99)	(9.84)
$\boldsymbol{\gamma_{i,1}}$	0.985***	0.899***	0.952***	0.791***	0.899***	0.925***	0.895***
	(24.22)	(696.14)	(60.45)	(10.30)	(13.01)	(6.48)	(80.77)
a	0.0163***						
	(6.79)						
b	0.9270***						
	(78.52)						

Panel B. Diagnostic tests of residuals

	CAD	EUR	GBP	JPY	MXN	NOK	SGD
Li-Mak test	2.91	3.18	0.85	0.77	0.13	17.17	2.89
	(0.99)	(0.99)	(0.99)	(0.99)	(0.99)	(0.11)	(0.99)
ARCH-LM test	4.48	4.70	2.00	0.15	0.03	21.38	11.69
	(0.99)	(0.99)	(1.00)	(1.00)	(1.00)	(0.37)	(0.93)

Note. Panel A reports parameters estimated by DCC-GARCH model for residual series obtained from the VHAR(Q) model. Parameters α and γ denote the ARCH and GARCH coefficient estimates from volatility equation Eq. (2.3A) in Appendix A.2.1. Parameters a and b are estimated by DCC specified in Eq. (2.5A) in Appendix A.2.1. For DCC-GARCH estimation, the t-statistics are given in parentheses. Panel B reports the Li-Mak (1994) test and ARCH-LM test for the residuals of the DCC-GARCH. For both panels, ***, ** and * indicate that the estimated parameters are statistically significant at the 1%, 5% and 10% level, respectively.

2.5.2 The static volatility connectedness results at both individual-currency and group-currency levels

Since our VHAR(Q)–DCC-GARCH has appropriately modelled the system of our realized volatility series as evidenced above, we now develop the calculation of connectedness measures within the underlying VHAR(Q)–DCC-GARCH model to examine the dynamic volatility connectedness among seven oil-dependent currencies at both individual -level and group-level currencies.

We develop the generalized connectedness index (GCI) of Diebold and Yilmaz (2012) and the block aggregation of connectedness matrix (BACM) of Greenwood-Nimmo et al. (2016) within our underlying VHAR(Q)–DCC-GARCH. Our block structure is defined by two groups, consisting of oil-exporting currencies (CAD, MXN, NOK) and oil-importing currencies (EUR, GBP, JPY, SGD). The block connectedness analysis allows us to answer several following questions: (1) Which is the major source of the system's total volatility connectedness (i.e., within-group connectedness or cross-group connectedness); (2) Which currencies are the main volatility shock transmitters among the two groups. The answers to these questions help FX traders evaluate whether they should take positions in both oil-exporting and oil-importing FX markets to gain diversification/ hedging benefits. If yes, what currencies they should focus on to effectively manage the risk of volatility shock transmission among the system. Table 2.4 and 2.5 reports the results of GCI and BACM, respectively. There are several findings worth noting from the two tables, as follow.

First, as can be seen from Table 2.5, we find that even though the total connectedness index of the whole system is relatively high at 50.42%, it is mainly attributed to the *within-group* spillover among oil-exporting or oil-importing currencies. If only looking at total connectedness index (50.42%), one may feel doubt of the hedging effectiveness of the FX portfolio of both oil-importing and oil-exporting currencies. The block connectedness analysis reveals that the average *within-group* spillover accounts for the majority of 71.92% of the total connectedness, while the average *cross-group* spillover between the oil-exporting group and the oil-importing group stands at a much lower percentage (28.08%). So, volatility linkage is more pronounced for currencies in the same group. Meanwhile, the low *cross-group* volatility spillover highlights the potential benefit of diversification and hedging in FX trading by holding currencies from two groups in an FX portfolio.

Second, the causal link in volatility from the exporting-group to the importing-group is much stronger than the opposite direction with the net-group connectedness of oil-exporters being positive at 6.82% (Table 2.5). Particularly, 17.45% of the variation in importing-group is explained by the volatility spillover from exporting-group while the figure of the opposite direction stands at lower (10.63%). Further, table 2.4 shows that the oil-importing currencies are highly affected by the past variations of the oil-exporting currencies, especially MXN and NOK. Specifically, the directional pairwise connectedness from MXN to oil-importing currencies ranges from the lowest of 11.71% (MXN-GBP) to the highest of 23.53% (MXN-JPY). The significant volatility transmission from NOK to oil-importing currencies is evidenced by high directional pairwise connectedness, 11.37% (NOK-GBP) and 14.20% (NOK-SGD). The strong linkage of these pairs is likely to contribute most to the cross-group volatility connectedness of the system. As such, MXN and NOK play the main role of volatility shock transmitters from the exporting-group to the importing-group.

Table 2.4 Connectedness matrix at individual-currency level

	Oil-exporting currencies			Oil-importing currencies				*Spillover from others*
	CAD	MXN	NOK	EUR	GBP	JPY	SGD	
CAD	33.91%	24.09%	10.14%	23.72%	2.70%	4.15%	1.30%	9.44%
	(0.106)	(0.060)	(0.016)	(0.046)	(0.084)	(0.056)	(0.008)	
MXN	1.55%	82.07%	5.15%	8.48%	0.55%	1.97%	0.23%	2.56%
	(0.008)	(0.014)	(0.004)	(0.018)	(0.047)	(0.046)	(0.002)	
NOK	2.04%	21.80%	44.86%	26.05%	2.34%	2.11%	0.80%	7.88%
	(0.009)	(0.069)	(0.013)	(0.025)	(0.066)	(0.100)	(0.005)	
EUR	2.02%	16.29%	10.81%	63.84%	3.44%	2.66%	0.94%	5.17%
	(0.012)	(0.112)	(0.022)	(0.039)	(0.068)	(0.064)	(0.006)	
GBP	2.65%	11.71%	11.37%	38.96%	30.25%	3.86%	1.21%	9.96%
	(0.016)	(0.109)	(0.125)	(0.056)	(0.059)	(0.062)	(0.007)	
JPY	2.04%	23.53%	5.35%	14.80%	1.75%	52.06%	0.47%	6.85%
	(0.013)	(0.054)	(0.010)	(0.148)	(0.096)	(0.047)	(0.003)	
SGD	4.45%	17.74%	14.20%	15.61%	4.48%	3.45%	40.07%	8.56%
	(0.017)	(0.100)	(0.027)	(0.036)	(0.066)	(0.069)	(0.092)	
Spillover to others	2.11%	16.45%	8.15%	18.23%	2.18%	2.60%	0.71%	
Net spillover	-7.34%	13.89%	0.27%	13.07%	-7.79%	-4.25%	-7.86%	
Total spillover index	50.42%							

Note. This table reports the average of individual currency-level directional connectedness across seven exchange rates. The standard deviations of spillover series are reported in parentheses.

Third, table 2.4 further reveals that the volatility transmission from oil-importing currencies to oil-exporting currencies are low, with directional pairwise connectedness indexes from importers to exporters below 3% for almost cases, except for the volatility spillover from EUR. Even though oil-importing currencies have marginal effects on the volatility of oil-exporting currencies, EUR shows its great interconnectedness with CAD and NOK, as evidenced by their directional pairwise connectedness indexes of 23.72% (EUR-CAD) and 26.05% (EUR-NOK). These exceptions can be explained by the important role of Norway and Canada as the EU's two large partners for exports and imports. For instance, in 2021, 60.5% of Norwegian goods exported to the EU.[13]

Finally, regarding the "*Spillover to others*" index reported in Table 2.4, SGD has the lowest figure of 0.71%, implying that SGD is least likely to spread volatility shocks to other currencies in the system. From the "*Spillover from others*" index in the last column, MXN is least influenced by the volatility transmission from other currencies in the system, since only 2.56% of its volatility comes from the past variation of other currencies. Meanwhile, CAD, GBP and SGD are most influenced by the variations of the other currencies in the system, with the highest "*Spillover from others*" indexes of 9.44%, 9.96% and 8.56%, respectively.

Table 2.5 Block connectedness between oil-exporting and oil-importing currencies

	Export	Import
Export	32.23%	10.63%
Import	17.45%	39.69%
Net Export Spillover	6.82%	
Net Import Spillover	-6.82%	
Total within-group spillover	71.92%	
Total cross-group spillover	28.08%	

Note. This table reports the average of group-level directional spillover among two groups of oil-exporters and oil-importers.

To sum up, our study provides strong evidence that the currencies in the different groups are less connected, and the oil-exporting currencies (i.e., MXN and NOK) are the net

[13] https://policy.trade.ec.europa.eu/eu-trade-relationships-country-and-region/countries-and-regions/

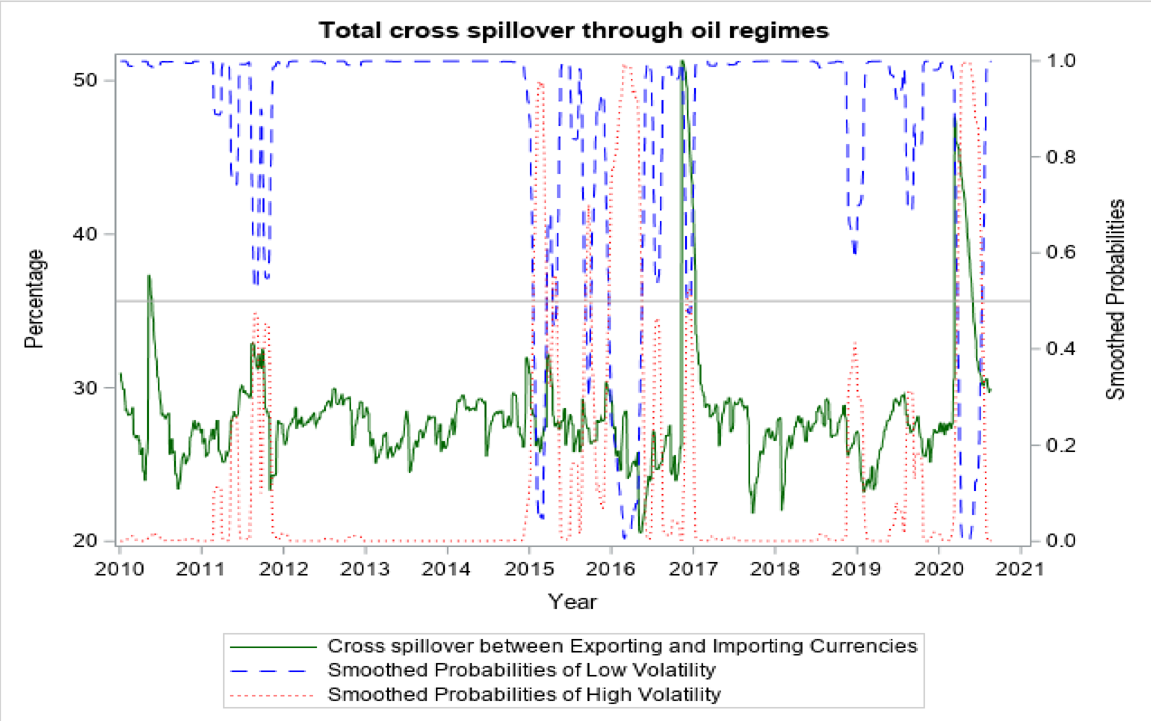
volatility transmitters in this cross-group connectedness. This highlights the potential diversification benefit of combining oil-exporting currencies and oil-importing currencies in an FX portfolio.

Note, the average results only allow us to assess the role of volatility transmitter or receiver over the full sample. Meanwhile, the dynamic total and net spillovers can be different at some points in time. Thus, section 2.5.3 below conducts the *time-varying* analysis of the different connectedness measures together with the changes in oil regime.

2.5.3 The time-varying connectedness results

To visually inspect the effect of the high-volatility oil market on the time-varying connectedness measures, Figure 2.2, 2.3, and 2.4 plot the various time-varying connectedness measures (i.e., Cross-group Spillover Index and Net Spillover Index of oil-exporting group, and the Net Spillover Index of each oil-exporting currency to the whole importing group) together with the smoothed probability of high-volatility regimes of the oil market over the research period. As can be seen from Figure 2.2, the Cross-group Spillover Index (CSI) of the currency system exhibit highly volatile during sample period and tends to increase remarkably when the probability of high-volatility of oil prices increases. Particularly, the CSI saw spikes of over 50% in the end of 2016 when US shale oil production significantly grew, and of about 48% in early 2020 when the Covid-19 pandemic broke out. These are two periods when oil prices witnessed the highest volatility during the research period. In contrast, the CSI fluctuated at a lower level of around 20% to 30% when the probability of high-volatility of the oil market is relatively low.

Figure 2.2 Cross-group spillover among oil-exporting and oil-importing exchange rates together with smoothed probability of oil regimes

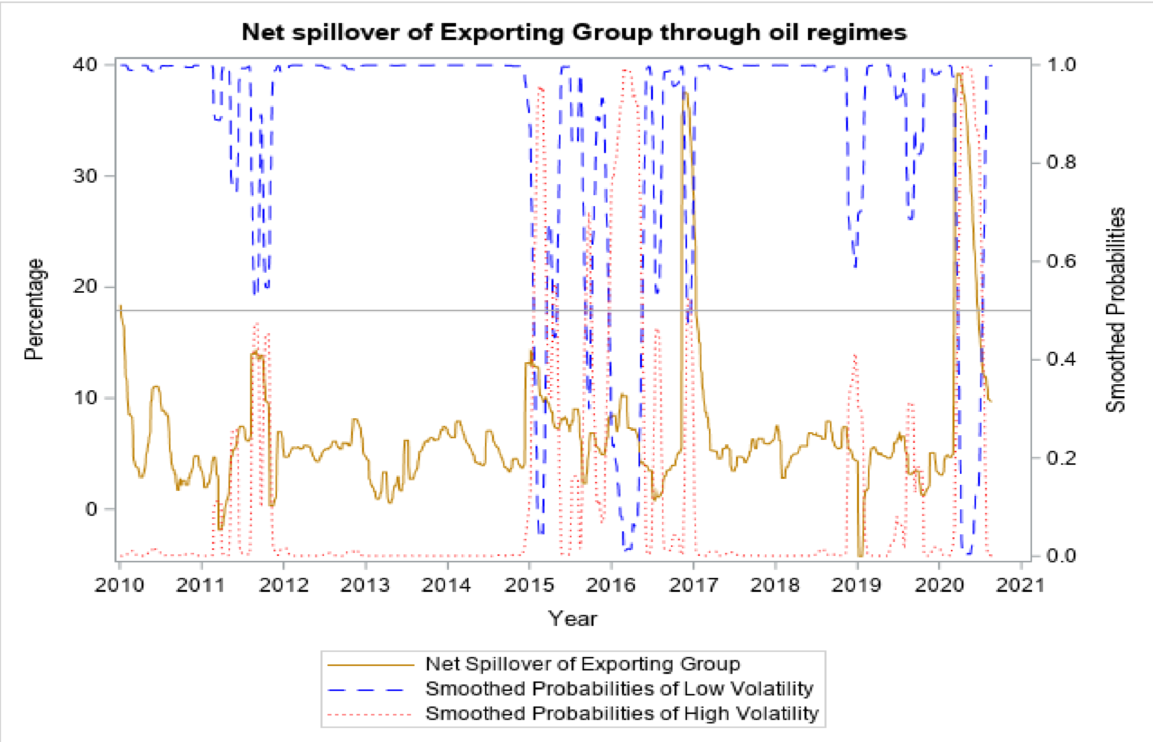


Note: This figure shows the time-varying cross-group spillover between oil-exporting and oil-importing currencies through different oil volatility regimes.

Figure 2.3 reveals the dominant role of the exporting group as the volatility shock driver of the system. The net spillover index of the exporting group is overwhelmingly positive during our sample period. More importantly, the largest increases of the net spillover of oil-exporters are observed as high as around 39% and 40% for the end of 2016 and early 2020, the most unstable periods of oil prices. Further, the two groups seem to have balanced volatility transmission (near zero net group-level volatility transmission) under the relatively low volatility of the oil market. This result is important in terms of the diversification benefits for trading currencies of both groups.

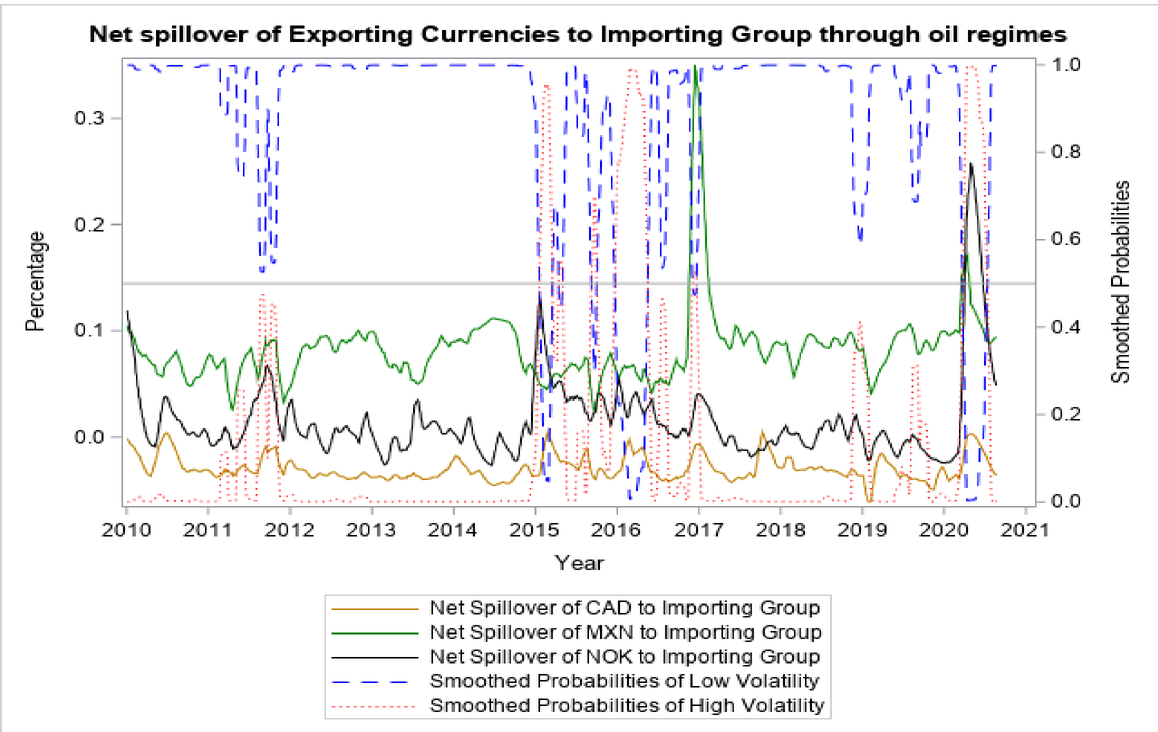
Figure 2.4 further illustrates that among oil-exporting currencies, MXN and NOK are the main drivers of volatility spillover from the exporting group to the importing group. We can see that the net spillovers of MXN and NOK to importing group were relatively low in the stable oil-price volatility regime but rose dramatically and peaked at their highest levels in the high volatile period of the oil market covering early 2015, end of 2016 and early 2020.

Figure 2.3 Net-group spillover of oil-exporting group together with smoothed probability of oil regimes



Note: This figure illustrates the time-varying net group spillover from exporting group to importing group through different oil volatility regimes.

Figure 2.4 Net spillover of individual oil-exporting currencies to oil-importing group together with smoothed probability of oil regimes



Note: This figure shows the time-varying net spillover from each oil-exporting currency, including CAD, MXN, NOK to total oil-importing group through different oil volatility regimes.

2.5.4 The effect of oil volatility regimes on volatility connectedness measures among oil-dependent currencies

We use the MS-AR(1) model to ascertain the probability of low- and high-volatility regimes of oil prices. Based on the estimated time series of the probability of high-volatility regimes of the oil market from the MS-AR model which is treated as binary variable, we then run the regressions in Eq. (2.12) and Eq. (2.13) and present the results in Table 2.6. The coefficients are estimated using the heteroskedasticity consistent standard errors to compute their *t*-statistics. First, table 2.6 shows that the probability of high-volatility oil regime is significantly and positively correlated with the cross-group spillover index (CSI) of the currency system, as evidenced by the estimated coefficient of *Oil-regime-dummy* being 5.348. This result implies that on average the CSI of the currency system increases by 5.348% when the oil market switches from a low to a high-volatility regime. As such, our study provides evidence of the higher risk propagation among the system of oil-dependent currencies following the switching of oil regime. Further, the significance of the estimated coefficients of our four control variables also confirms the appropriateness of our selection of these variables as controls in the regression. Specifically, the results indicate that a 1% increase in stock market volatility can raise the CSI of currency system by 1.33%, consistent with the findings of Mo et al., (2023). Additionally, the Fed Fund Rate has a negative impact on the CSI of currencies, with a 1% increase in the FFR leading to an 8.890% decrease in the CSI of sample currencies by 8.89%. The study also provides evidence that the value of the USD and the Geopolitical Risk (GPR) index have significant positive effects on currency connectedness, supporting the research of Xu and Lien (2022), Salisu et al. (2022) and Duan et al. (2021).

The higher connectedness risk between these currencies due to high oil volatility diminishes the portfolio's diversification benefit. This finding is of great important of FX traders as it highlights the vital role of the information of the oil market's regime in determining the risk of connectedness between oil-dependent currencies.

Table 2.6 The effect of high-oil-volatility regime on FX connectedness measures

	Cross-market spillover index	Spillover to others						
	CSI	CAD	EUR	GBP	JPY	MXN	NOK	SGD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Oil_regime_dummy	5.348**	2.57***	3.40**	0.17	-2.22	11.75***	20.91***	1.39***
	(1.97)	(3.78)	(-1.95)	(0.20)	(-1.35)	(2.39)	(9.40)	(5.11)
VIX	1.330***	0.232***	-2.06***	-0.04	0.65***	0.16	2.09***	0.065***
	(11.39)	(5.98)	(-21.14)	(-1.34)	(7.68)	(0.61)	(12.31)	(4.19)
GPR	0.021*	0.003	0.05***	-0.01**	0.01	0.02	-0.04***	0.002*
	(1.66)	(1.05)	(3.36)	(-2.07)	(1.34)	(1.00)	(-3.41)	(1.68)
USD	1.050***	-0.086***	-1.67***	0.31***	-0.09	1.05***	1.42***	-0.05***
	(9.49)	(-4.57)	(-15.76)	(11.04)	(-1.56)	(5.55)	(15.18)	(-4.19)
FFR	-8.890***	-1.01***	12.58***	0.29	-0.68	-0.65	-15.41***	-0.79***
	(-9.80)	(-5.19)	(13.02)	(0.98)	(-0.92)	(-0.42)	(-20.70)	(-9.29)
Intercept	83.93***	18.29***	32.6***	-11.28***	14.25***	28.74***	-95.36***	7.87***
	(9.12)	(8.97)	(35.72)	(-4.56)	(2.78)	(1.72)	(-9.63)	(7.88)
N. Obs.	2,188	2,188	2,188	2,188	2,188	2,188	2,188	2,188
Adj. R-squared	0.2521	0.1539	0.4232	0.1129	0.0580	0.0415	0.5488	0.1785
F-statistics	148.40***	80.53***	321.94***	56.67***	27.94***	19.94***	533.07***	96.02***

Note. This table reports the estimated results of the models represented in Eq. (2.12) and Eq. (2.13) to evaluate the effects of the high oil volatility regime on the cross-group connectedness among seven sample oil-dependent currencies and the "Spillover to others" index of each currency. The reported t-statistics are computed using heteroskedasticity-consistent robust standard errors. ***, ** and * represent that the estimated parameters are statistically significant at 1%, 5% and 10% significance level, respectively.

Our finding holds consistent with the previous results reported by Ding and Vo (2012), Baruník et al. (2019) and Alam et al. (2019). The authors find that the volatility spillovers from crude oil to exchange rates increase when oil market is highly volatile, hence increasing FX markets' volatility. Subsequently, the increases in the volatility of exchange rates in the high volatility periods of the oil market may transmit quickly across the system of foreign exchange markets, causing high volatility connectedness across exchange rates (Diebold and Yilmaz, 2012). This implies the positive relationship between FX connectedness measures and the probability of *high*-oil-volatility regime p_t. In this vein, the oil market's switch from a low to a high volatility regime induces a stronger interconnectedness among oil-dependent currencies, hence reducing diversification benefit of the oil-dependent FX portfolio.

Second, the results of the effect of the oil market's regime on the "Spillover to others" index of each currency reveal that the switching to high-volatility oil-regime intensifies the role of the oil-exporting currencies (i.e., most likely MXN and NOK) in propagating risk among the currency system. Specifically, a switch to high-volatility state of the oil market increases the "Spillover to others" indexes of MXN and NOK by 11.75% and 20.91%, respectively. Meanwhile, the shock transmissions of oil-importing currencies, such as GBP and JPY, are not affected by the oil regime. So, these currencies can play the role of volatility stabilizer of the currency system when the oil market enters a high-volatility regime. Our finding has a crucial implication for FX portfolio risk management as FX portfolio manager can utilize the information related to the oil market's conditions to adjust the weights of currencies which propagate the most risk spillovers during the times of high volatility in the oil market.

Further, it is worth addressing a potential concern that treating the estimated probability of high-volatility oil regime as a dummy variable in our Eq. (2.12) and Eq. (2.13) may introduce an estimation bias in terms of the significance and the sign of the effect of oil volatility regime. To address this issue, we also conduct an additional analysis by re-estimating the Eq. (2.12) and Eq. (2.13). In this re-estimation, the main regressor is the natural logarithm of the estimated probability of high-volatility oil regime from the MS-AR model. We then compare the significance as well as the sign of the coefficient of high-volatility oil regime in both cases. The results are presented in Appendix A.2.5. As can be seen, there is a significant and positive relationship between the estimated probability of the oil's high-volatility regime and the Cross-group Spillover Index (CSI) of the sample currencies, as evidenced by the coefficient of the probability of oil-high-volatility regime (0.002). The "Spillover to others" indexes of the main oil-exporting currencies (e.g., MXN and NOK) significantly increase following an increase in the estimated probability of high-volatility oil regime. This suggests that there is consistency in both the significance and the sign of the relationship between the high-volatility oil-regime and the oil-dependent FX connectedness, regardless of whether the estimated probability of high-volatility oil regime is treated as a binary variable or a continuous variable in our main regressions. In the main empirical results, we report the outcomes of Eq. (2.12) and Eq. (2.13) with the main regressor being the dummy variable of the estimated probability of oil-high-volatility regime as they enable us to design an FX portfolio formulation, as detailed in the Implication section (Section 2.6).

To sum up, our econometric results confirm that the switches to high-volatility regime of the oil market intensify the volatility linkage between the two groups of oil-dependent currencies. That is, the diversification benefits of an FX portfolio comprising both oil-importing and oil-exporting currencies may decline due to higher FX-interconnectedness risk when oil prices are in highly volatile states. This finding is of great importance to FX traders when deciding their position in these foreign exchange markets following the information of oil's volatility-regime. To highlight the crucial implication of our study for oil-dependent FX trading, we deliver our oil-regime-based portfolio simulation in Section 2.6 of this study.

2.5.5 Robustness check

There is a potential concern that currency volatility may be influenced by a variety of country-specific economic fundamentals, market activity, transaction costs and stock market volatility. These factors may then induce significant changes in volatility connectedness across the selected currencies.[14] In this section, we conduct a robustness analysis to address this concern.

In estimating the realized volatilities of selected currencies, we use an extended VHAR(Q) model that now includes additional exogenous variables with available daily data set. The limited availability of daily frequency data restricts our regression to four explanatory variables: (1) the yield volatility of one-year US treasury bill; (2) the yield volatility of one-year domestic treasury bill; (3) the volatility of bid-ask spreads, and (4) the CBOE implied volatility of the S&P 500 index (VIX). We collect the data on the rates of country-specific one-year treasury bills from Global Financial Data. The source of data on closing bid-ask spreads and the VIX is DataStream.

First, we specify the extended model, referred to as VHAR-X(Q), as follows:

$$RV_t = c^{(d)} + \underbrace{\left(\beta^{(d)}\iota + \beta_Q^{(d)} RQ_{t-1}^{1/2}\right)}_{\beta_t^{(d)}} \circ RV_{t-1} + \beta^{(w)} RV_{t-1/t-5} + \beta^{(m)} RV_{t-1/t-22} + \beta_i X_{i,t} + \varepsilon_t^{(d)} \qquad (2.14)$$

where $X_{i,t}$ denotes a set of four exogenous variables to control for, as mentioned above. The volatility of interest rates (one-year US treasury bill and one-year domestic treasury bill) is calculated by the 5-day standard deviation of the yields on one-year treasury notes of the country. The volatility of bid-ask spreads is measured by the 5-day standard deviation of the closing bid-ask spread of an exchange rate. These variables represent shocks to interest rates,

[14] In terms of fundamental economic variables, the theoretical literature has widely documented the factors that influence the supply and demand of foreign exchange rate can indirectly cause the exchange rate volatility, such as GDP, inflation, money supply growth, interest rates, capital flows, trade flows and industrial production growth (See, e.g., Morana, 2009; Giannellis and Papadopoulos, 2011; Mirchandani, 2013; and among others). At microstructure level, using high frequency data, Bollerslev and Melvin (1994) find a significant relationship between bid-ask spreads and conditional volatility.

spreads and stock markets and are thought to cause fluctuations in the realized volatilities of exchange rates. The VHAR-X(Q) model is estimated using OLS procedure and the results are reported in Appendix A.2.6. They show that the volatility of one-year US treasury bill and the volatility of one-year domestic treasury bill are the determinants of realized volatilities of four in seven sample currencies. The effect of the volatility of bid-ask spreads is not relevant for realized volatility in all cases whereas the coefficients on the stock market volatility are statistically significant in all the realized volatility series.

Next, we use the VHAR-X(Q) as the baseline function to derive the GCI based on the same method as applied in the previous sections. Panels A and B of the table A.2.7 reported in Appendix A.2.7 show the results of average individual pairwise connectedness, total cross-group connectedness and net group connectedness. From there, one can compare the results of the GCI computed from respectively VHAR(Q) and VHAR-X(Q) and on respectively the individual and group levels. For most pairwise directional connectedness and cross-group connectedness, there are no significant changes in the directions of connectedness as revealed by our benchmark analyses. We thus conclude that, in general, the VHAR-X(Q)-based results reported in Appendix A.2.7 are in line with the VHAR(Q)-based ones reported in this study. This implies that our principal conclusions of FX connectedness are robust when we further include in the benchmark model some additional exogenous variables deemed to be relevant to the volatility of an exchange rate.

2.6 Financial implication

In this section, we conceive a dynamic FX trading strategy depending on oil-regime switching. This strategy is designed for a hypothetical FX trader based on our primary empirical findings. Our formulated trading strategy is deemed to help FX traders achieve the most of the diversification benefit of the oil-dependent FX portfolio and better manage the portfolio risk spillover by reducing the interconnectedness risk of FX portfolio during the highly volatile periods of the oil market.

We suppose that at the month *t*, a hypothetical FX trader holds a baseline portfolio of both oil-exporting (e.g., CAD, MXN, and NOK) and oil-importing currencies (e.g., EUR, GBP, JPY, and SGD) with an equal weight assigned to each currency for diversification purpose and hedging against oil price risk. Based on our results in Section 2.5.4, a switch from a low-volatility state to a high-volatility state of the oil market strengthens the cross-group volatility connectedness among the oil-dependent currencies. Further, in our previous findings, the two major oil-exporting currencies (i.e., MXN and NOK) are identified as the main drivers of the increasing FX volatility connectedness, as evidenced by the largest increases in their "Spillover to others" indexes when the oil market is in a high-volatility state (see Section 2.5.4). On the contrary, it is observable in Section 2.5.4 that the shock transmissions from JPY and GBP to the system are not influenced by oil volatility regime, implying that these currencies play the role of volatility stabilizers in the portfolio when the oil market switches to a highly volatile time. These findings align with previous studies, which have documented that oil-exporting currencies are more susceptible to oil volatility shocks than oil-importing currencies (Reboredo, 2012; and Yang et al., 2017).

As a result, we utilize the estimated probability of the high-volatility-oil regime from the MS-AR model at the month *t* to decide whether the oil market is in high volatility state and determine the dynamic portfolio adjustment in month *t*+1. If the oil market is estimated to switch to a highly volatility state at time *t*,[15] we reduce, to varying degrees (as presented in each Dynamic Oil-Regime-dependent portfolio in Table 2.7), the weights of volatility shock transmitters (i.e., MXN and NOK), and increase the weights of the volatility shock stabilizer

[15] Note, in this study, the oil market is considered to be in high-volatility states if the estimated probability of high-volatility regime of the oil market is larger than 0.5, and in low-volatility regime otherwise.

(i.e., GBP and JPY), respectively, in month *t*+1. If the oil market is estimated to enter a low-volatility regime, we keep the weights of each currency unchanged. By diminishing the weights of volatility shock transmitters and increasing the weights of shock stabilizers during high-volatility oil regimes, we expect to reduce the volatility connectedness among currencies in the portfolio, hence lowering portfolio risk.

We evaluate the relative risk-return performances of our dynamic oil-regime-dependent trading strategy compared to a buy-and-hold strategy and present the results in Table 2.7. From the table, one can see that our conceived dynamic trading strategy achieves better performance in all scenarios relative to that of the static strategy, in terms of risk, return and risk-adjusted return (the Sharpe ratio). The Dynamic Oil-Regime-dependent Portfolio 3 (Dynamic 3) involves the highest weight reduction of volatility shock transmitters (7%) while the Dynamic 1 has the lowest weight reduction of volatility shock transmitters (3%). Our evaluation results reveal that the oil-regime-dependent adjustments help reduce risk, and enhance return and risk-adjusted return in all cases of Dynamic Oil-Regime-dependent portfolios in comparison with the Buy-and-Hold portfolio. Particularly, the average monthly return of Dynamic 3 is enhanced remarkably by 19.36% (-0.0031 in Buy-Hold vs. -0.0025 in Dynamic 3). The risk measured by standard deviation is significantly reduced by 7.97% from 0.01908 in Buy-Hold to 0.01756 in Dynamic 3. It is noteworthy that the larger the weights of MXN and NOK are reduced, the more benefits in terms of enhancing return and risk measurement will be reaped from our suggested dynamic portfolios. Pertaining to the risk-adjusted performance, all our dynamic portfolios produce a better Sharpe ratio than the Buy-Hold portfolio. For example, the Sharpe ratio increases by 2.28%, 5.48%, 6.85% in Dynamic 1, Dynamic 2, Dynamic 3, respectively comparted to Buy-Hold portfolio. The demonstrated outperformances of the dynamic trading strategy highlight the financial implication of our empirical findings: One can enhance FX portfolio risk management by utilizing the effects of oil volatility regime on the volatility spillover between oil-exporting and oil-importing currencies.

Table 2.7 Evaluation of FX portfolio performance of dynamic oil-dependent trading strategy

Portfolios	Portfolio Description	Avg. Ret	Std. Dev	Sharpe Ratio
Buy-Hold Portfolio	The portfolio includes the equally weighted seven oil-exporting and oil-importing currencies (14.286%) at the beginning of the period (Jan 2010). The weights of currencies are unchanged.	-0.0031	0.01908	-0.219
Dynamic Oil-Regime-Dependent Portfolio 1	The portfolio is designed with the equal weight of 14.286% for each oil-exporting and oil-importing currency at the beginning of the period (Jan 2010). Since Feb 2010, we monthly estimate the probability of high-volatility oil regime based on the MS-AR model and reduce the weights of MXN and NOK by 3% and increase the weights of JPY and GBP by 3% if the estimated probability of high-volatility oil market is higher than 0.5. If the estimated probability of high-volatility oil market is lower than 0.5, we keep the weights of currencies unchanged.	-0.0029	0.01862	-0.214
Dynamic Oil-Regime-Dependent Portfolio 2	The portfolio is designed with the equal weight of 14.286% for each oil-exporting and oil-importing currency at the beginning of the period (Jan 2010). Since Feb 2010, we monthly estimate the probability of high-volatility oil regime based on the MS-AR model and reduce the weights of MXN and NOK by 5% and increase the weights of JPY and GBP by 5% if the estimated probability of high-volatility oil market is higher than 0.5. If the estimated probability of high-volatility oil market is lower than 0.5, we keep the weights of currencies unchanged.	-0.0027	0.01843	-0.207
Dynamic Oil-Regime-Dependent Portfolio 3	The portfolio is designed with the equal weight of 14.286% for each oil-exporting and oil-importing currency at the beginning of the period (Jan 2010). Since Feb 2010, we monthly estimate the probability of high-volatility oil regime based on the MS-AR model and reduce the weights of MXN and NOK by 7% and increase the weights of JPY and GBP by 7% if the estimated probability of high-volatility oil market is higher than 0.5. If the estimated probability of high-volatility oil market is lower than 0.5, we keep the weights of currencies unchanged.	-0.0025	0.01756	-0.204

Note. This table reports average return (Avg. Ret) and standard deviation of monthly % return (Std. Dev), and the Sharpe ratio of the Buy-Hold strategy and the Dynamic Oil-Regime-dependent trading strategy. The Sharpe ratio is computed as the difference between average portfolio monthly return and the average monthly return of 3-month U.S. Treasury bill (T-bill) divided by the standard deviation of portfolio monthly returns.

2.7 Concluding remarks

The frequent high volatility in the oil market has increased the volatility spillover from the oil market to oil-dependent currency markets, in turn spurring strong volatility connectedness across these oil-dependent currencies. It is of interest to FX market participants if they can better understand the dynamics of such FX volatility connectedness following the information of the oil market's volatility and then form a dynamic FX trading strategy to exploit the diversification benefits therefrom. To this end, we apply the VHAR(Q) model, together with the generalized connectedness index and the method of block aggregation of the connectedness matrix, to examine the dynamic volatility linkages between oil-exporting and oil-importing currencies with respect to the oil's volatility regime. Our results can be summarized as follows.

First, there are significant volatility spillovers between the sample oil-dependent currencies whereas the FX connectedness is mainly caused by the strong linkage between the currencies in the same group (i.e., within-group connectedness). Meanwhile, the average cross-group spillover is relatively low, suggesting the potential diversification benefits and hedging opportunities of holding currencies of both groups. Second, this cross-group connectedness is mostly attributed to the volatility causalities from the oil-exporting currencies to the oil-importing currencies, and concentrated in the short-run. Third, the oil-exporting currencies play a consistent role of the net volatility transmitters across two groups regardless of different oil volatility regimes. Fourth, most importantly, the time-varying analysis shows that cross-group volatility spillover between oil-exporting and oil-importing currencies tends to increase significantly when the oil market switches from a low-volatility to a high-volatility regime, forming an empirical base to design an oil's regime-dependent FX trading strategy.

Our study has practical implications for FX traders in terms of asset allocation and risk management. Since our study provides strong evidence that the cross-group volatility connectedness across oil-dependent currencies is more pronounced in high volatility periods of the oil market, FX portfolio managers should cater to the information of the oil market's volatility-regime switches in order to monitor the risks of FX volatility spillover. That is, an FX portfolio manager who holds both oil-exporting and oil-importing currencies should actively rebalance the portfolio by reducing the weights of the main volatility drivers in response to a shift of the oil market from a low to a high volatility time. This dynamic oil's regime-dependent trading strategy evidently results in a better performance of the FX portfolio gauged by return, risk, and risk-adjusted return, compared to the static trading strategy.

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.

Student name:	Thao Thac Thanh Nguyen
Name and title of main supervisor:	Professor Xiaoming Li
In which chapter is the manuscript/published work?	Chapter 2
What percentage of the manuscript/published work was contributed by the student?	70%

Describe the contribution that the student has made to the manuscript/published work:
Thao is the main author of this paper, and while her superviors have made substantial contributions, reflected through co-authorship, the paper is essentially the work of Thao. She has made contributions to conceptualization, methodology applied, data circulation, software, original draft writing, and revisions. The supervisors contributed to the paper by providing critical comments, insightful advices, supervision, and revising the paper.

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CHAPTER THREE

The Nexus between European Sectoral Credit Default Swap and Natural Gas Markets: The Russian-Ukrainian War Effect

Chapter 3 presents the second essay of the thesis. This essay examines the significance and the sign of the causal relationship between European sectoral CDS (Credit Default Swap) and natural gas markets at the corporate sectoral level using Granger causality test. Further, applying both the mean-based and the quantile-based-connectedness measures, this study uncovers the dynamic pattern of the return connectedness between European sectoral CDS and natural gas markets at the conditional mean and tails of the return distributions. Crucially, this study also provides quantitative evidence underscoring the significant intensification of return shock transmission among the sampled markets due to the Russian-Ukrainian war.

3.1 Introduction

The Russian-Ukrainian conflict in 2022 has initiated a period of strained political relations between Russia and Europe. In response to economic sanctions imposed by Europe, Russia halted gas supplies to European markets, causing a substantial upswing in gas prices across the area. This posed a significant threat to Europe's energy security as Russian gas accounted for over 40% of Europe's gas imports, as figured in 2020.[16] European industries, which heavily rely on gas as a crucial input in their manufacturing processes,[17] faced higher production costs, diminishing corporate profitability and potential financial difficulties. Consequently, the ongoing supply-driven gas crisis in Europe was likely to exert detrimental impacts on the European corporate debt market. This study, therefore, aims to investigate how the European sectoral corporate credit default swap (CDS, hereafter) markets react to the

[16] See Figure 3.1 for the EU production, trade, and imports of natural gas in 2020.

[17] See, European energy consumption by source in Figure 3.2.

shocks in the natural gas market and vice versa, with a special focus on the evolution of this relationship during the times of war.

Prior to exploring the dynamics of the interrelationship between the European gas and sectoral CDS markets, we conduct initial tests to examine the causal relationship between these markets. These tests are built upon two hypotheses formulated based on our proposed channels, which aim to explain the direction and the sign of the causality between sectoral CDS markets and the gas market. The first channel supports a potential positive causality running from the natural gas to sectoral CDS markets. As natural gas is an important energy source for industrial production, higher gas prices can put inflationary pressure on the economy, lead to reduced corporate profitability and in turn increase credit default risk, which is reflected in higher CDS spreads. Previous studies have documented the positive correlation between natural gas prices and inflation rates (Ajmera et al, 2012; Zhang et al., 2017; Liptáková et al., 2021; and Binder, 2018). Meanwhile, the rising inflation rates prompt policymakers to implement restrictive monetary policies, which subsequently dampen corporate profitability through increased interest payments (Bernanke and Gertler, 1995). Moreover, Callen et al. (2009) underscore that higher corporate earnings are interpreted by market participants as evidence of lower firm credit risk, which in turn is reflected in lower CDS spreads. In other words, the corporate profitability is negatively correlated with CDS spreads. As a result, we hypothesize a positive causality running from natural gas to sectoral CDS markets. The explanation of this channel is related to the changes in the supply side of the gas market, so we term it as *"the supply-side-based channel"*.

In the reverse direction of the causality, we contemplate the second channel that suggests the potential negative causal relationship from credit default swap spreads to natural gas prices. This channel stems from the idea that higher CDS spreads signal economic decline, triggering a decrease in energy prices due to lower energy demand. Research by Friedmand

and Kutter (1992), Krishnamurthy and Muir (2017), and Gertler and Lown (1999) points out that rising CDS spreads can serve as a leading indicator of corporate insolvency, foreshadowing output declines. Additionally, Kilian (2009) and Apergis and Payne (2010) emphasize that the contracting economic activity reduces energy consumption, resulting in a decline in energy prices. In this vein, we conjecture the hypothesis that there exists a negative causal link from the credit default swap markets to natural gas market. This channel is built up based on the changes in the demand side of the gas market, thereby it is termed *"the demand-side-based channel"*. To test the proposed hypotheses, we decompose shocks to the natural gas and CDS markets into positive shocks and negative shocks and then conducts the Granger Causality test between these components. Our test results provide the first evidence supporting that the sign of the causal relationship between natural gas and credit markets depends on the direction of the causality. Specifically, we detect a significant positive causal link from the natural gas to sectoral CDS markets, whereas the opposite direction of the causality is negative.

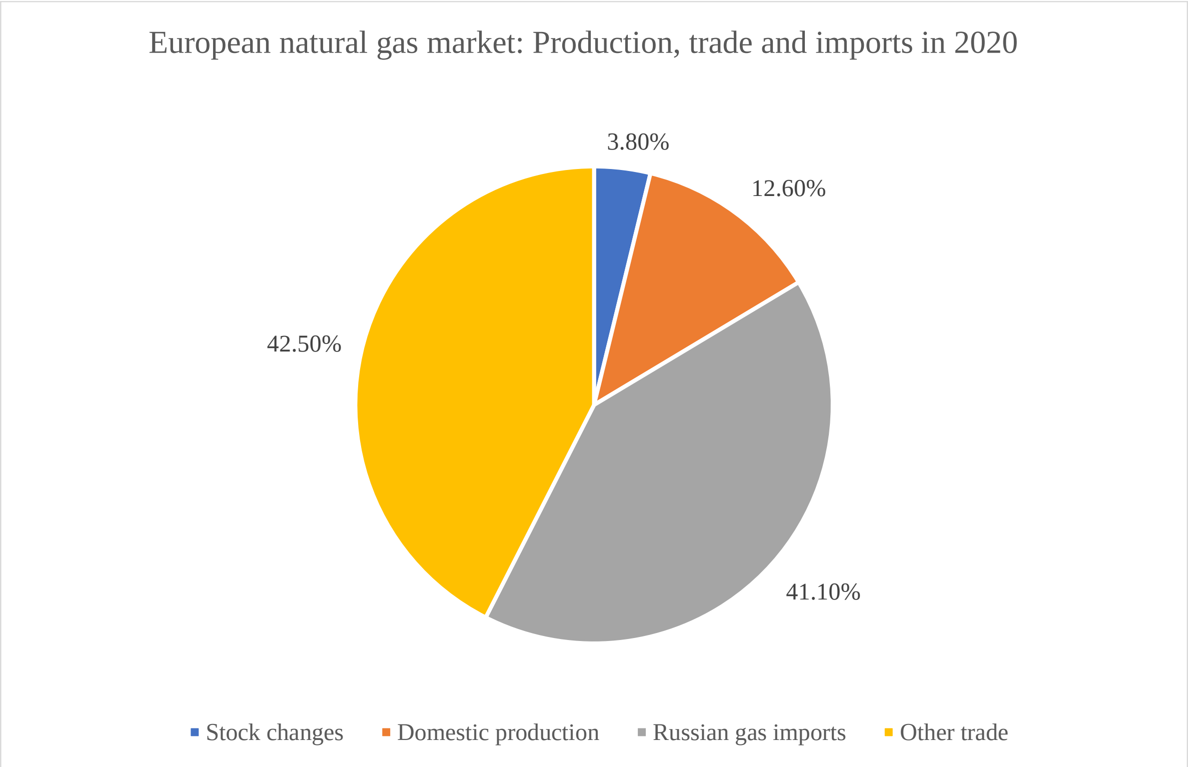
Despite the significant causal relationship between natural gas and credit default swap markets, there has been limited research exploring the interconnectedness between the gas market and the credit markets at corporate sector level. This study fills the void by exploring the dynamics and determinants of return connectedness between European corporate sectoral CDS markets and natural gas, and testing whether this interdependence changes during the recent crisis events. More importantly, we further answer the question of how the ongoing Russian-Ukrainian conflict shapes the return interconnectedness between European natural gas and sectoral credit default swap markets. We concentrate on sectoral CDSs instead of sovereign CDS to uncover how different sectors response to energy price changes. Besides, our sector-level analysis would have practical implications for fixed-income investors and portfolio managers, who are concerned about diversification and investment at sector level.

To investigate the dynamic pattern of return connectedness between natural gas and credit markets, we rely on the daily sectoral five-year CDS index prices of the EU as the proxies for corporate credit risk of nine industry sectors including: Automotive, Banking, Chemicals, Construction Materials, Industrials, Manufacturing, Oil & Gas, Transportation, and Utilities. The sample period ranges from Aug 01, 2008 to Aug 31, 2022. We apply the mean-based connectedness framework of Diebold and Yilmaz (2012) and quantile-based connectedness framework of Ando, et al. (2022) to investigate the return connectedness between European CDS markets and gas markets at both the mean and tails of conditional distributions. The results of our study help us assess how the behavior of return connectedness between the sample markets varies depending on the shock size (i.e., average shocks and extreme large shocks). Next, we quantitatively document the impact of Russian-Ukrainian war on the return shock transmission between European sectoral CDS markets and natural gas with respect to all potential drivers of this nexus. Our research endeavor would provide a first comprehensive understanding of the return connectedness between the gas market and corporate sectoral CDS markets in Europe at both conditional mean and tails of return distributions with a special focus on the impact of the on-going Russian-Ukrainian war.

Our results of the return connectedness can be outlined as follows. First, we find evidence of substantial increases of Cross-market Spillover Index (CSI) between natural gas and sectoral CDSs, rising from 8.23% at the mean to 56.09% and 56.49% at the lower and upper tails, respectively. This indicates that the extreme large positive/ negative shocks significantly amplify the return shock transmission between the natural gas market and sectoral CDSs. Our finding suggests that during market turbulence times the return fluctuations in the natural gas markets are highly informative to changes in sector CDSs and vice versa. Further, we observe a symmetrical pattern in cross-market spillover index measured at both tails, implying that the extreme positive or negative return shock exert equal influences on return shocks transmission across the system. Second, the gas market consistently acts as net return shock receiver from sectoral CDS markets, especially during extreme events. This suggests that investors in European natural gas market should pay more attention to the sectoral CDSs which are the net shock transmitters under the extreme market conditions. Third, our time-varying analysis shows that the Cross-market Spillover Indexes (CSIs) between natural gas and European sectoral CDS is highly volatile over research period regardless of this index measured at the mean or at the tails of return distributions. At the lower and upper tails, the CSIs fluctuate within a wide bound of 32%-98%. The upward spiral times of CSIs all coincided with the periods of Global financial crisis (2008-2009), the Eurozone debt crisis (2010), the supply-driven global oil price decline (2015), the Chinese stock market turbulence (2015), and the COVID-19 pandemic-induced crisis. Finally, we provide quantitative evidence of the magnifying effect of the Russian-Ukrainian war on the return shock spillover between European sectoral CDS markets and natural gas regardless of the shock size (i.e., average shocks or extreme large shocks). Our finding is robust to different regression models used to estimate the war effect. Specifically, our daily-regression results unveil that the war time has increased the return spillover effect among the sample markets by 25% with average shocks, 11.78% with extreme negative shocks, and 17.03% with extreme positive shocks. This investigation contributes to the growing literature on the effects of the Russian-Ukrainian war on global financial markets, as documented in studies by Adekoya et al. (2022), Izzeldin et al. (2023), and Lo et al., (2022).

The remaining sections of the study are organized as follows. Section 3.2 reviews related literature and develops hypotheses. Section 3.3 presents the methodologies applied in this study. Section 3.4 illustrates the data and offers the descriptive statistics. We present and analyze the main empirical findings about the Granger Causality test conducted between natural gas and European sectoral CDS markets; and the dynamic pattern of the gas-CDS connectedness in Section 3.5. Determinants of the connectedness are investigated in Section 3.6. Section 3.7 reports the results of robustness checks. Section 3.8 concludes.

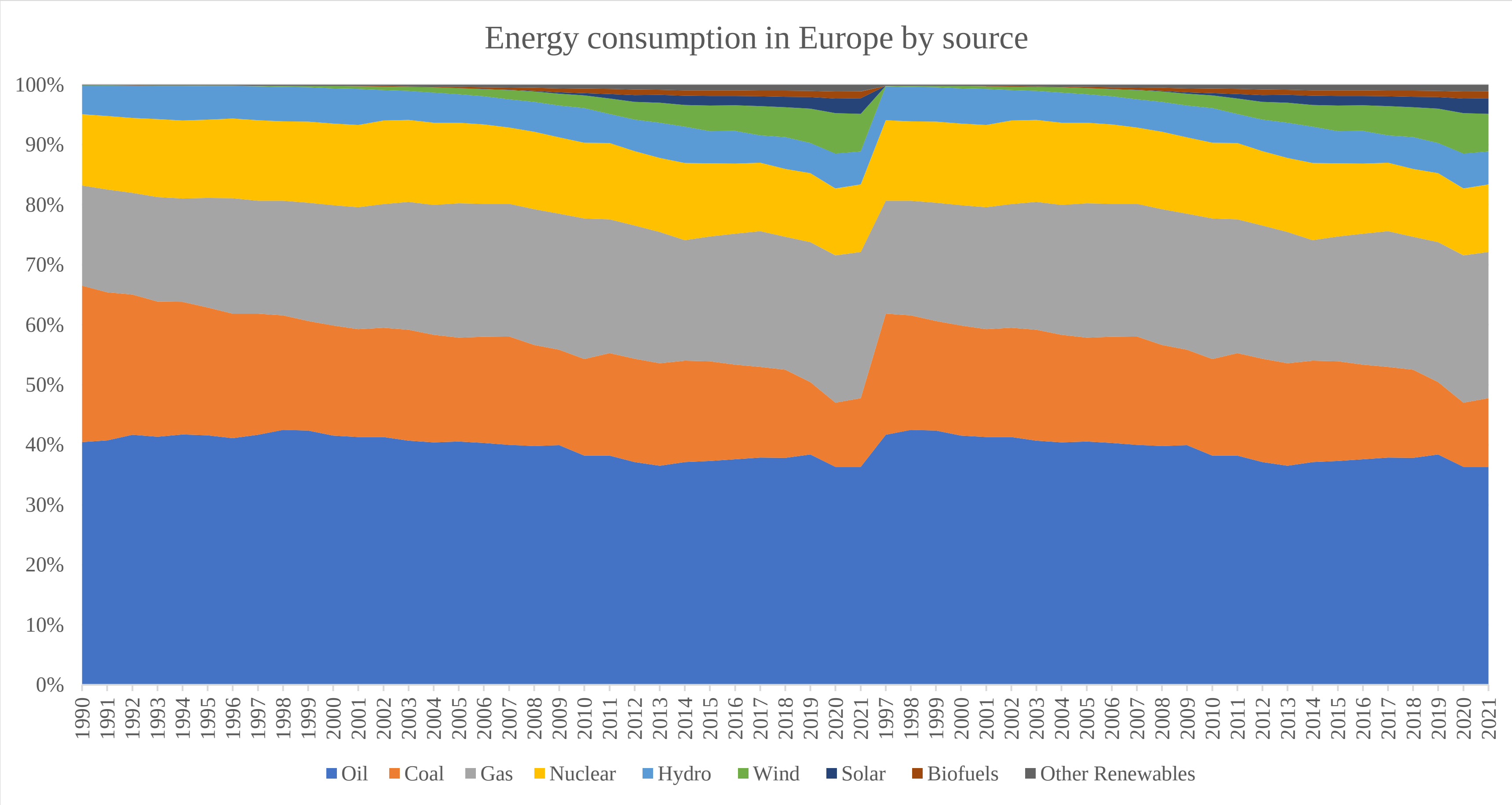
Figure 3.1 EU natural gas production, trade and imports in 2020



Source: Eurostat (including estimates for non-reported data)

Notes: This figure shows the shares of EU production, Russian gas imports and other trade in total EU gas consumption in 2020 (in percentage)

Figure 3.2 European energy consumption by source



Source: BP Statistical Review of World Energy
("Other renewables" includes geothermal, biomass and waste energy)
Note: This figure displays the energy consumption in Europe by source from 1990 to 2021.

3.2 Literature review and hypothesis development

3.2.1 Natural gas – CDS market nexus

Our study is closely aligned with an emerging strand of energy finance that investigates the impacts of energy prices on CDS spreads and their spillover effects. The extant literature has mainly focused on the nexus between crude oil and CDS markets at both sovereign level (e.g., Bouri et al., 2017; Bouri et al., 2019; Pavlova et al., 2018; Dai et al., 2018; Chuffart et al., 2019; Wang et al., 2020; to name a few) and sectoral level (Da Fonseca et al., 2016; Lahiani et al., 2016; Balcilar et al., 2020; Shahzad et al., 2017; among others).

Despite the prominent position of gas in industrial production, the literature on the relationship between natural gas and corporate debt market is limited. Recently, given the growing dependence of the European economies on Russian gas, numerous studies have unveiled the interdependence in EU-Russia gas market (Finon et al., 2008; Casier, 2011; Flouri et al., 2015; Sziklai et al., 2020) and the impact of Russian gas disruption on European economies and financial markets (Bouwmeester et al., 2017; Di Bella et al., 2022; Lo et al., 2022). In the wake of the ongoing gas crisis in Europe induced by the geopolitical conflicts between Russia and Ukraine, we are motivated to explore the relationship between European gas and credit markets, a leftover issue in extant literature.

In this study, we contemplate two channels to explain the bi-directional causality between CDS markets and natural gas. The first channel explains the causality running from the natural gas market to the sectoral CDS markets. As gas is an important fuel for industrial production, higher natural gas prices would imply higher inflationary pressure on the economy, leading to lower corporate profitability and higher credit default risk (higher CDS spreads). Specifically, Ajmera et al. (2012) find a positive effect of natural gas prices on inflation rates. Binder (2018) further shows that consumer inflation expectations in the U.S. positively correlate with gas prices. In turn, increasing inflation rates might induce policymakers to implement restrictive monetary policies, which subsequently reduce corporate profitability through higher interest payment (Bernanke and Gertler, 1995). In addition, extant literature documents that corporate profitability is an important driver of CDS spreads (Callen et al., 2009; Pires et al., 2015). For instance, Callen et al. (2009) find that corporate earnings, measured by either cash flows or accruals, negatively and significantly influence CDS premia. Notably, they empirically show that an increase of 1 percent in ROA reduces CDS spreads by about 5 percent. Based on these discussions, we expect that higher natural gas prices would lead to higher credit risks, supporting the positive causality running from the natural gas market to sectoral CDS markets. So, we formulate the first hypothesis as follows,

Hypothesis 1*: Positive (negative) return shocks of the gas market cause positive (negative) return shocks of sectoral CDS market.*

In the reverse direction, we conjecture the second channel, that explains the negative causality running from CDS spreads to natural gas prices. This channel suggests that increasing credit risk in the economy reduces energy prices as it informs the declines in economic growth. Krishnamurthy & Muir (2017) asserts that an increase in CDS spreads is a forward-looking indicator of increasing expected insolvency by corporation, which presages the declines in output. Specifically, one standard deviation increase in spreads forecasts about a 7% and 8% drop in GDP in the next 3 and 5 years, respectively. The forecasting power of credit spreads for economic growth is also supported by previous studies (e.g, Friedman and Kutter, 1992; Gilchrist and Zakrajšek, 2012; Gertler and Lown, 1999; and among others). Since energy markets are sensitive to changes in economic activity (Kilian, 2009), lower economic prospects might reduce the demand for energy commodities (i.e., energy consumption) and drive down their prices. For example, during the Global Financial Crisis (2008-2009), natural gas consumption in the European Union has decreased from 516.6 billion cubic meters in 2008 to

484.5 billion cubic meters in 2009. Based on the aforementioned arguments, we formulate the second hypothesis as follows,

Hypothesis 2: *Positive (negative) return shocks of sectoral CDS market cause negative (positive) return shocks of the natural gas market.*

Our study tests the two hypotheses using the technique of Granger and Yoon (2002) to decomposes the shocks into negative shocks and positive shocks and applying Granger-Causality test to provide the first comprehensive examination of the direction and the sign of the causal relationship between natural gas and sectoral CDS markets.

To provide a thorough investigation of the nexus between natural gas and CDS markets, we further scrutinize whether the average shocks and extreme shocks propagate distinctively across the sectoral CDS markets and natural gas by exploring the return shock connectedness at both extreme and normal market conditions. As such, our study would provide evidence of how the interconnectedness between European sectoral CDS and the gas markets changes under extreme events (i.e., European ongoing gas crisis).

3.2.2 War effect on financial markets

Recently, the Russian-Ukrainian war launched on February 24, 2022, has attracted substantial attention from researchers worldwide with most of their recent studies focusing on the consequences of war on specific financial markets. These studies include Izzeldin et al. (2023), Boungou et al. (2022), Lo et al. (2022), Gaio et al. (2022), Ferriani and Gazzani (2022), Umar et al. (2022), Nerlinger and Utz (2022), Bougias et al. (2022), and among others. Regarding the war effects on stock markets, Izzeldin et al. (2023) point out that the volatility of global stock markets increased instantaneously after the war inception, however, the increasing effects were fading over time. Further, Lo et al. (2022) find that the exacerbating effect of the war on a stock markets' volatility is conditional upon a country's dependence on

Russian commodities. Ahmed et al. (2022) document that European stocks experienced significant negative abnormal return subsequent to the war, with the extent of the stock price reactions varying across industries, countries, and company sizes. Pertaining to commodity markets, Izzeldin et al. (2023) find that commodities' volatility also increased as a result of the war with wheat and nickel being the most affected. Umar et al. (2022) provide evidence that most clean energy, conventional energy, and metal markets exhibit abnormal positive returns following the war. In addition, they reveal that the impact of the war was more prolonged on many commodities, such as gas oil, gasoline, heating oil, nickel, and palladium. Finally, concerning the credit markets, Bougias et al. (2022) detect that the ongoing conflict between Russia and Ukraine results lead to elevated credit spreads and increased default probabilities. Further, they also note that these detrimental effects are more pronounced for companies with heavy reliance on the Russian economy. More importantly, Ferriani and Gazzani (2022) reveal that enterprises characterized by high energy intensity and carbon emission intensity experienced a more substantial rise in CDS spreads.

Meanwhile, few studies have explored the impact of the conflict between Russia and Ukraine on the risk transmission among financial markets. For instance, focusing on commodity market, Wang et al. (2022) compute the connectedness indexes across commodities based on the time-varying parameter vector autoregressive (TVP-VAR) and point out that the contagion risk across commodities increased substantially after the war started. Adekoya et al. (2022) apply the time-varying parameter vector autoregressive (TVP-VAR)-based connectedness approach to examine the intraday volatility spillover between the oil market and other financial markets. They document that the role of oil has changed from net receiver of volatility shocks in the pre-war period to net transmitter of volatility shocks in the post-war period. However, its net transmitter role was transitory and died out quickly. In a similar vein, Umar et al. (2022) employs the TVP-VAR-based connectedness approach and the frequency connectedness framework to investigate the return and volatility spillover between Russian, European financial markets, and the global commodity markets. They document that the overall spillover effects are higher during the war than the pre-war period and the stronger effects are perceived in both short-term and long-term connectedness. However, the transitory return connectedness is larger than persistent return connectedness. Further, Umar et al. (2022) reveal that oil switched from net absorber to net driver of shocks in the post-war time. This finding conforms to the empirical results reported by Adekoya et al. (2022).

In line with the aforementioned literature, we formulate the third hypothesis about the effect of the Russian-Ukrainian war on the interconnectedness between natural gas and European sector CDS markets as follows,

Hypothesis 3: *The Russian-Ukrainian war intensifies the shock transmission among natural gas and European sectoral CDS returns.*

While having shown that the interconnectedness in global financial markets increased in the post-war period, the above-cited studies have two common limitations. First, they are limited only to the connectedness at the conditional mean of the distributions. Second, the impact of the Russian-Ukrainian war was not quantitatively analysed and their conclusions were mainly drawn from their observations. Our research, thereby, turns to explore the return spillover between European sector CDSs and the gas market at both conditional mean and tails of return distributions while the war effect is quantitatively accounted for by estimating both daily- and monthly-regression models. As such, our work fills the void left over in the literature and provides first evidence of the war effect on return connectedness between corporate debt market and natural gas at both normal and extreme conditions (i.e., extreme large positive and negative shocks).

3.3 Methodologies

3.3.1 Granger-causality test

As we contemplate that the sign of causal effect between sample markets may be different depending on the direction of causality, as discussed in Hypotheses 1 and 2, we rely on the technique of Granger and Yoon (2002) to separate the data into cumulative positive and negative changes, and then tests the Granger causality relationship between these components. In our study, suppose that we have ten return series,[18] $y_{Gas,t}$ and $y_{CDS_i,t}$, where $i = 1, \dots, 9$, representing nine sectoral CDSs and $t = 1, 2, \dots, T$. The $y_{Gas,t}$ and $y_{CDS_i,t}$ are represented by the following random walk processes as,

$$y_{GAS,t} = y_{GAS,t-1} + \varepsilon_{GAS,t} = y_{GAS,0} + \sum_{k=1}^{t} \varepsilon_{GAS,k} \tag{3.1}$$

and

$$y_{CDS_i,t}, = y_{CDS_i,t-1}, + \varepsilon_{CDS_i,t} = y_{CDS_i,0} + \sum_{k=1}^{t} \varepsilon_{CDS_i,k} \tag{3.2}$$

where $\varepsilon_{GAS,k}$ and $\varepsilon_{CDS_i,k}$ denote white noise error terms; the constants $y_{GAS,0}$ and $y_{CDS_i,0}$ take the initial values.

According to Granger and Yoon (2002), positive and negative return shocks of natural gas can be defined as follows: $\varepsilon^{+}{}_{GAS,k} = \max(\varepsilon_{GAS,k}, 0)$ and $\varepsilon^{-}{}_{GAS,k} = \min(\varepsilon_{GAS,k}, 0)$, respectively. Similarly, positive and negative return shocks of sectoral CDS_i are expressed as $\varepsilon^{+}{}_{CDS_i,k} = \max(\varepsilon_{CDS_i,k}, 0)$ and $\varepsilon^{-}{}_{CDS_i,k} = \min(\varepsilon_{CDS_i,k}, 0)$, correspondingly. By this decomposition, we have $\varepsilon_{GAS,k} = \varepsilon^{+}{}_{GAS,k} + \varepsilon^{-}{}_{GAS,k}$ and $\varepsilon_{CDS_i,k} = \varepsilon^{+}{}_{CDS_i,k} + \varepsilon^{-}{}_{CDS_i,k}$. Therefore, Eqs. (3.1) and (3.2) can be re-written as follows,

[18] Which are the return series of natural gas and nine sectoral CDSs.

$$y_{GAS,t} = y_{GAS,t-1} + \varepsilon_{GAS,t} = y_{GAS,0} + \sum_{k=1}^{t} \varepsilon^{+}{}_{GAS,k} + \sum_{k=1}^{t} \varepsilon^{-}{}_{GAS,k} \tag{3.3}$$

and

$$y_{CDS_i,t} = y_{CDS_i,t-1} + \varepsilon_{CDS_i,t} = y_{CDS_i,0} + \sum_{k=1}^{t} \varepsilon^{+}{}_{CDS_i,k} + \sum_{k=1}^{t} \varepsilon^{-}{}_{CDS_i,k} \tag{3.4}$$

So, we have cumulative sums of positive and negative shocks of each variable as follows: $y^{+}_{GAS,t} = \sum_{k=1}^{t} \varepsilon^{+}{}_{GAS,k}$; $y^{-}_{GAS,t} = \sum_{k=1}^{t} \varepsilon^{-}{}_{GAS,k}$; $y^{+}_{CDS_i,t} = \sum_{k=1}^{t} \varepsilon^{+}{}_{CDS_i,k}$; and $y^{-}_{CDS_i,t} = \sum_{k=1}^{t} \varepsilon^{-}{}_{CDS_i,k}$. It is important to note that each positive or negative shock causes permanent impact on the underlying variable.

In Hypothesis 1, we would like to test whether the positive return shocks of natural gas Granger cause positive return shocks of sectoral CDSs. Therefore, presuming that vector $y^{+}_{t} = (y^{+}_{GAS,t}, y^{+}_{CDS_1,t}, y^{+}_{CDS_2,t}, \ldots, y^{+}_{CDS_9,t})$, the Granger causality test can be conducted for the following Vector Autoregressive (VAR) model of order *p*,

$$y^{+}_{t} = \alpha + A_1 y^{+}_{t-1} + \cdots + A_p y^{+}_{t-p} + u^{+}_{t} \tag{3.5}$$

where α is 10×1 intercept vector, A_j (with $j = 1, \ldots, p$) are 10×10 matrices of coefficients, and u^{+}_{t} is 10×1 vector of error terms. The optimal lag order p is selected based on the information criterion.

After checking the stationary of the time series, we test the null hypothesis of the k^{th} element of y^{+}_{GAS} which does not Granger-cause the w^{th} element of $y^{+}_{CDS_i}$ following the Wald test. So, H_0: the column k, row w in A_j (with $j = 1, \ldots, p$) equal 0, is tested using the test method as follows,

$$Wald = (C\beta)'[C((Z'Z)^{-1} \otimes S_U)C']^{-1}(C\beta) \tag{3.6}$$

where $\beta = vec(D)$ and $D = (\alpha, A_1, \ldots A_p)$, *vec* represents the column-stacking operator; *C* is an indicator matrix dimension $p \times n(1 + np)$ take the element values of ones for restricted parameters and zeros for the remaining parameters; *n* is number of equations in VAR model;

$\otimes$ is the Kronecker product. S_U is the variance-covariance matrix of unrestricted VAR model and $S_U = \frac{\hat{\delta}'_U \hat{\delta}_U}{T-q}$, with $(n \times T)$ matrix $\delta = (u_1^+, \dots u_T^+)$; T is the number of observations; q is the number of parameters in each equation of the VAR model. The Wald test statistic follow a χ^2 distribution. The hypothesis of Granger non-causality H_0 is rejected if the estimated Wald test is beyond the critical values.

In Hypothesis 2, the testable hypothesis is that positive return shocks of sectoral CDSs Granger cause negative return shocks of the gas market. In the similar vein, we assume to have $y_t^{-+} = (y_{GAS,t}^-,\ y_{CDS_1,t}^+, y_{CDS_2,t}^+, \dots, y_{CDS_9,t}^+)$. Therefore, the Granger causality test can be conducted for the following VAR model:

$$y_t^{-+} = \gamma + B_1 y_{t-1}^{-+} + \cdots + B_p y_{t-p}^{-+} + \epsilon_t^+ \qquad (3.7)$$

where γ is 10×1 intercept vector, B_j (with $j = 1, \dots, p$) are 10×10 matrices of coefficients, and ϵ_t^{-+} is 10×1 vector of error terms. We continue applying the Wald test to test the Granger causality as detailed above.

3.3.2. Quantile connectedness measures

To examine the return connectedness between European sectoral CDS markets and natural gas with respect to extreme return shocks, we rely on the quantile-based connectedness approach introduced by Ando et al. (2022). This approach involves the estimation of a VAR system on an equation-by-equation basis at a specific conditional quantile, $\tau \in (0,1)$, using quantile regression. Subsequently, the measures of connectedness introduced by Diebold and Yilmaz (2012) are derived from the baseline quantile VAR model.

In this study, our primary results obtained from a quantile-based connectedness approach are compared with the findings derived from the general mean-based connectedness of Diebold and Yilmaz (2012) to examine the different behaviors of return connectedness between these sample markets at conditional mean and at extreme quantiles of return distributions.

Now we present the key econometric method of our research, the quantile-based connectedness framework. Using the Akaike Information Criteria (AIC), we estimate the optimal lag order p of a VAR process of n assets at τ th conditional quantile, $\tau \in (0,1)$. The VAR model can be specified as follows:

$$y_t = C_{0(\tau)} + \sum_{\ell=1}^{p} C_{\ell(\tau)} y_{t-\ell} + e_{t(\tau)} \tag{3.8}$$

where y_t is the $n \times 1$ vector of returns for n sample assets, $C_{0(\tau)}$ is the $n \times 1$ intercept vector, and $e_{t(\tau)}$ is the $n \times 1$ vector residual at τ th quantile. $C_{\ell(\tau)}$ is the ℓ^{th} $n \times n$ matrix of autoregressive coefficients at τ th quantile.

We estimate the VAR model using the equation-by-equation quantile regression with the single equation specified as,

$$y_{jt} = C_{j(\tau)}^{\top} z_t + e_{jt(\tau)} \tag{3.9}$$

where *j=1, 2…, n* and z_t indicates the vector of all regressors encompassing the intercept with dimension $(np+1) \times 1$, $C_{j(\tau)}$ denotes the autoregressive coefficients estimated at τ th quantile. Under the assumption that the residuals conform to the conditional quantile restriction, $Q_t(e_{jt(\tau)}|z_t) = 0$, we can follow the approach proposed by Koenker and Xiao (2006) to specify the τ th conditional quantile function of y_{jt} as,

$$Q_\tau(y_{jt}|z_t) = C_{j(\tau)}^{\top} z_t \tag{3.10}$$

where Q_τ represents the conditional quantile function of y_{jt} at quantile τ.

We estimate the autoregressive coefficients $\theta_{j(\tau)}$ by adopting the technique proposed by Koenker and Hallock (2001). This involves solving a problem at a specific quantile τ as follows,

$$\min_{\mathcal{C}_{j(\tau)}} \sum_{t=1}^{T} (\tau - \boldsymbol{I}[y_{jt} \leq \mathcal{C}_{j(\tau)}{}_{j(\tau)}^{\top} z_t])(y_{jt} - \mathcal{C}_{j(\tau)}^{\top} z_t) \quad (3.11)$$

where T represents the total number of observations in the sample; and the indicative function $\boldsymbol{I}[\bullet]$ taking the value of 1 if $y_{jt} \leq \mathcal{C}_{j(\tau)}^{\top} z_t$ and 0 otherwise.

Then, the measures of connectedness are derived within the underlying quantile VAR model. To this end, we re-write the Eq. (3.8) in representation of an infinite moving average as follows,

$$y_t = \mu_{(\tau)} + \sum_{k=1}^{\infty} A_{k(\tau)} e_{t-k(\tau)} \quad (3.12)$$

where $\mu(\tau)$ and $A_k(\tau)$ are determined as,

$$\mu_{(\tau)} = \left(I_m - \mathcal{C}_{1(\tau)} - \cdots - \mathcal{C}_{p(\tau)}\right)^{-1} \mathcal{C}_{0(\tau)}$$

$$A_{k(\tau)} = \begin{cases} 0 \text{ for } k < 0; \\ I_m \text{ for } k = 0; \\ \mathcal{C}_{1(\tau)} A_{k-1(\tau)} + \cdots + \mathcal{C}_{p(\tau)} A_{k-p(\tau)} \text{ for } k > 0 \end{cases}$$

Using the above-estimated coefficients of vector moving average $A_{k(\tau)}$ in Eq. (3.12), we quantify the variation of the *i*th variable in y_t induced by the shocks to *j*th variable by computing the generalized forecast error variance decomposition (GFEVD) of the *i*th variable caused by *j*th variable for a forecast horizon H at τth quantile as follows,

$$\theta_{ij(\tau)}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_{h(\tau)} \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} e_i' A_{h(\tau)} \Sigma A'_{h(\tau)} e_i} \quad (3.13)$$

where $\theta_{ij(\tau)}(H)$ represents the extent to which the variance of *h*-step-ahead forecast error of the variable *i*th are contributed by the *j*th variable; σ_{jj} refers to the *j*th element of the diagonal of the Σ matrix; Σ denotes the $n \times n$ variance matrix of vector error terms; and e_i is the selection vector which takes a value of one for the *i*th element and zero otherwise. Then, we normalized each entry of the variance decomposition matrix as follows,

$$\tilde{\theta}_{ij(\tau)}(H) = \frac{\theta_{ij(\tau)}(H)}{\sum_{j=1}^{n} \theta_{ij}(H)} \tag{3.14}$$

Based on the computed GFEVD, we construct five key connectedness measures at a specific quantile. The first measure is the total spillover index (*TSI*) at a given τth quantile:

$$TSI(\tau) = \frac{\sum_{i,j=1;i\neq j}^{n} \tilde{\theta}_{ij(\tau)}(H)}{n} \times 100 \tag{3.15}$$

The directional spillover index received/ transmitted by variable i from/ to all other variables j at τth quantile is respectively defined as:

$$\mathcal{S}_{i.(\tau)} = \frac{\sum_{j=1;i\neq j}^{n} \tilde{\theta}_{ij(\tau)}}{n} \times 100 \tag{3.16}$$

$$\mathcal{S}_{.i(\tau)} = \frac{\sum_{j=1;i\neq j}^{m} \tilde{\theta}_{ji(\tau)}}{m} \times 100 \tag{3.17}$$

The net spillover from variable i to all other variables j at τth quantile is defined as,

$$NSI_{i(\tau)} = \mathcal{S}_{.i(\tau)} - \mathcal{S}_{i.(\tau)} \tag{3.18}$$

In our study, the total connectedness index (TCI) covers both the *cross-market* connectedness between the natural gas and the CDS markets and the *within-CDS* market connectedness (i.e., spillover effects across sectoral CDSs). As such, we compute the fifth connectedness measure named the *cross-market* spillover index (CSI) that captures only the return shock spillover between the CDS markets and the gas market. The CSI is calculated as the average of the gross return shock that the gas market transmits to and receives from the sectoral CDS markets. Specifically, the CSI at τth quantile is computed as follows,

$$CSI(\tau) = \frac{\mathcal{S}_{.Gas(\tau)} + \mathcal{S}_{Gas.(\tau)}}{2} \tag{3.19}$$

where $\mathcal{S}_{.Gas(\tau)}$ is the directional return spillover that the gas market transmits to all considered sectoral CDS markets at quantile τ as in Eq. (3.17), and $\mathcal{S}_{Gas.(\tau)}$ is the directional return spillover index that the gas market receives from all considered sectoral CDS market as in Eq. (3.16).

3.4 Data and descriptive statistics

3.4.1 Sample and data

In this study, we employ daily closing prices (i.e., spreads) of nine sectoral CDSs in the EU including: Automotive (AUT), Banking (BNK), Chemicals (CHM), Construction Materials (CM), Industrials (IND), Manufacturing (MAN), Oil & Gas (OG), Transportation (TRA), and Utilities (UTL). Following Norden and Weber (2009) and Hammoudeh et al. (2013), the spreads of 5-year CDS contract are used as the proxy for corporate credit risk since they represent the most frequently traded term with a very small bid-ask spread and are highly informative. We collect the 5-year CDS index prices from Thomson Reuters DataStream for the sample period ranging from August 01, 2008 to August 31, 2022. Our sample period includes several critical events in the global financial markets that are anticipated to exert significant influences on the corporate credit and energy commodity markets, such as the Global Financial Crisis (2007-2009), the Eurozone debt crisis (2009-2012), the COVID-19 pandemic (2020-2022), and the Russian-Ukrainian war (2022). Based on the daily CDS index price series, we compute the daily return of each sectoral CDS as the variation between the natural logarithm of the price of day t and the price of day $t-1$.

To proxy for the European gas market, we employ the price series of EEX Gas Price Reference EGIX for the Germany market (thereafter, EGIX). This index is constructed by the European Energy Exchange as the arithmetic mean of the daily volume-weighted-average prices of all trades of the largest nationwide natural gas hub in Germany – the Trading Hub Europe (THE).[19] We use Germany's gas price as a proxy for European gas market for two main reasons. First, Germany is the largest natural gas consumer in the Europe, followed by Italy

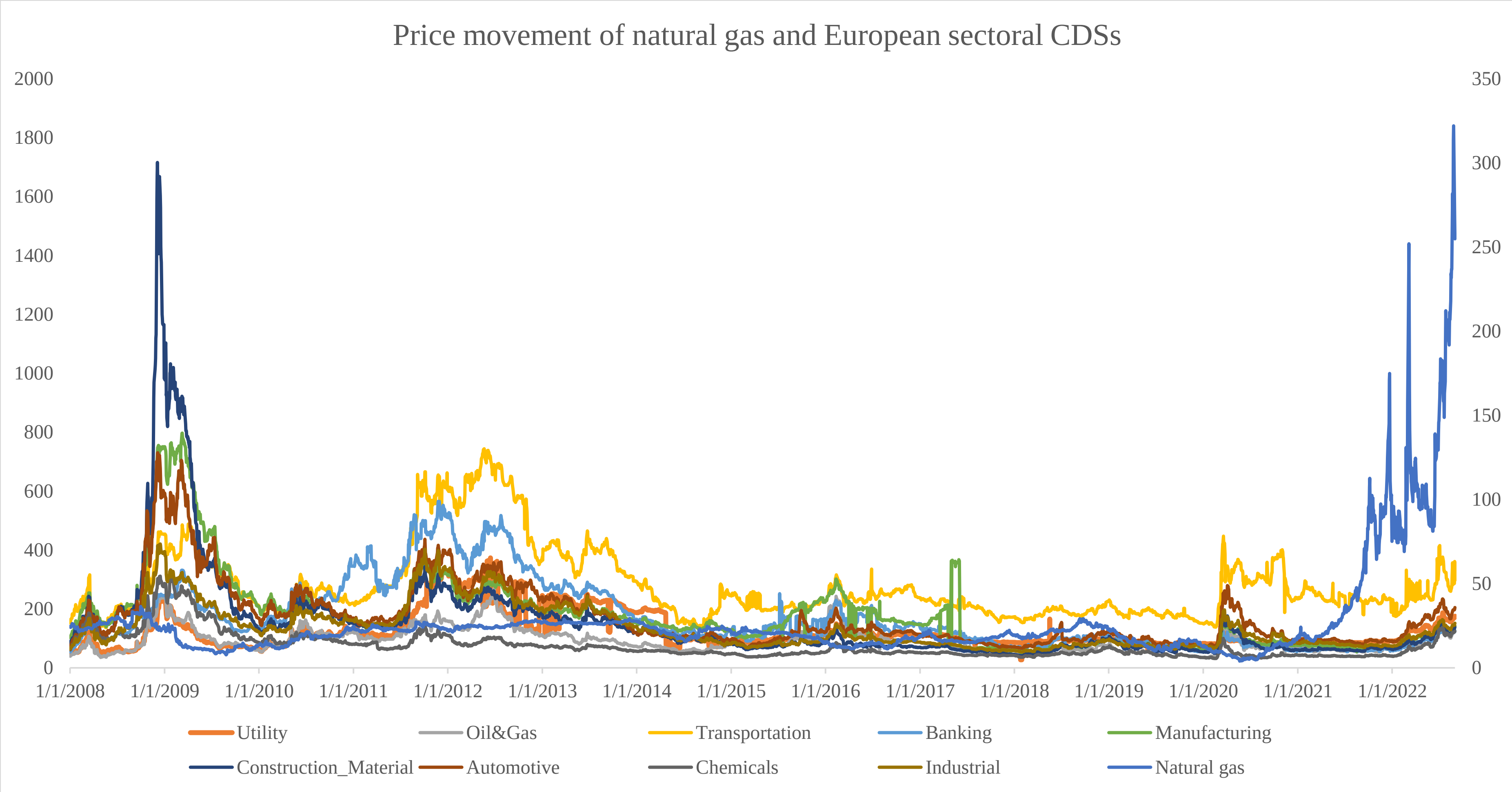
[19] THE was established in October 2021 by the merge of two largest natural gas hubs in Germany, namely, NetConnect Germany (NCG) and GASPOOL (GPL).

and Netherlands. Worldmeters statistics show that Germany consumed 3,296,687 million cubic feet (MMcf) of natural gas in 2017, ranking 8th in the world for natural gas consumption.[20] Second, among EU countries, Germany is the largest economy with its GDP of USD 3.601 trillion in 2021. Additionally, Petrovich (2013) finds that natural gas prices across various European gas hubs are strongly correlated, with the lowest correlation coefficient of 84%.

Figure 3.3 plots the co-movement of the prices of sectoral CDS and natural gas. The left vertical axis indicates the CDS prices measured in basis points while the right secondary axis displays the gas prices in Euro per MWh.

[20] https://www.worldometers.info/gas/germany-natural-gas/#gas-consumption

Figure 3.3 Price movement of natural gas and European sectoral CDSs



Notes: This figure illustrates the price series of each sample markets during the research period.

3.4.2 Descriptive statistics

Table 3.1 reports the descriptive statistics of daily return series of the nine European sectoral CDS markets and natural gas. As can be seen, all return series of sample assets experience positive daily average returns. Within sectoral CDSs, Utilities (UTL) has the highest daily average return (0.015%), with Oil & Gas (OG) and Automotive (AUT) following closely at 0.013%. In reverse, Manufacturing (MAN) (0.004%) and Construction Materials (CM) (0.006%) exhibit the lowest figures of daily average returns. In contrast to the sectoral CDS markets, the natural gas has much higher value of daily average return, reaching 0.026%.

Pertaining to risk measures, despite having the lowest value of average return, the Manufacturing (MAN) demonstrates the highest volatility among the sectoral CDS markets, with (10.87), followed by Utilities (UTL) (8.715) and Banking (BNK) (5.328). By contrast, the lowest return variances belong to Industrials (IND) (1.041), Chemicals (CHM) (1.309), Construction Materials (CM) (1.703), and Automotive (AUT) (1.719). The volatility of natural gas stands at the middle range among the selected assets, recorded at 2.262.

As further shown in Table 3.1, the European sectoral CDSs exhibit both negative and positive skewness. Specifically, the skewness numbers of AUT, CHM, CM, IND, and OG are positive, indicating the frequent occurrence of extreme positive returns in these sectoral CDSs. Inversely, the BNK, MAN, TRA, and UTL have negative skewness, implying that these sectoral CDSs exhibit more negative return shocks than positive return shocks. Regarding the gas market, its positive skewness value of 1.374, indicating the gas market experiences extreme positive returns more frequently than negative ones. Moreover, both the sectoral CDSs and the gas market are prone to high likelihood of extreme high and low returns, as evidenced by the excess positive kurtosis of their returns. This finding emphasizes the importance of considering the connectedness not only at the mean but also at the extreme quantiles of return distributions when modelling the return shock transmission between the European sectoral CDS markets and the gas market.

We conduct the diagnostic tests of the return series in the last three columns of Table 3.1, including Jarque-Bera test, ERS unit root test, and Ljung-Box Q test. First, the Jarque-Bera statistics provide strong evidence against the assumption of normal distribution for the return series of all assets. Second, the significant results of ERS unit root indicate the absence of a unit root in all return time series, confirming their stationarity. Finally, the Ljung-Box Q statistics, computed up to 10 lags, imply the presence of significant serial correlation in all return series for the European sectoral CDSs and the gas market.

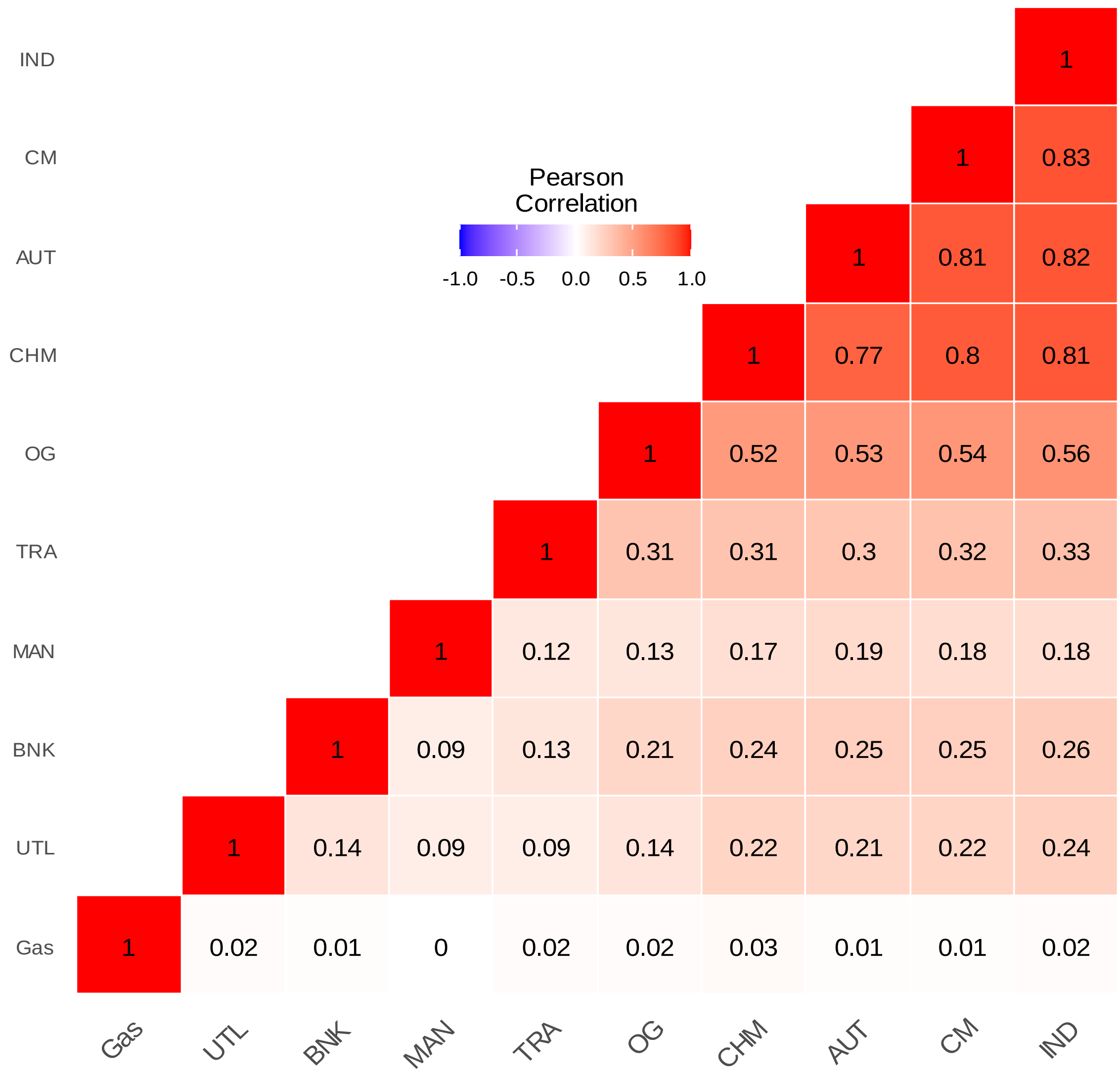
Table 3.1 Descriptive statistics

Name	Mean	Variance	Skewness	Ex. Kurtosis	Jarque-Bera	ERS	LB Q(10)
Natural Gas	0.026	2.262	1.374	22.321	80651.797***	-14.875***	851.251***
AUT	0.013	1.719	0.208	12.286	24098.064***	-15.442***	149.931***
BNK	0.010	5.328	-0.122	35.264	198307.475***	-23.048***	267.655***
CHM	0.008	1.309	0.758	12.097	23703.250***	-24.312***	138.457***
CM	0.006	1.703	1.039	10.285	17555.588***	-24.828***	176.159***
IND	0.010	1.041	1.013	13.175	28333.797***	-16.831***	145.426***
MAN	0.004	10.874	-0.737	223.830	7989192.085***	-29.806***	772.196***
OG	0.013	2.478	1.350	53.199	452454.920***	-24.972***	43.132***
TRA	0.008	3.285	-0.005	32.846	172030.418***	-21.286***	206.138***
UTL	0.015	8.715	-1.144	109.496	1912628.693***	-33.888***	122.604***

Note: This table reports the descriptive statistics of daily return series of European natural gas and nine sectoral CDS markets between August 01, 2008 and August 31, 2022. LB Q(10) represents the Ljung-Box Q-statistics up to the 10^{th} order autocorrelation. Jarque-Bera statistics indicate the test for the normality of sample data. ERS test represents the unit root test. *** denotes the cases where the null hypothesis of no autocorrelation (for LB Q test), and normal distribution (for JB test), and a presence of a unit root (for ERS test) are rejected at the 1% significance level.

Figure 3.4 provides the matrix of pairwise correlation of the sample return series. The results show that the natural gas return exhibits positive correlation with each sectoral CDSs, albeit at relatively low levels (below 0.1). Meanwhile, the correlation coefficient values between sectoral CDSs are relatively high. Notably, the pairs of CM and IND (0.83), and AUT and IND (0.82) exhibit the highest pairwise correlation coefficients among the sectoral CDSs. By contrast, the pairs of UTL and MAN (0.09), MAN and BNK (0.09), and TRA and UTL (0.09) are among the lowest pairwise correlations between sectoral CDSs.

Figure 3.4 Contemporary correlation matrix of return series



Note: This graph displays the matrix of pair-wise correlation coefficients among European natural gas and nine sectoral CDS markets for the research period between August 01, 2008 and August 31, 2022.

3.5 Empirical results

This section offers thorough analyses of the return connectedness between the European sectoral CDS markets and the gas market, including five subsections as follows. Subsection 3.5.1 presents the results of Granger causality tests used to test Hypotheses 1 and 2. After documenting their causal link, subsection 3.5.2 discusses the static return connectedness at the conditional mean between the gas and sectoral CDS markets. Subsection 3.5.3 provides the average quantile-based connectedness results of the system (i.e., lower and upper tail connectedness). Subsection 3.5.4 and 3.5.5 turn to analyse several time-varying connectedness measures at both conditional mean and tails of return distributions.

3.5.1 Results of Granger causality tests

Before estimating the dynamic patterns of the return spillover effects between natural gas and sectoral CDS markets, we proceed to test the significance and the sign of the causal link between these markets using the procedure described in subsection 3.3.1. First, we decompose return shocks of the selected markets into negative and positive shocks and show their descriptive statistics in Panel A of Table 3.2. We find that on average, CDSs of banking (BNK) and manufacturing (MAN) sectors have the highest negative and positive return shocks. On the contrary, the lowest positive and negative return shocks are given to industrials (IND) and chemicals sector (CHM). In terms of volatility, utility sector (UTL) exhibits most volatile positive shocks, whereas manufacturing (MAN) sector experiences the highest negative shock fluctuations. Finally, the results of Augmented Dickey Fuller (ADF) test indicate that all positive and negative shock series are stationary.

Panel B of table 3.2 presents the results of Granger causality test, using the series of positive and negative shocks of the selected assets. In Hypothesis 1, we expect that positive (negative) return shocks of natural gas would Granger cause positive (negative) return shocks of sectoral CDSs. As a result, the null hypothesis used to test Hypothesis 1 is that positive (negative) shocks of natural gas does not Granger cause positive (negative) shocks of sectoral CDSs (i.e., H_0: $\varepsilon^{+}_{GAS,t} \nRightarrow \varepsilon^{+}_{CDS_i,t}$ and H_0: $\varepsilon^{-}_{GAS,t} \nRightarrow \varepsilon^{-}_{CDS_i,t}$). As shown in Panel B, the Wald test statistics for Hypothesis 1 equal to 22.28 and 30.84, respectively and their p-Values are both lower than 1%. These results statistically reject the null hypothesis in both cases and lend support to Hypothesis 1 of the positive causal link from the natural gas market to the sectoral CDS markets.

Panel B also reveals the testing results of Hypothesis 2, which states that positive (negative) return shocks of CDS markets Granger cause negative (positive) return shocks of natural gas market. The corresponding null hypothesis is that negative (positive) return shocks of natural gas are not affected by positive (negative) return shocks of sectoral CDS markets (i.e., H_0: $\varepsilon^{+}_{CDS_i,t} \nRightarrow \varepsilon^{-}_{GAS,t}$ and H_0: $\varepsilon^{-}_{CDS_i,t} \nRightarrow \varepsilon^{+}_{GAS,t}$). The Wald test statistics for Hypothesis 2 have values of 28.25 and 15.17 and are both statistically significant at 1% and 10%, respectively. These figures reject the null hypothesis, and indicate that there exists a negative causal link from the sectoral CDS markets to the natural gas market.

To sum up, the results of Granger causality tests confirm that there is a significant causal relationship between natural gas and sectoral CDS markets in Europe. Specifically, the shocks to the natural gas market have a positive causal effect on shocks to the sectoral CDS markets, whereas shocks to sectoral CDS markets exert a negative causal effect on shocks of the natural gas market. So, the results are consistent with our hypothesized channels about the sign of the causality.

Table 3.2 Results of Granger Causality Tests

Panel A. Positive and negative return shocks' statistics

Name	Positive shocks			Negative shocks		
	Mean	Std. Dev.	ADF test	Mean	Std. Dev.	ADF test
Natural Gas	0.42	1.06	-2,974***	-0.42	0.89	-2,878***
AUT	0.43	0.83	-2,589***	-0.43	0.78	-3,322***
BNK	0.56	1.49	-3,218***	-0.56	1.47	-3,489***
CHM	0.36	0.76	-2,657***	-0.36	0.66	-3,060***
CM	0.42	0.86	-2,666***	-0.42	0.73	-3,411***
IND	0.33	0.67	-2,596***	-0.33	0.58	-3,432***
MAN	0.49	1.95	-1,959***	-0.49	2.18	-2,954***
OG	0.41	1.11	-2,475***	-0.41	0.95	-2,974***
TRA	0.41	1.24	-2,927***	-0.41	1.14	-2,886***
UTL	0.42	1.98	-3,295***	-0.42	2.07	-3,362***

Panel B. Tests' results

Hypothesis	Null hypothesis	Wald test statistic	p-Value
1	H_0: $\varepsilon^{+}_{GAS,t} \nRightarrow \varepsilon^{+}_{CDS_i,t}$	22.28***	0.0080
	H_0: $\varepsilon^{-}_{GAS,t} \nRightarrow \varepsilon^{-}_{CDS_i,t}$	30.84***	0.0003
2	H_0: $\varepsilon^{+}_{CDS_i,t} \nRightarrow \varepsilon^{-}_{GAS,t}$	28.25***	0.0090
	H_0: $\varepsilon^{-}_{CDS_i,t} \nRightarrow \varepsilon^{+}_{GAS,t}$	15.17*	0.0860

Note: Table 3.2 Panel A presents the descriptive statistics and diagnostic test of the series of positive and negative shocks for the selected assets. Positive and negative shocks are calculated using procedures as described in subsection 3.3.1. Std. Dev. denotes standard deviation. ADF test is the test statistic of the Augmented-Dickey Fuller test of stationarity. Table 3.2 Panel B presents the Wald test statistics and their corresponding p-Value of the Granger causality test. In Hypothesis 1, the null hypothesis is that positive (negative) return shock of natural gas market does not Granger cause positive (negative) shocks of sectoral CDSs. In Hypothesis 2, the null hypothesis is that negative (positive) return shocks of natural gas market are not affected by positive (negative) shocks of sectoral CDS markets. *** and * indicates statistical significance at 1% and 10% significance levels, respectively.

3.5.2 Average return spillover at the mean of return distributions

Having shown that there exists a causal linkage between natural gas market and sectoral CDS markets with different signs depending on the direction of the causality, we go further to explore the direction and magnitude of their return shock spillovers in subsequent subsections. First, we employ the standard generalized connectedness measures proposed by Diebold and

Yilmaz (2012) to gauge the return spillover at the conditional mean among the European natural gas and sectoral CDS markets, as reported in Table 3.3. The results of mean-based connectedness reveal the behavior of return spillover effects among the sample markets at normal market condition. There are several findings standing out from the results.

First, the Total Spillover Index (TSI) of the system stands at relatively high figure of 60.21% at the conditional mean of return distributions. However, this high value is primarily caused by the within-return connectedness among the sectoral CDSs. Meanwhile, the cross-market return connectedness between the gas market and sectoral CDSs is relatively low under normal market condition, illustrated by the Cross-market Spillover Index (CSI), standing at 8.23%. Further, the "*Directional pairwise spillover*" indexes of nine sectoral CDSs with natural gas, as shown in the first column of Table 3.3, show that only less than 1% of the return variations of each sectoral CDS can be explained by the past variations of the gas market. This implies that the European sectoral CDS markets were less likely to be influenced by the return spillover from the gas market under normal market condition. In the opposite direction, the past variations of all sectoral CDSs contribute to 12.30% of the gas market's return variation, as shown by the "*Spillover from others*" index of the gas market in the last column of Table 3.3. Notably, the European sectoral CDS markets have a greater influence on the natural gas market at normal market conditions than the other way around.

Second, the roles as a shock transmitter or receiver of the sectoral CDS markets and the gas market in this network connectedness are unveiled by the Net Spillover Indexes (NSIs) in Table 3.3. Particularly, our analysis reveals that under normal market condition the gas market acts as the return shock receiver in the system, as indicated by the negative value of its Net Spillover Index (NSI), reaching -8.09%. This finding aligns with previous studies supporting the role of the gas market as information shock receiver (i.e., Dai and Zhu, 2022; Geng et al., 2021). Among sectoral CDSs, the net drivers of return spillover are Manufacturing (MAN), Construction Materials (CM), Automotive (AUT), Chemicals (CHM), and Industrials (IND) while the net receivers include Utilities (UTL), Oil & Gas (OG), TRA (Transportation), and Banking (BNK). It is worth noting that Automotive (AUT) and Construction Materials (CM) stand out as the most important transmitters of return shocks. On the contrary, Transportation (TRA) and Banking (BNK) emerge as the largest absorbers of shocks in the system.

Table 3.3 Average return connectedness at the mean of the conditional distributions

	Gas	UTL	OG	TRA	BNK	MAN	CM	AUT	CHM	IND	*Spillover from others*
Gas	87.7	1.45	1.57	0.94	0.96	1.20	1.56	1.59	1.40	1.62	12.30
UTL	0.65	49.98	8.69	3.05	3.59	6.65	6.55	7.10	6.23	7.51	50.02
OG	0.47	8.19	31.98	4.85	4.32	8.54	10.64	10.86	9.04	11.11	68.02
TRA	0.51	4.74	6.42	41.64	3.10	7.86	9.05	9.02	8.33	9.33	58.36
BNK	0.80	4.97	5.58	3.25	54.79	5.94	6.23	6.63	5.45	6.35	45.21
MAN	0.37	5.59	7.84	5.18	4.04	35.44	10.62	10.90	9.46	10.55	64.56
CM	0.31	4.70	7.83	5.49	3.50	9.20	23.62	15.53	14.21	15.60	76.38
AUT	0.37	5.11	7.76	5.31	3.59	9.26	15.42	24.58	13.30	15.30	75.42
CHM	0.32	4.81	7.20	5.41	3.23	8.74	15.51	14.62	25.21	14.96	74.79
IND	0.40	5.44	8.25	5.53	3.63	9.07	15.61	15.41	13.71	22.97	77.03
Spillover to others	4.21	45.00	61.14	39.02	29.96	66.45	91.19	91.66	81.12	92.34	
NSI	-8.09	-5.02	-6.88	-19.34	-15.24	1.89	14.81	16.24	6.33	15.30	
TSI	**60.21**										
CSI	**8.23**										

Note: This table reports the average return connectedness indexes between European natural gas and nine sectoral CDS markets based on mean-based connectedness approach of Diebold and Yilmaz (2012). *TSI* denotes the Total Spillover index of the whole system. *NSI* denotes the net spillover index of each market. *CSI* denotes the cross-market spillover index between CDS and sectoral CDS markets.

3.5.3 Average return spillover at extreme quantiles of return distributions

As the descriptive statistics of return series suggest that the extreme positive and negative return shocks occur quite frequently for all sample assets, we go further to investigate how the return connectedness among the sample system changes in extreme market conditions (i.e., extreme positive and negative return shocks) by extending our return connectedness analysis at lower/ upper quantiles of return distributions. The results of connectedness measured at the lower tail ($\tau = 0.1$) and upper tail ($\tau = 0.9$) are presented in Table 3.4 and 3.5, respectively. Intriguingly, the results show that the Total Spillover Indexes (TSI) of the system are substantially strengthened at both lower and upper quantiles of distributions, compared to those at the mean of conditional distributions. In details, the TSIs are 76.34% and 76.90% at the lower and upper quantiles, respectively, which are higher than the figure of 60.21% at the mean of distributions. More importantly, the results of tail connectedness show that the cross-market spillover indexes (CSI) presenting the return spillover effects from European gas to sectoral CDS markets and vice versa, are remarkably larger at the lower and upper tails of the return distributions. Specifically, the CSI rises dramatically from 8.23% at the conditional mean to 56.09% and 56.49% at the lower and the upper tails, respectively. These findings imply that while the return shock connectedness between the gas market and sectoral CDSs is moderate at the normal market conditions, it substantially increases when there are extremely negative or positive return shocks to these markets.

As evidenced by the "*Spillover from others*" indexes of natural gas in Table 3.4 and 3.5, we point out that 69.11% (68.86%) of return variations in the natural gas market are driven by extremely large positive (negative) return shocks of all sectoral CDSs. In contrast, the contribution of average shocks from sectoral CDSs to the return variation of the gas market is much lower, accounting for only 12.30%. In the opposite direction, the extreme shocks to the gas market also exert more influence on the return of European sectoral CDS markets than the average shocks. On average, over 3.5% return variations in all sectoral CDSs are explained by the extreme positive and negative return shocks to natural gas while only below 1% of return changes in all sectoral CDSs can be attributed natural gas's average shocks. This finding suggests that the current European gas crisis is likely to be more informative to the changes in European sectoral CDS markets.

Regarding the role of each market in network return shock transmission, the Net Spillover Indexes (NSI) in Tables 3.4 and 3.5 indicate that Transportation (TRA) and Banking (BNK) continue to be largest net receivers of extreme external return shocks. By contrast, there is a noticeable change in the ranking of largest net shock transmitters as Industrials (IND) emerges as the largest net driver of extreme positive shocks and the second most important transmitter of extreme negative shocks. Natural gas is consistently the net shock receiver in the system regardless of the connectedness index measured at the conditional mean or tails of return distributions.

Table 3.4 Average return connectedness measured at lower quantile $\tau = 0.1$

	Gas	UTL	OG	TRA	BNK	MAN	CM	AUT	CHM	IND	*Spillover from others*
Gas	30.89	4.79	7.44	6.8	8.11	6.58	8.77	9	8.64	8.97	69.11
UTL	3.5	41.09	7.13	5.14	5.47	6.76	7.57	7.82	7.52	8	58.91
OG	4.92	6.23	20.3	7.53	7.45	8.65	11.37	11.36	10.69	11.49	79.7
TRA	4.92	5.73	8.65	23.29	7.03	8.33	10.63	10.54	10.2	10.69	76.71
BNK	6.64	5.42	8.45	7.44	24.55	7.84	10.01	10.18	9.43	10.03	75.45
MAN	3.84	5.43	8.37	6.62	6.63	29.86	9.94	9.96	9.44	9.9	70.14
CM	4.72	5.73	9.29	7.85	7.29	9.05	16.56	13.33	12.85	13.33	83.44
AUT	4.85	5.93	9.29	7.72	7.34	8.99	13.33	16.87	12.52	13.16	83.13
CHM	4.81	5.84	9.08	7.8	7.14	8.91	13.27	13.01	16.95	13.18	83.05
IND	4.86	6.04	9.54	7.82	7.34	8.99	13.28	13.2	12.69	16.23	83.77
Spillover to others	43.06	51.17	77.23	64.73	63.79	74.11	98.18	98.41	93.98	98.76	
NSI	-26.05	-7.74	-2.46	-11.98	-11.66	3.96	14.74	15.28	10.93	14.98	
TSI	**76.34**										
CSI	**56.09**										

Note: This table reports the average return connectedness indexes across the sample markets, estimated based on the quantile-VAR-based connectedness at the lower quantile τ=0.1. *TSI* denotes the Total Spillover index of the whole system. *NSI* denotes the net spillover index of each market. *CSI* denotes the cross-market spillover index between natural gas and sectoral CDS markets.

Table 3.5 Average return connectedness measured at upper quantile $\tau = 0.9$

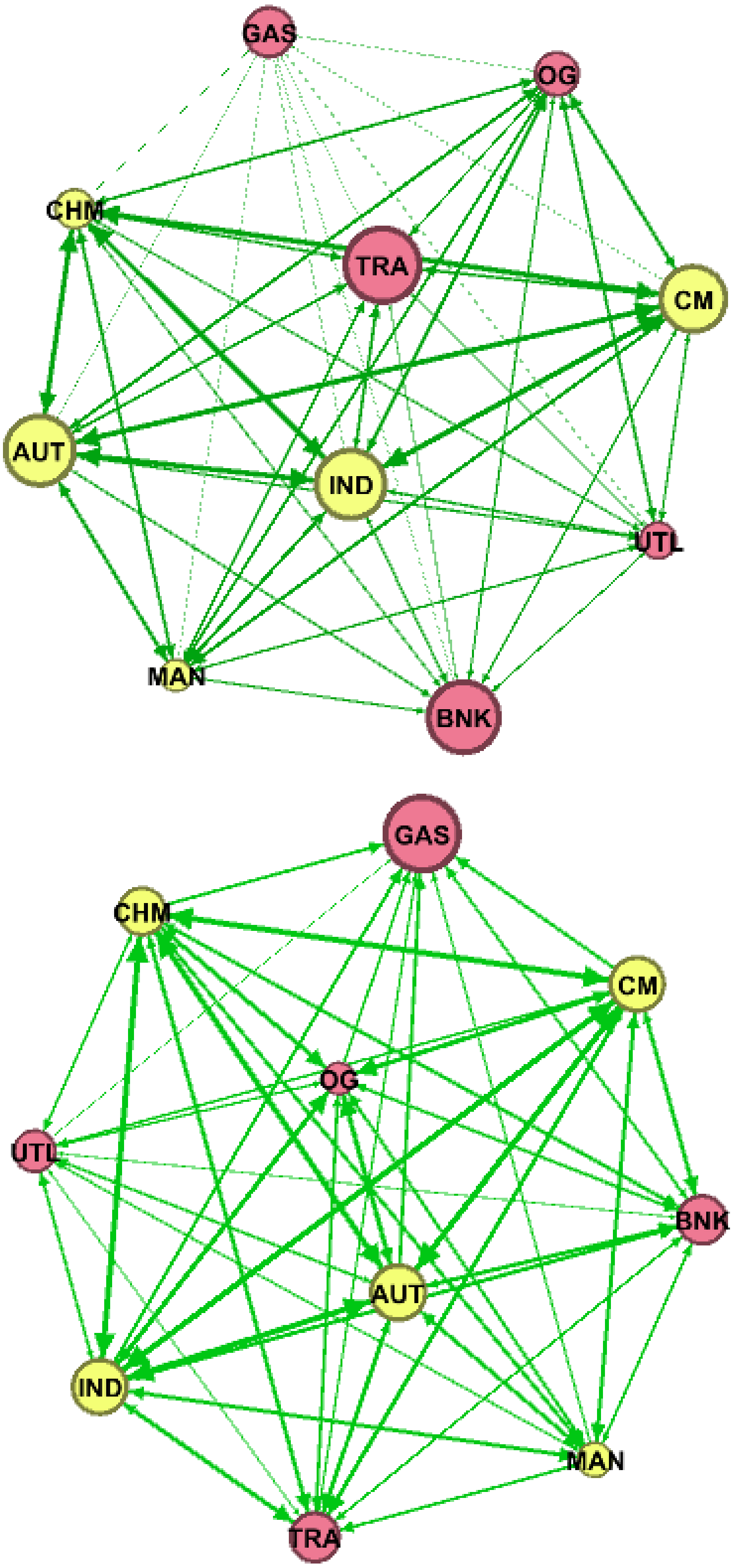
	Gas	UTL	OG	TRA	BNK	MAN	CM	AUT	CHM	IND	*Spillover from others*
Gas	31.14	4.91	7.16	6.63	8.21	6.82	9.04	8.86	8.54	8.7	68.86
UTL	3.75	39.63	7.34	4.89	5.6	6.98	7.79	7.98	7.66	8.38	60.37
OG	5	6.51	19.64	7.32	7.43	8.64	11.48	11.42	10.72	11.83	80.36
TRA	5.07	5.63	8.66	22.37	7.15	8.65	10.7	10.58	10.29	10.9	77.63
BNK	6.59	5.53	8.62	7.05	23.62	8.46	10.08	10.14	9.65	10.26	76.38
MAN	4.26	5.47	8.42	6.56	6.95	28.46	10.07	10.11	9.62	10.06	71.54
CM	4.84	5.73	9.46	7.83	7.24	9.12	16.31	13.38	12.74	13.35	83.69
AUT	4.9	5.88	9.26	7.64	7.34	9.12	13.35	16.97	12.32	13.22	83.03
CHM	4.88	5.85	9.26	7.66	7.17	9.01	13.36	12.93	16.71	13.19	83.29
IND	4.85	6.14	9.71	7.69	7.42	9.05	13.27	13.28	12.45	16.15	83.85
Spillover to others	44.12	51.65	77.89	63.27	64.53	75.84	99.13	98.67	93.99	99.9	
NSI	-24.73	-8.71	-2.47	-14.36	-11.85	4.3	15.44	15.64	10.7	16.05	
TSI	**76.90**										
CSI	**56.49**										

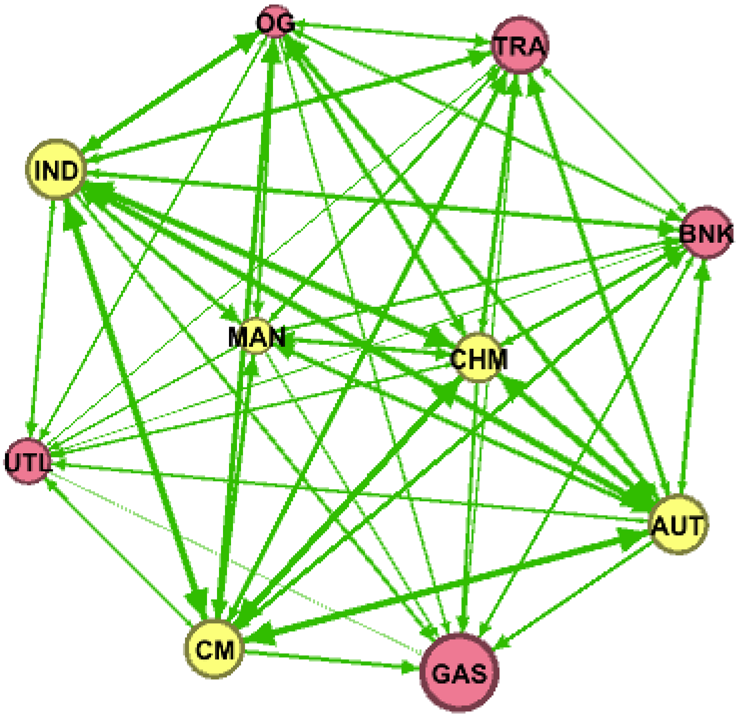
Note: This table reports the average return connectedness indexes across the sample markets, estimated based on the quantile-VAR-based connectedness at the upper quantile τ=0.9. *TSI* denotes the Total Spillover index of the whole system. *NSI* denotes the net spillover index of each market. *CSI* denotes the cross-market spillover index between natural gas and sectoral CDS markets.

Figure 3.5 illustrates the graphs of network connectedness across European sectoral CDS markets and the gas market including the network return connectedness at mean (Figure 3.5a) and at lower tail (Figure 3.5b), and at upper tail (Figure 3.5c) of distributions. The colour of a node in yellow (pink) colour represents whether the market acts as a net transmitter (receiver) of return spillover in the system. The magnitude of the net return spillover index of each market is represented by the node's size. The strength of the pairwise spillover effect is depicted by thickness of the arrow edge.

In Figure 3.5a, regarding the return connectedness at the conditional mean of return distributions, we observe that natural gas (GAS), Transporation (TRA), Oil & Gas (OG), Utilities (UTL), and Banking (BNK) act as net return shock receivers while Automotive (AUT), Industrials (IND), Construction Materials (CM), Chemicals (CHM), and Manufacturing (MAN) are net return shock transmitters. AUT, IND, and CM stand out as the most prominent ones among the net transmitters, as shown by their largest node sizes. Meanwhile, CHM and MAN are the weak shock transmitters. In Figure 3.5b and 5c, AUT, IND, and CM are consistently the most significant net transmitters of extreme return shocks to other markets in the system. This finding suggests that investors in the European sectoral CDS markets should focus on these shock transmitters to better monitor the risk of their CDS portfolio. Notably, the gas market becomes the largest absorbers of external return shocks from sectoral CDS markets under extreme market conditions. As such, the extreme shocks to European sectoral CDSs market are highly informative for predicting the gas market's return variation.

Figure 3.5 Network connectedness at mean, lower quantile and upper quantile of return distributions

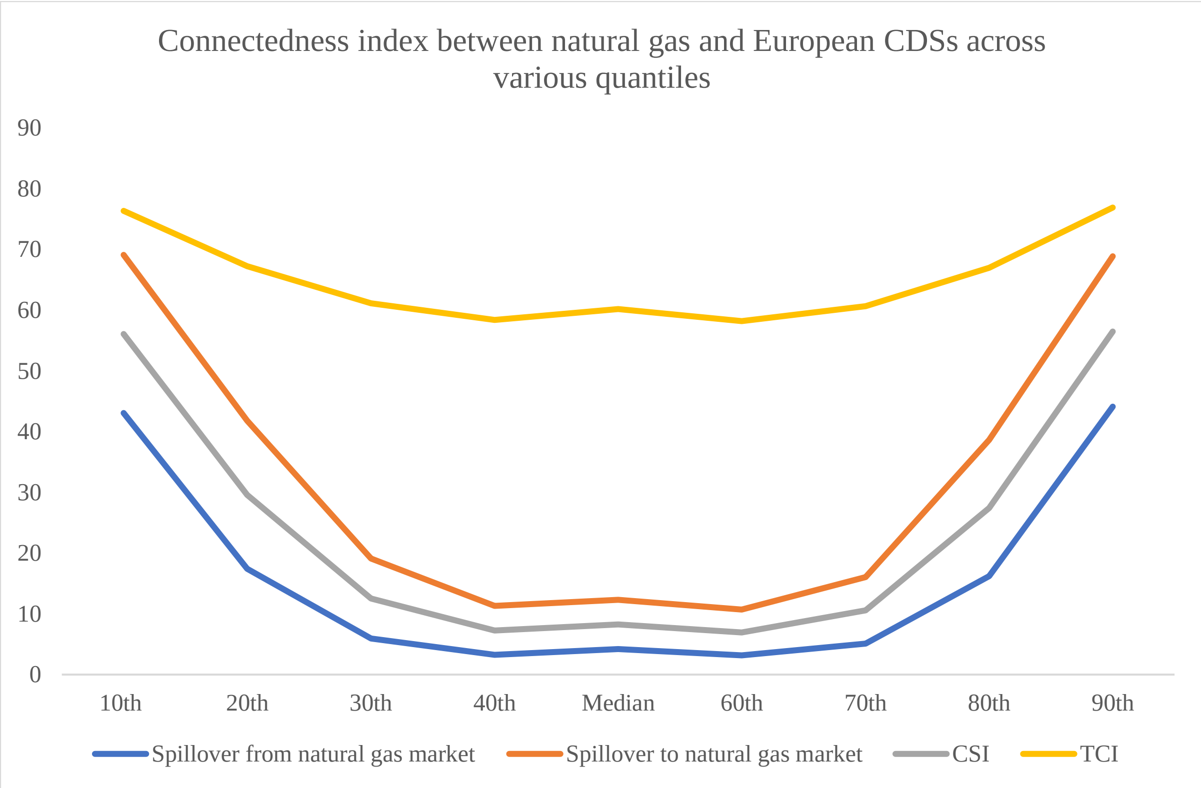




Note: These graphs display the return connectedness between European natural gas and nine sectoral CDS markets at the mean (Figure 3.5a), at the lower quantile (Figure 3.5b), and at the upper tail (Figure 3.5c), respectively. The node color represents the role of net transmitter (yellow) and net receiver (pink) of return shocks. The node size illustrates the magnitude of net return shock spillover of each market. The thickness of the arrow is defined by the strength of directional pair-wise spillover.

We go further to examine the changes in four connectedness measures, including the TSI, the CSI, the "*Spillover from others*" and the "*Spillover to others*", of the gas market at different quantiles, displayed in Figure 3.6. First, all four indexes exhibit significant increases in their values at both tails of return distributions (i.e., lower and upper quantiles). This suggests that the shock size is the key determinant of the magnitude of the return shock transmission across the European CDS markets and natural gas. In other words, the transmission of extreme large shocks between the gas market and the European corporate debt market is much more pronounced than the average shock transmission. This remark conforms to our previous findings obtained from Tables 3.3, 3.4 and 3.5. Second, the cross-market spillover index (CSI), the "*Spillover from others*" index, and the "*Spillover to others*" index of the gas market are much more volatile at upper and lower quantiles. This finding implies that the cross-market spillovers between the European sectoral CDS markets and the gas market is the primary contribution to the rise in the TSI of the system observed at extreme quantiles. Finally, the symmetrical nature of the CSI measured at the upper and lower quantiles indicates that extreme negative and positive shocks have comparable effects on the return spillover of the system.

Figure 3.6 Average spillover indexes between natural gas and European sectoral CDS markets across different quantiles



Notes: This figure shows the Total Spillover Index (TSI) of the whole system, the Cross-market Spillover Index (CSI), "Spillover from others" index of natural gas and "Spillover to others" index of natural gas across different quantiles.

3.5.4 Time-varying cross-market spillover index (CSI)

We extend our analysis by adopting a rolling window approach within the quantile-based connectedness to capture the dynamic pattern of cross-market return spillover effects at different quantiles of conditional distributions, with a 200-day window length and a *10*-step forecast ahead.

As depicted in Figure 3.7, at the conditional median and the conditional mean, the CSIs exhibit similar trends, with significant fluctuations spanning from 1% up to 38%. Notably, the

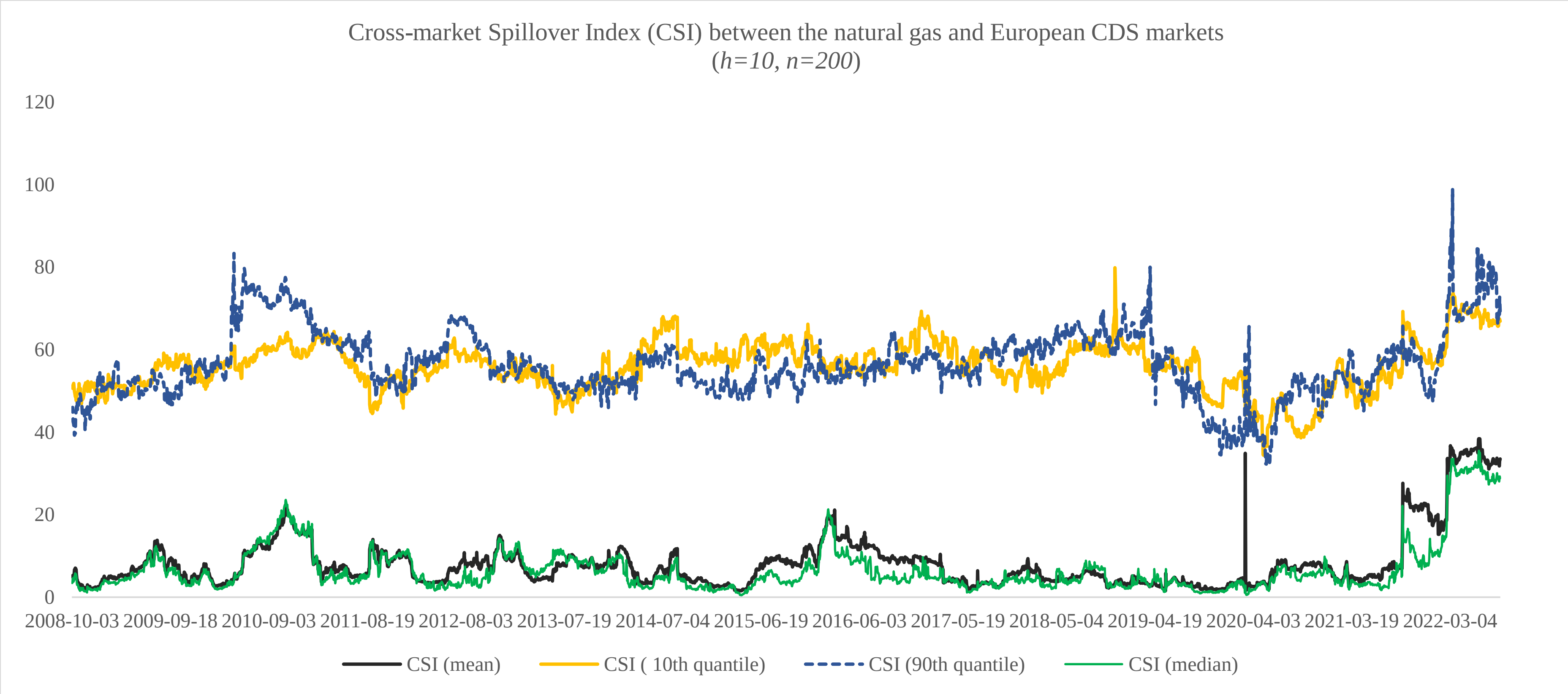
CSIs started at a fractional level in October 2008 then surged substantially during the late stage of the Global Financial Crisis (2009). It soared again reaching its multi-years high during the middle of the Eurozone debt crisis in November 2010.[21] During the Eurozone debt crisis, the sovereign credit default swap markets have experienced enormous fluctuations, which were transmitted to sectoral CDSs (e.g., Bratis et al, 2020; Keddad and Schalck, 2020). Afterward, the indexes experienced a downward trend until April 2015. From April 2015 to February 2016, the indexes experienced an upward spiral, aligning with a period of mounting global financial risks. A number of events occurred during this period, including the fall in global energy price due to booming U.S. shale oil production in 2015,[22] the termination of the U.S. quantitative easing program in October 2014, the Chinese stock market turbulence in 2015. After February 2016, the spillover effects between the European sectoral CDS markets and the natural gas declined gradually until the onset of the COVID-19 outbreak around the world in April 2020. Since the beginning of the pandemic, the indexes started to increase, which conforms to recent research about the interconnectedness among financial markets in the context of the COVID-19 pandemic (e.g., Bouri et al., 2021; Song et al., 2021; Farid et al., 2022). The upward trend in the CSI accelerated in end of 2021 when sign of uncontrolled inflation posed threat of monetary tightening in the world largest economies comprising the U.S. and major European countries, then threatening the global equity and commodity markets. After experiencing a correction at the beginning of 2022, the CSIs resumed their upward trend and attained unprecedented high levels in February 2022 when the Russian-Ukrainian war was launched.[23]

Turning to the CSIs computed at the upper and lower quantiles, we document three major findings. First, similar to the CSIs measured at the conditional mean of distributions, the

[21] See, Calice et al. (2013) for the chronology of the Eurozone debt crisis (2009-2011).
[22] During the mid-2014 and early 2015, the worldwide economy experienced dramatic decreases in oil price driven by supply factors, such as soaring U.S. shale oil production, receding geopolitical concerns, and shifts in OPEC policies.
[23] Specifically, the Russia-Ukraine war started on February 24, 2022.

CSIs at the lower and upper tails exhibit substantial fluctuations spanning between 32% and 98% throughout the sample period. Notably, while the CSIs measured at lower and upper quantiles exhibit high volatility over time, they consistently maintain higher levels than the those observed at the conditional mean of return distributions. This observation corroborates our earlier conclusion that investors' behavior in the gas market and sectoral CDSs is more influenced by extreme large shocks than by average shocks of the other market. Second, while there are differences in the short-term variations of the CSIs at the upper and lower tails, the evolutions of CSIs at upper and lower tails displays a relatively similar pattern over research period. Third, while previous studies document the asymmetric behavior in the connectedness among financial assets with the stronger connectedness recorded at the left tail, as documented in the work of Ang and Bekaert (2002), our study provides evidence that extreme positive and negative return shocks are spilled in a symmetrical way among the system.

Figure 3.7 Time-varying cross-market spillover index between natural gas and European CDS markets at different quantiles



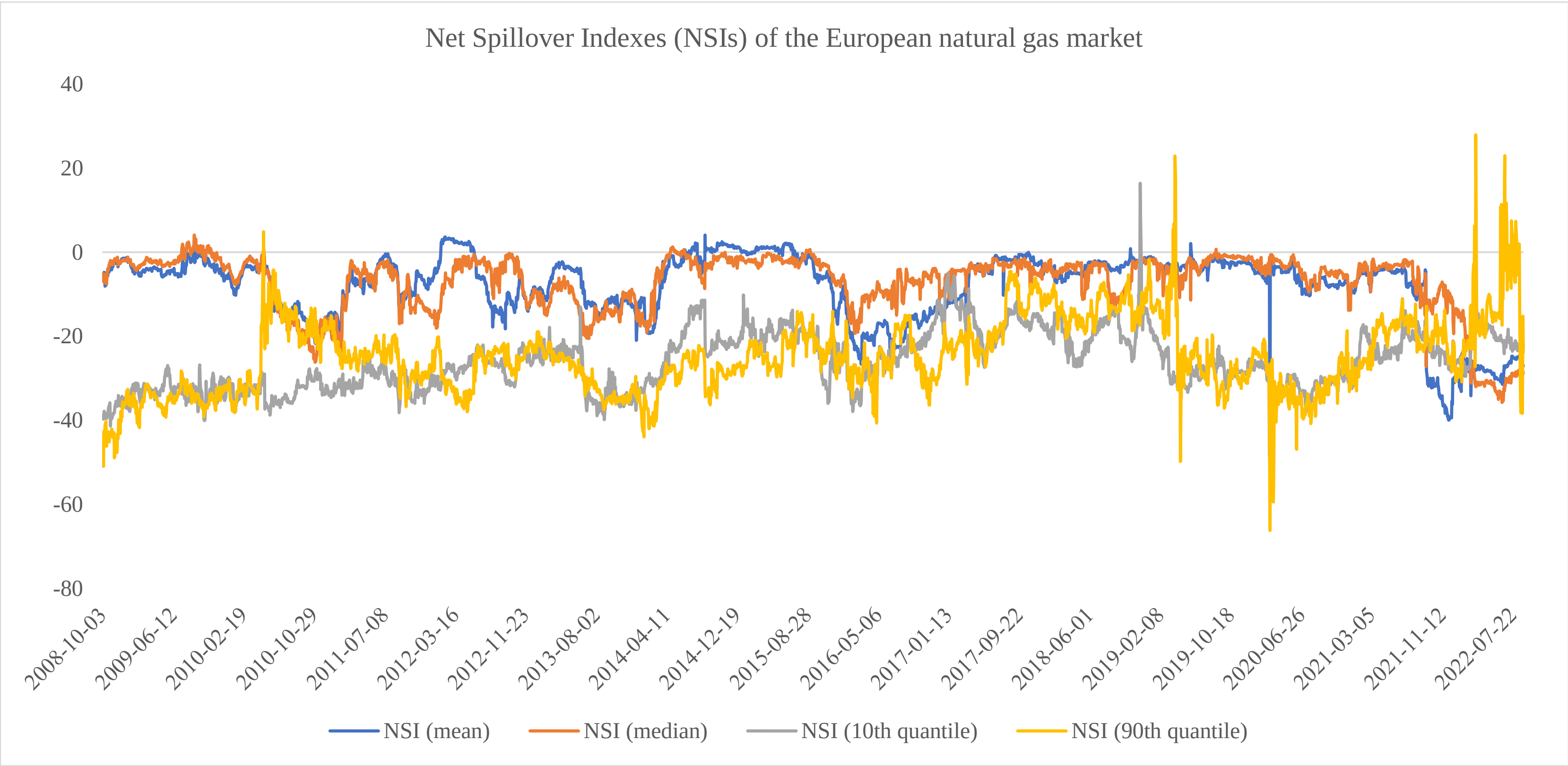
Note: This figure shows the time-varying cross-market spillover index (CSI) between the natural gas market and the CDS markets at the conditional mean, median, lower tail (10th quantile) and upper tail (90th quantile) of the return distributions using the rolling-window approach with the window length of 200 days (n=200) and the number of h-step forecast ahead of 10 (h=10).

3.5.5 Time-varying analyses of the net spillover index (NSI) and net pairwise spillover index (NPSI) of the gas market

Figure 3.8 displays the time-varying evolution of the European gas market's Net Spillover Index (NSI) calculated at both tails, at the conditional median, and at the conditional mean. Interestingly, we find that the NSIs were rarely above the zero line during the sample period. The dynamic NSIs of the gas market are often below zero regardless of the index measured at different quantiles or at the mean of return distributions, indicating that the European gas market is a consistent net absorber of both extreme and average shocks from the European sectoral CDS markets. These findings solidify our previous conclusion that the European gas market is consistently the net return shock absorber from sectoral CDSs regardless of different sizes of the shock.

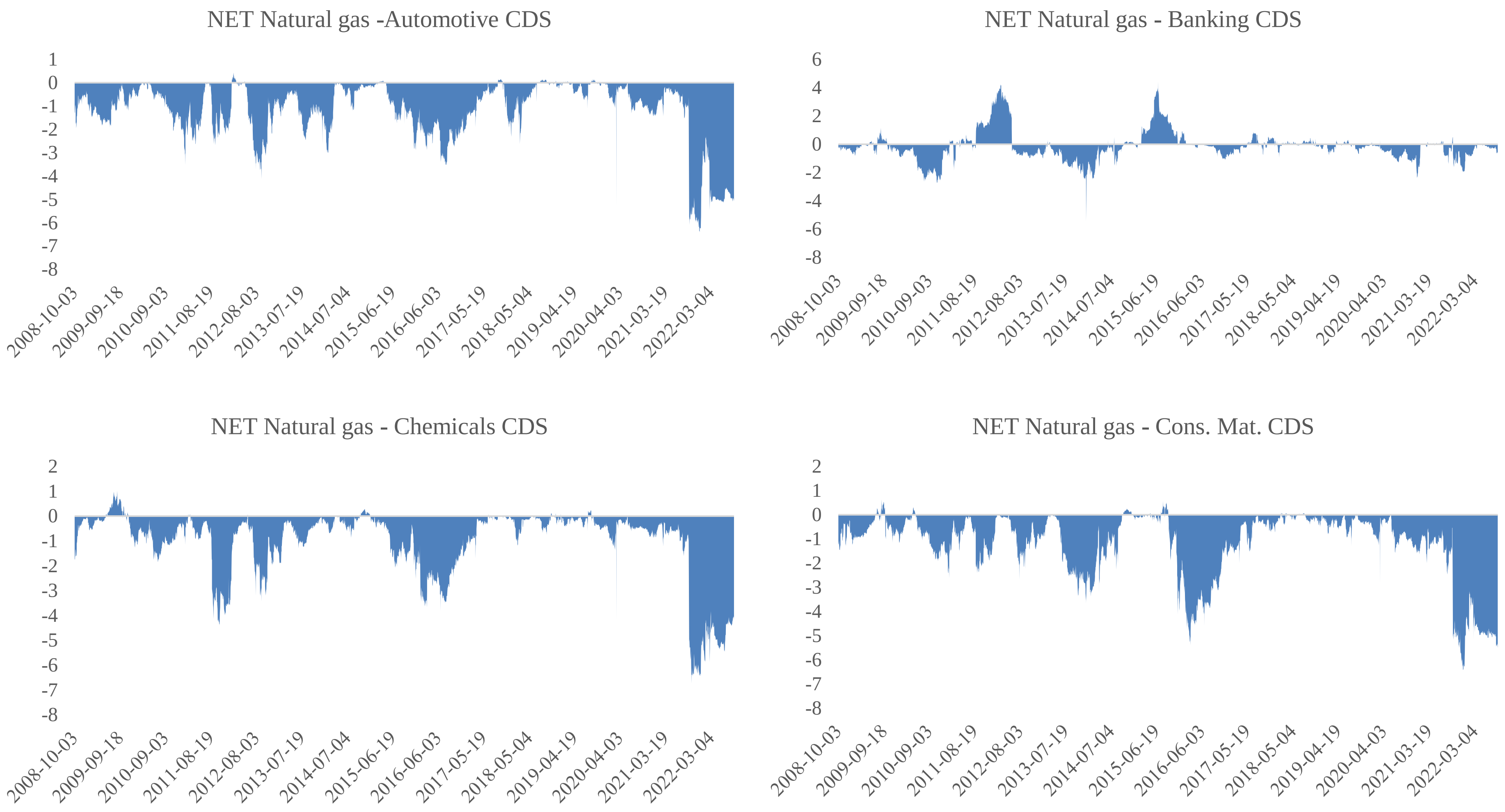
To get more insight into the time-varying role of the European gas market in the return relationship with European sectoral CDS markets, we display the dynamic net pairwise spillover indexes (NPSI) of the gas with each European sectoral CDS, computed at the conditional mean, in Figure 3.9. We detect that the NPSIs of natural gas are heterogeneous with different European sectoral CDSs. Specifically, with sectors including Automotive (AUT), Chemicals (CHM), Construction Materials (CM), Industrials (IND), Manufacturing (MAN), and Oil & Gas (OG), the NPSIs of natural gas are persistently negative for the sample period. This implies that the gas market acts as a shock absorber from these sectoral CDSs. On the contrary, the NPSIs of natural gas with Banking (BNK), Transportation (TRA), Utilities (UTL) was fluctuating between above and below the zero line, indicating that the role of the gas market switched between being net receiver and net transmitter of return shocks over time.

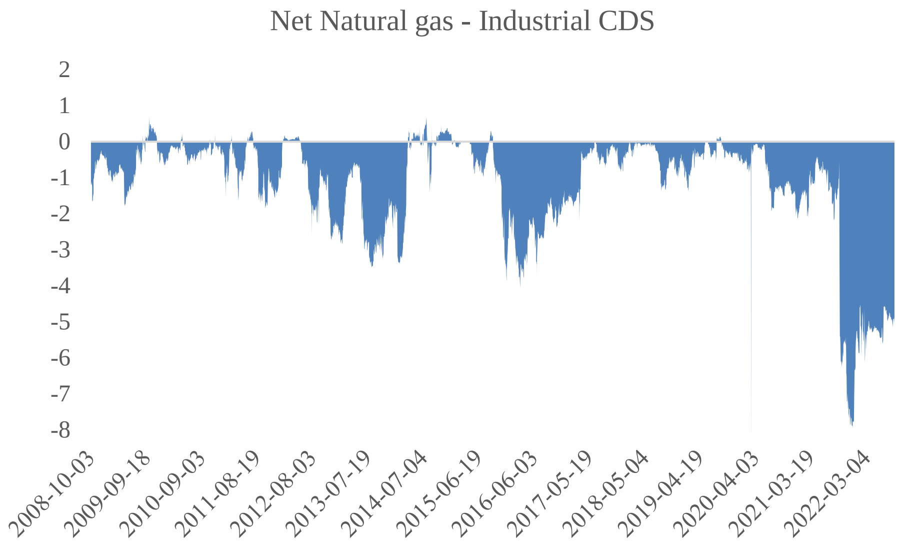
Figure 3.8 Time-varying net spillover indexes of the European natural gas market estimated at mean, at median and at different quantiles of return distributions

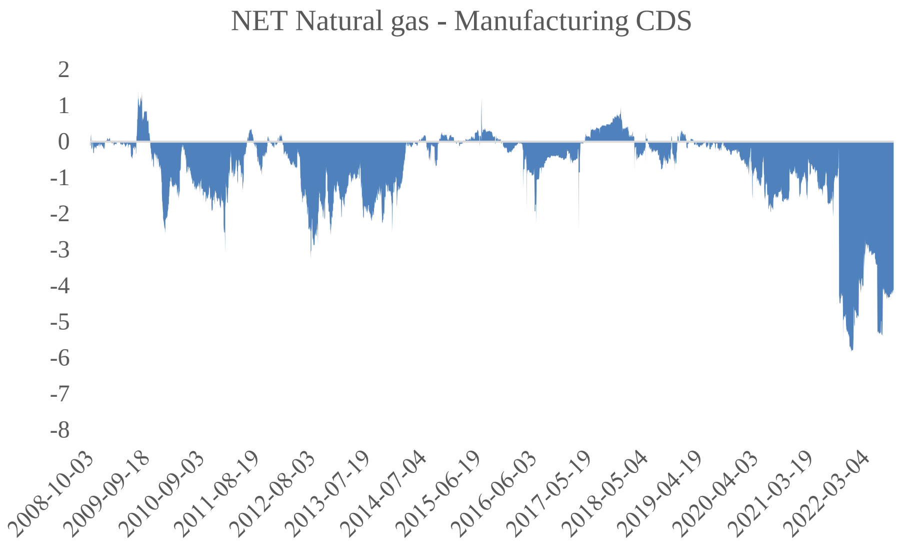


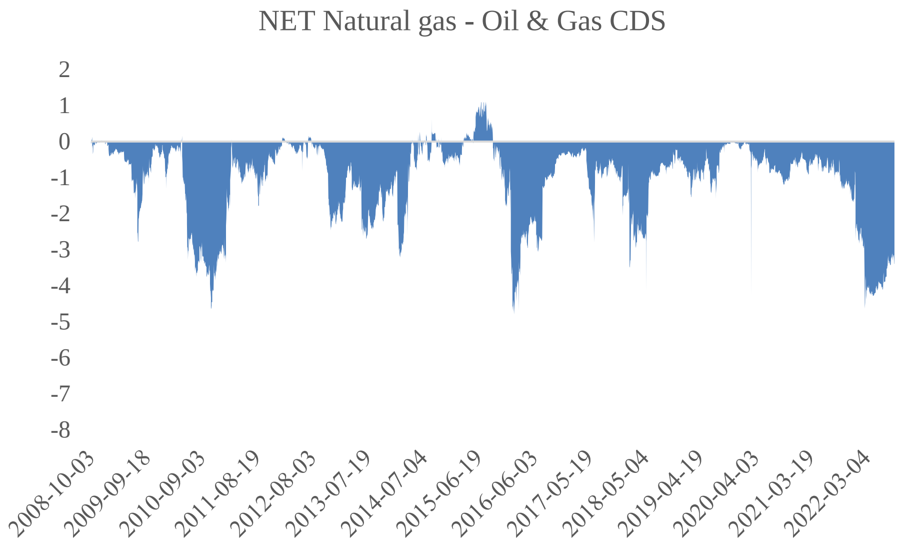
Note: This figure shows the time-varying net spillover indexes (NSIs) of the natural gas market at the conditional mean, median, lower tail (10th quantile) and upper tail (90th quantile) of the return distributions.

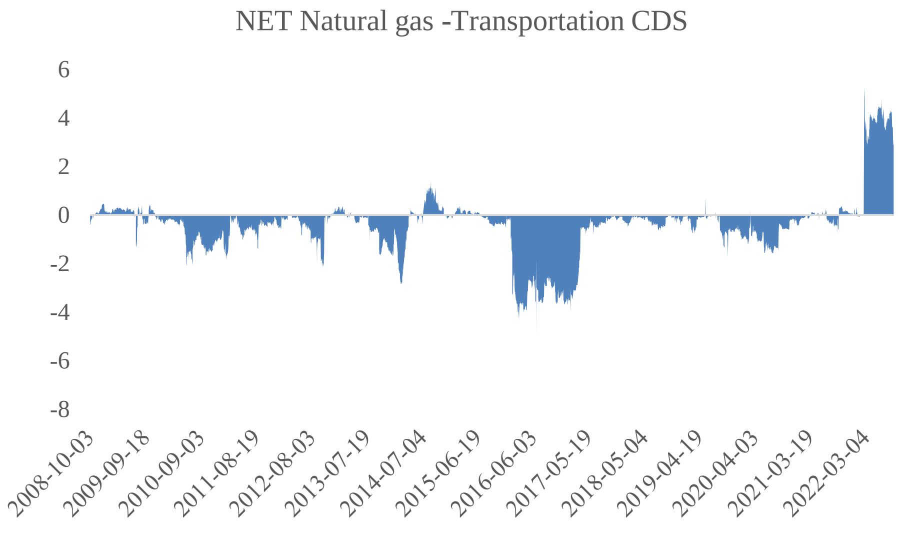
Figure 3.9 Time-varying net pairwise spillover indexes (NSPIs) of the natural gas with each European sectoral CDS at the mean of return distributions

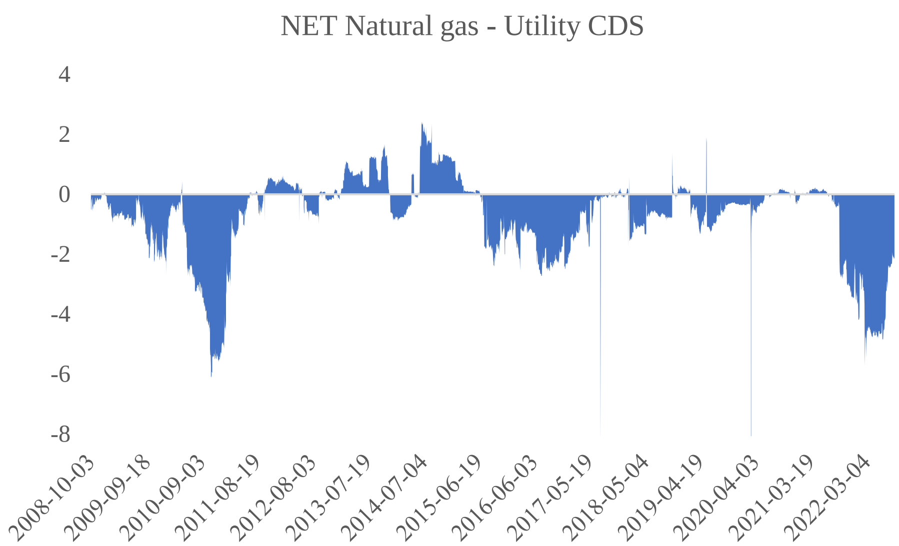



Net Natural gas - Industrial CDS
2
1
0
-1
-2
-3
-4
-5
-6
-7
-8
2008-10-03
2009-09-18
2010-09-03
2011-08-19
2012-08-03
2013-07-19
2014-07-04
2015-06-19
2016-06-03
2017-05-19
2018-05-04
2019-04-19
2020-04-03
2021-03-19
2022-03-04


NET Natural gas - Manufacturing CDS
2
1
0
-1
-2
-3
-4
-5
-6
-7
-8
2008-10-03
2009-09-18
2010-09-03
2011-08-19
2012-08-03
2013-07-19
2014-07-04
2015-06-19
2016-06-03
2017-05-19
2018-05-04
2019-04-19
2020-04-03
2021-03-19
2022-03-04


NET Natural gas - Oil & Gas CDS
2
1
0
-1
-2
-3
-4
-5
-6
-7
-8
2008-10-03
2009-09-18
2010-09-03
2011-08-19
2012-08-03
2013-07-19
2014-07-04
2015-06-19
2016-06-03
2017-05-19
2018-05-04
2019-04-19
2020-04-03
2021-03-19
2022-03-04


NET Natural gas -Transportation CDS
6
4
2
0
-2
-4
-6
-8
2008-10-03
2009-09-18
2010-09-03
2011-08-19
2012-08-03
2013-07-19
2014-07-04
2015-06-19
2016-06-03
2017-05-19
2018-05-04
2019-04-19
2020-04-03
2021-03-19
2022-03-04



Note: These graphs illustrate the time-varying net pair-wise spillover indexes of the natural gas market with each of nine European sectoral CDS markets at mean of return distribution.

3.6 Determinants of the cross-market connectedness (CSI) between European natural gas and sectoral CDS markets: The role of the Russian-Ukrainian war

In this section, we empirically test Hypothesis 3 by investigating the impact of the conflict between Russia and Ukraine on the interconnectedness between the European sectoral CDS markets and natural gas, controlling for several potential drivers of the gas-CDS nexus. In line with the research of Bouri et al. (2021), we utilize both daily and monthly regression models as certain explanatory variables relevant to the relationship are only available at the monthly frequency.

3.6.1 Daily regression model

Our previous results show that the cross-market spillover index (CSI) between the European natural gas and sectoral CDS markets is volatile exhibiting significant variations during research period. Notably, there are remarkable jumps in the CSIs at the beginning of 2022, which is coincided with the start of the Russian-Ukrainian war. So, in this subsection, we investigate the war effect on the CSI, after controlling for potential drivers of the index by estimating the following daily regression model,

$$CSI_t = \gamma_0 + \gamma_X X_t + \gamma_{WAR} WAR_t + \varepsilon_t \tag{3.20}$$

where CSI_t is the daily dynamic cross-market spillover index (CSI) estimated at the mean, upper, and lower tails; γ_0 denotes the intercept; and ε_t represents the error term. Vector X_t denotes a set of seven control variables, γ_X are the estimated corresponding autoregressive coefficients. WAR_t is our variable of interest, reflecting the Russian-Ukrainian war effect on the interconnectedness, which takes a value of 1 if the data is between February 24, 2022 and August 31, 2022 and 0 otherwise.

The selected control variables are all obtainable on a daily basis including: (1) the expected volatility for the Dow Jones EuroStoxx 50 index ($VSTOXX$);[24] (2) the European stock market return, proxied by the return of the STOXX Europe 50 Index (RET); (3) the Chicago Board Options Exchange Crude Oil ETF Volatility Index (OVX); (4) the European risk-free rate, proxied by the Europe Overnight Indexed Swap rates (RFR) (Dubecq et al., 2016; Pinter and Boissel, 2016); (5) the geopolitical risk index (*GPR*) introduced by Caldra and Iacoviello (2022); (6) a binary variable for winter period, taking a value of 1 if the data is in winter time (i.e., December, January, and February) and 0 otherwise (*WINTER*); (7) a dummy variable (*COVID*) representing the period of European economic recession induced by the COVID-19 pandemic, which is assigned a value of 1 if the date is between January 01, 2020 and June 30, 2020,[25] and 0 otherwise.

Note, all selected explanatory variables are deemed to be relevant in explaining the price volatility and the connectedness between the European gas market and sectoral CDS markets. Among seven regressors, the first two are stock market indicators, which are frequently used to explain the volatility of CDS spreads. First, following Berndt et al. (2005), Tang and Yan (2010), we use $VSTOXX$ as a proxy for the business environment in Europe. According to Annaert et al. (2013), the stronger the stock volatility, the higher the uncertainty about the economic outlook, leads to more fluctuations in the CDS market. Besides, the stock market's high volatility is considered as an indicator of investor fear gauge, which is also factored in the gas prices (Geng et al., 2021). Further, numerous studies, including Ji et al., (2019); Bouri et al., (2021) and Liew et al. (2022) have extensively documented how stock market volatility amplifies the interconnectedness of global assets. Second, we follow Collin-Durfresn et al. (2001), Duffie et al. (2007), and Ericsson et al. (2009) by including the European

[24] Dow Jones Euro STOXX 50 is a stock index of 50 largest companies in Europe based on market capitalization.
[25] The first half of 2020 recorded the sharp recession in Europe due to the outbreak of the pandemic with the decline in GDP in Q1-2020 and Q2-2020 of -3.4% and -11.5%, respectively. Source: https://ec.europa.eu/eurostat/databrowser/view/teina011/default/table?lang=en

stock index return (RET) as control variable. According to Annaert et al. (2013), this variable allows us to capture the fluctuations in the general business environment, which could exert significant impacts on the CDS spreads, hence driving their volatility.

The third control variable (OVX) describes the market expectations regarding the volatility of the crude oil market. An increase in OVX indicates an anticipated rise in crude oil volatility. Previous research by Ding (2021) demonstrates a significant intercorrelation between OVX and natural gas volatility, with mixed results of negative and positive correlation. This evidence implies that OVX can be used to capture the expected fluctuations in the gas market.

As the fourth control variable, we employ Risk-Free Rate (RFR) as a proxy for Europe's monetary policy stance and the trend of interest rate in the Union. According to Wang (2020), a low interest rate environment can potentially contribute to financial instability by amplifying the interconnections between global stock markets and energy markets. Importantly, Duffee (1998), Bharath and Shumway (2008), Collin-Dufresn et al. (2001), and Das et al. (2009) document that fluctuations in default risk are driven by changes in interest rates. Specifically, periods of low interest rates are often associated with economic recession, which subsequently widen the credit risk (e.g., CDS spreads) in the economy.

The fifth control variable in our model is GPR proposed by Caldara and Iacoviello (2022) to gauge global geopolitical risk. The GPR is positively correlated with the connectedness across commodity markets, as documented in the research of Gong and Xu (2021)

In addition, our model incorporates two binary variables in Eq. (3.20). The first one, $WINTER$, takes into consideration the seasonality of the volatility in the European gas market, as noted by Martínez and Torró (2015). Particularly, during the winter times, the European gas prices are more volatile compared to the rest of the year. Consequently, this seasonality may contribute to a stronger return transmission between the sectoral CDSs and the gas market. Finally, the second binary variable, $COVID$, addresses the intensifying impact of the COVID-19 pandemic on the interconnectedness of global financial assets, as emphasized in the work of Farid et al., 2022 and Bouri et al., 2021.

We employ the Ordinary Least Squares (OLS) procedure to estimate Eq. (3.20) and compute the t-statistics of estimated coefficients applying the method of Newey and West's (1987) to ensure robust standard errors. The corresponding results are presented in Table 3.6. First, the values of adjusted R-squared in all model specifications stand at relatively high level, spanning from 31.15% for the CSI at the upper quantiles to 61.98% for the CSI at the conditional mean of the distributions. Also, the F-statistics of all model specifications demonstrates strong statistical significance, confirming that the chosen explanatory variables effectively explain the fluctuations of the CSI. Second, among seven control variables, only RFR and OVX exert a statistically significant effect with consistent sign on the CSIs at both tails and mean of return distributions. Particularly, our results show that the Cross Spillover Indexes (CSIs) are positively correlated with OVX regardless of the index measured at the mean or the tails of return distributions. This finding suggests that the expected increases in the energy market volatility intensifies the return shock transmission among the European gas and sectoral CDS markets. Meanwhile, the negative coefficients of RFR in all model specifications indicate that low-interest rate environment consistently increases the CSIs at all selected quantiles and mean. In Columns (1), (2), and (3), the estimated parameters of RFR are -0.551, -1.88 and -2.94, implying that a 1% reduction in the European risk-free rate will result in 0.551%, 1.88%, and 2.95% increase in the CSI measured at the mean, lower, and upper quantiles, respectively. Our findings conform to the research of Wang (2020), who reveals that a decrease in interest rates magnifies the interconnectedness between the stock market and the energy commodity market.

Third, the effects of the remaining control variables on the CSI vary depending on this index measured at mean, lower or upper quantiles. This highlights the necessity to examine the determinants of quantile-based connectedness. We find that the CSI measured at the conditional mean of return distributions is positively affected by the implied volatility of European stock market ($VSTOXX$), whereas, there are negative effects of European stock market's volatility on the CSIs at both tails. Additionally, the proxy of stock market return (RET) exhibits a negative correlation with only the CSI at the lower quantile, suggesting that the bearishness of the stock market heightens the spillover effect of extremely negative shocks between the European sectoral CDS markets and the gas market. Further, the effects of geopolitical risk (GPR) are also different for mean-based connectedness and quantile connectedness. We find that the measure of global geopolitical risk (GPR) positively and significantly influence the CSI at the extreme tails. By contrast, its impacts on the CSI at the normal market condition is insignificant as evidenced by the coefficients of GPR in Column (1).

In addition, the effects of two control binary variables, $WINTER$ and $COVID$, are also varied across model specifications, conditional on the CSI proxy used. First, we find that under normal market conditions (i.e., Column (1)), the interconnectedness between the European gas and sectoral CDS market strengthens in winter months. This is explainable as Martínez and Torró (2015) find that the European gas market exhibits stronger return volatility during the winter. By contrast, under extreme market conditions, the winter time significantly reduces the positive shocks transmission across the sample markets, whereas it does not affect negative shock transmission among the markets. In a similar vein, the coefficients of $COVID$ indicate that the influence of the COVID-19 pandemic only statistically significant for the CSI measured at the upper tail. Particularly, its coefficient estimate is positive, suggesting that the pandemic increases the extreme positive shock transmission between the gas market and the sectoral CDSs. The increase of the return spillover between European sectoral CDS markets and natural gas during the COVID-19 pandemic is consistent with previous studies investigating the pandemic effect on financial risk interconnectedness. For example, Farid et al. (2022) document that the COVID-19 pandemic intensifies the transmission of extreme large shocks among energy commodities, agriculture commodities, and metals.

Most importantly, table 3.6 shows a unanimous increasing effect of the Russian-Ukrainian war on the return shock transmission between the European natural gas and sectoral CDS markets at mean and at both tails of distributions. Specifically, the coefficient estimates of WAR are positive and statistically significant at the 99% confidence level for all cases. Regarding the magnitude of the effects, the coefficient estimate of WAR is the largest among those of explanatory variables in each model specification. Specifically, the estimated parameters of WAR are significantly positive at 25.00, 11.78, and 17.03 in Columns (1), (2), and (3), respectively. These figures imply that after controlling for potential explanatory variables, the CSIs at the mean, upper, and lower tails have increased by 25%, 17.03%, and 11.78% during the Russian-Ukrainian war. These large numbers emphasize the sizeable impacts of the war on the return shock spillover between natural gas and CDS markets in Europe. Our finding of the magnifying effect of the war on the return connectedness is consistent with recent evidence from Umar et al. (2022), Wang (2020), and Adekoya et al. (2022).

Table 3.6 Drivers of the return connectedness using daily regression model

Dep. Variables	CSI (mean)	CSI (lower tail)	CSI (upper tail)
	(1)	(2)	(3)
VSTOXX	0.080***	-0.179***	-0.051**
	(5.73)	(-12.34)	(-1.97)
RET	23.01	-53.81***	-15.23
	(1.63)	(-3.56)	(-0.57)
OVX	0.057***	0.04***	0.143***
	(7.16)	(4.94)	(9.44)
RFR	-0.551***	-1.88***	-2.94***
	(-3.52)	(-11.02)	(-11.92)
GPR	0.0004	0.024***	0.016***
	(0.21)	(12.20)	(5.43)
WINTER	1.353***	0.256	-1.22***
	(9.32)	(1.47)	(-4.94)
COVID	0.875	1.414	5.67***
	(1.23)	(1.36)	(2.90)
WAR	25.00***	11.78***	17.03***
	(97.27)	(38.62)	(31.06)
Intercept	5.60***	58.74***	61.09***
	(16.97)	(193.75)	(117.89)
N. Obs.	3,630	3,630	3,630
Adj. R-squared	0.6198	0.3175	0.3115
F-statistics	740.16***	211.94***	206.14***

Note: This table presents the estimated coefficients and their *t*-statistics using daily regression model specified in Eq. (3.20), where *CSI* is computed based on a window length of 200 days and a 10-step forecast horizon. The *CSI* is defined in Eq. (3.19). The Eq. (3.20) is estimated using OLS regression with *t*-statistics are adjusted for heteroskedasticity and autocorrelation following Newey-West's (1987) standard errors. *VSTOXX* is the expected volatility for the Dow Jones EuroStoxx 50 index; *RET* is proxy for the return of STOXX Europe 50 index; *OVX* is the Chicago Board Options Exchange Crude Oil ETF Volatility index; *RFR* is the European risk-free rate; *GPR* is the geopolitical risk index. *WINTER* is a dummy variable for winter months, which take a value of 1 if the data is in December, January, and February and 0 otherwise. *COVID* is the dummy variable for the COVID-19 pandemic-induce recession period in Europe, which take value of 1 if the data is between January 01, 2020 and June 30, 2020, and 0 otherwise. *WAR* is the binary variable for the war effect, which is equal 1 if the data is between February 24, 2022 and August 31, 2022, and 0 otherwise. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively.

3.6.2 Monthly regression model

Besides the daily regression model, we further investigate the Russian-Ukrainian war effect on the CSIs using monthly data. This approach is motivated by the fact that some certain key drivers of the CSIs (i.e., macroeconomic and uncertainty variables) are only available on a monthly frequency. By examining the drivers of the natural gas – sectoral CDS nexus based on monthly regression model, we aim to provide an additional robustness check. So, we estimate the monthly regression model as follows,

$$CSI_k = \delta_0 + \delta_X^\top X_k + \delta_Y^\top Y_k + \delta_{WAR} WAR_k + \epsilon_k \tag{3.21}$$

where variables CSI, X, and WAR are defined as the same in Eq. (3.20), except that they are monthly variables; δ_0 is the intercept; and ϵ_k is the error term. Y is the vector of three newly-added monthly control variables, including: European Economic Policy Uncertainty index ($EEPU$) from Baker et al. (2016); the term spread ($TERMSPR$) measured as the difference between Euro-area 10-year and 5-year government benchmark bond yields; and the default spread ($DFSPR$), proxied by the spread between ICE BofA Euro High Yield Index Effective Yield and Euro-area 10-year government benchmark bond yield.

Among the three new control variables, $EEPU$ considers the potential effect of economic policy uncertainty (EPU) in Europe on the interconnectedness between the gas and sectoral CDS markets. Baker et al. (2016) construct $EEPU$ for Europe by counting and normalizing the number of articles containing the terms "uncertain" or "uncertainty", "economic" or "economy", and on or more policy-relevant terms in ten newspapers of five major European countries (i.e., France, Germany, Italy, Spain, and the United Kingdom).[26] Previous studies, such as Geng et al. (2021), and Scarcioffolo and Etienne (2021), find that EPU is interrelated with the natural gas market's volatility. In addition, EPU is also a driver of

[26] These newspapers include Le Monde and Le Figaro for France, Handelsblatt and Frankfurter Allgemeine Zeitung for Germany, Corriere Della Sera and La Stampa for Italy, El Mundo and El Pais for Spain, and The Times of London and Financial Times for the United Kingdom.

CDS spreads' volatility (Wang et al., 2019) and CDS spreads' correlation (Shahzad et al., 2018; and Yfanti et al., 2023). Further, the existing literature has also documented the destabilizing effect of EPU by intensifying the contagion risk among financial assets, as evidenced in the studies of Youssef et al. (2021) and Adekoya et al. (2021).

The second additional control variable, $TERMSPR$, measures the slope of the term structure, which is extensively accepted as a predictive indicator of business cycle (Estrella and Mishkin, 1997). A higher slope predicts improved economic environment and lower credit spreads (Annaert et al., 2013). Further, Karali and Ramirez (2014) find that energy markets experience higher volatility when the term spread contracts. In addition, Saeed et al. (2021) and Bouri et al. (2021) document that contracting term spread is associated with heightened risk spillovers in commodity and energy markets. The last added control variable, $DFSPR$, is an important indicator of financial market stability, reflecting the overall credit risk level (Benkert, 2004). As such, increasing default spreads imply more strained credit market, more fluctuations in credit spreads, and higher risk aversion in the marketplace.

We estimate Eq. (3.21) by OLS procedure and report the corresponding results in Table 3.7. First, compared to the results of daily regression, there are some changes in the sign and statistical significance of old control variables at the monthly frequency. For instance, the implied volatility of the European stock market ($VSTOXX$) only positively influence the CSI at the mean of distributions, but not the CSIs at both tails. Also, the stock market return (RET) becomes insignificant in explaining monthly CSIs regardless of connectedness measured at the mean or tails. Additionally, the OVX does not contribute to explaining the variations in CSI at the lower tail whereas the RFR does not exert significant effect on CSI at the mean of distributions.

Second, we find that the coefficient estimates of newly added control variables are statistically significant in at least one model specification in Table 3.7. This observation lends support to our utilization of the monthly regression model in addition to the daily model. Specifically, in Table 3.7, we find that the term spread $(TERMSPR)$ is negatively correlated with the CSIs at the upper and lower quantiles. This finding implies that when the yield curve is flattening, the extreme return shock transmission between European natural gas and sectoral CDSs will be more severe. This relationship is explainable as narrowing term spread is widely seen as a leading indicator to predict economic downturn or recession. Further, the default spread $(DFSPR)$ is shown in Column (2) to positively affect the interconnectedness of extreme negative return shocks (i.e., CSI at the lower tail). Besides, the coefficient estimates of $EEPU$ suggest that the European economic policy uncertainty is significant in intensifying the CSIs at the mean and upper tail.

Lastly and most importantly, the results of Eq. (3.21) continue to underline the crucial role of the Russian-Ukrainian war on the interconnectedness between the European sectoral CDS markets and the gas market. In all three model specifications (1), (2), and (3) of Table 3.7, the coefficient estimates of WAR are positive and highly statistically significant, standing at 24.00, 10.29, and 15.20, respectively. These figures are quite close to the daily estimations in Table 3.6 and indicates that on a monthly basis, the CSIs at the mean, lower, and upper quantiles during the war period are 24%, 10.29%, and 15.2% higher than during the pre-war period, respectively. In summary, the monthly regression results corroborate our previous findings derived from daily regression model that the war effect significantly increases the return shock spillover between the European gas and sectoral CDS markets.

Table 3.7 Drivers of return connectedness using monthly regression model

Dep. Variables	CSI (mean)	CSI (lower tail)	CSI (upper tail)
	(1)	(2)	(3)
VSTOXX	0.141**	-0.137	0.103
	(2.05)	(-1.38)	(0.69)
RET	-11.05	-31.89	0.536
	(-0.39)	(-0.80)	(0.01)
OVX	0.074***	0.012	0.237***
	(2.68)	(0.23)	(4.44)
RFR	1.44	-2.29***	-2.78***
	(1.47)	(-3.12)	(-2.20)
TERMSPR	-0.11	-0.477**	-0.384*
	(-0.90)	(-2.51)	(-1.78)
DFSPR	0.192	0.341**	0.096
	(1.26)	(2.44)	(0.41)
EEPU	0.010**	-0.002	0.017**
	(1.99)	(-0.24)	(1.95)
GPR	-0.011*	0.027***	0.016
	(-1.73)	(3.01)	(1.48)
WINTER	1.659**	0.422	-0.669
	(2.50)	(0.50)	(-0.57)
COVID	3.09	-2.97	13.60**
	(0.98)	(-0.53)	(2.37)
WAR	24.00***	10.29***	15.20***
	(17.38)	(5.32)	(6.25)
Intercept	5.11***	59.12***	58.08***
	(3.52)	(27.38)	(22.61)
N. Obs.	181	181	181
Adj. R-squared	0.6236	0.2903	0.2919
F-statistics	25.55***	7.06***	7.11***

Note: This table presents the estimated coefficients and their *t*-statistics using monthly regression model specified in Eq. (3.21), where *CSI* is computed based on a window length of 200 days and a 10-step forecast horizon. The *CSI* is defined in Eq. (3.19). The Eq. (3.21) is estimated using OLS regression with *t*-statistics are adjusted for heteroskedasticity and autocorrelation following Newey-West's (1987) standard errors. *VSTOXX* is the expected volatility for the Dow Jones EuroStoxx 50 index; *RET* is proxy for the return of STOXX Europe 50 index; *OVX* is the Chicago Board Options Exchange Crude Oil ETF Volatility index; *RFR* is the European risk-free rate; *GPR* is the geopolitical risk index. *WINTER* is a dummy variable for winter months, which take a value of 1 if the data is in December, January, and February and 0 otherwise. *COVID* is the dummy variable for the COVID-19 pandemic-induce recession period in Europe, which take value of 1 if the data is between January 01, 2020 and June 30, 2020, and 0 otherwise. *WAR* is the binary variable for the war effect, which is equal 1 if the data is between February 24, 2022 and August 31, 2022, and 0 otherwise. Three monthly exogenous variables added includes: EEPU is the European Economic Policy Uncertainty index; TERMSPR is the difference between Euro area 10-year and 5-year government benchmark bond yields; DFSPR is the spread between ICE BofA Euro High Yield Index Effective Yield and Euro area 10-year government bond yield. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively.

3.7 Robustness checks

In this section, we provide the summary of several robustness checks conducted to affirm the reliability of our key empirical findings presented in the previous sections. First, one might be concerned that our selection of the number of days (n) in the rolling-window approach and the number of h-step forecast ahead may influence the time-varying results of connectedness. To eradicate this concern, we re-estimate the time-varying cross-market spillover index (CSI) measured at the conditional mean and at different quantiles of distributions using 250-day rolling window and 20-step forecast ahead. Appendix A.3.1 reports the overtime evolution of the CSI. We can observe the similarity in the evolvement of the CSIs in comparison with our main findings in Figure 3.8. Thereby, our key finding of dynamic CSIs between European natural gas and sectoral CDS markets is robust to different choices of h-step forecast ahead and the window length in rolling method.

Second, another concern that our proxy for the European natural gas market, EGIX, might not be a representative of the whole gas market in Europe, which is fragmented with many natural gas hubs. To rule out this possibility, Appendix A.3.2 plots the daily dynamics of EGIX together with the natural gas price series of two other major natural gas hubs in Europe, namely, the Title Transfer Facility (TTF) in Netherlands and the Punto di Scambio Virtuale (PSV) in Italy. It is observable that EGIX and the two other natural gas proxies fluctuated almost identically during the sample period with very high correlation.[27] This observation implies that our key empirical results are not dependent on the choice of natural gas proxy in Europe.

In exercising a final robustness check, we adopt the Generalized Feasible Least Squares (GFLS) regression to re-estimate the Russian-Ukrainian war effect on the CSIs at the mean and lower/ upper quantiles, as specified by Eqs. (3.20) and (3.21).[28] To conserve space, we report the new regression results in Appendices A.3.3 and A.3.4, respectively. As reported in the appendices, for most control variables, there are no significant changes in the coefficient estimates and their statistical significance in comparison with our main results in Tables 3.5 and 3.6. More importantly, the coefficient estimates of WAR are consistently positive and highly significant across alternative model specifications regardless of estimation methodology. This robustness test corroborates our benchmark result of the magnifying effect of the war on the return shock connectedness between the European sectoral CDS markets and the gas market.

3.8 Conclusion

Russia's unprovoked war against Ukraine has devastated Russia's relationship with Europe. Russia has decided to suspend gas supply to EU markets in response to economic sanctions imposed by western economies on Russia. This action of Russia has raised concerns about the energy insecurity in Europe and further driven up the energy prices in European economies. The disruption in supply of gas, which is a primary raw material for European industries, has caused adverse negative effect on European corporate debt market. This motivates us to scrutinize how the European sectoral corporate credit default swap (CDS)

[27] The correlation coefficient between EGIX and TTF gas prices is 0.9982, while the correlation between EGIX and PSV gas prices is 0.9962.
[28] The GFLS approach addresses the issue of heteroscedasticity in a regression model when dependent variable of the model, CSI in this case, is estimated based on another model (Lewis and Linzer, 2005).

markets react to the shocks in the gas market and vice versa, and how this relationship changes during the recent energy crisis. We contemplate two channel to explain the causal relationship between the natural gas and CDS markets, and the sign of this relationship should depend on the direction of the causality.

To this end, we first apply the Granger causality test to investigate the significance and the sign of the causal relationship between these markets. We find that shocks of the natural gas market significantly cause positive effect on European sectoral CDS markets, highlighting the positive causal link from the energy commodity to the credit market. By contrast, the shocks of CDS markets negatively Granger cause the shocks to natural gas market.

We then adopt the generalized connectedness measures of Diebold and Yilmaz (2012) and quantile-based connectedness framework of Ando et al. (2022) to gauge the magnitude and direction of the return spillover effects between these markets under normal and extreme market conditions.

Our results of return spillovers can be summarized as follows. First, our static connectedness results show that the cross-market spillover effect between European natural gas and sectoral CDS markets is moderate at normal market condition, however this index substantially increases at extreme positive/ negative market conditions. The behaviors of cross-market spillover index measured at the right and left tails exhibit symmetrical patterns, implying the return connectedness between sectoral CDS markets and natural gas evolves similarly when there are extreme positive or negative return shocks.

Second, the gas market is consistently a net return shock absorber from sectoral CDS markets regardless of the connectedness measured at the conditional mean or tails of return distributions. Further, we document that during the extreme market condition, the natural gas market become the primary shock absorber in the system. The role of sectoral CDS markets varies between being net return shock receiver and net return shock transmitter.

Third, our time-varying analyses of return connectedness unveil that the cross-market spillover index is highly volatile over sample period regardless of this index measured at the mean or at the tails of distributions. The increases in the time-varying cross-market connectedness are all explained by various financial uncertainty events.

Finally, our study yield evidence of the magnifying effect of the Russian-Ukrainian war on the shock transmission between European gas and sectoral CDS returns regardless of average shocks or extreme shocks. This conclusion is robust to different regression models applied to estimate the war effect. Our analyses of the determinants of return connectedness also confirm that cross-market return linkage between natural gas and sectoral CDSs is significantly positively correlated with the oil market's volatility (*OVX*) while negatively correlated with the interest rate. Other factors, such as the stock market return, the geopolitical risk, the effect of winter times and the COVID-19 pandemic, are heterogeneous depending on the connectedness index measured at mean, lower or upper tails.

A thorough understanding of the nature and the property of financial market linkage across different quantiles has crucial implications for not only portfolio risk management, asset allocation but also for stabilizing-policy formulation in response to systemic crises. First, we document that there is positive causal effect running from natural gas to CDS markets while the opposite direction is negative causality. Investors in natural gas and CDS markets should bear in mind of this distinguished feature of the causal relationship and take the type of shocks into consideration when deciding their position in these markets. Second, our finding that extreme return shocks propagate much stronger between the European CDS markets and the natural gas market compared to average shocks highlights the necessity to monitor the system's tail risk propagation when investing in natural gas and CDS markets under extreme negative/ positive market conditions. To better manage their portfolio risk and stability, investors in gas and CDS markets should adjust their trading strategies following the information of extreme fluctuations in these markets. Regarding policy-decision making, as our study suggests that extreme shocks to the system affect the return linkage of the system in different way compared to average shocks, the policymakers should not limit their analyses within the average shock propagation, but should go beyond to capture the spillover effect of extreme systemic shocks to make informed stabilizing policy. Most importantly, our study timely informs investors and policymakers about the intensifying effect of the on-going Russian-Ukrainian war on the return shock spillover across natural gas and credit markets regardless of average shocks or extreme shocks. As the war might endure with no expected ending in near future, this finding has important implication for investors and policymakers to take into account the destabilizing effects of the war in order to manage their portfolio risk and maintain financial stability in the Eurozone.

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.

Student name:	Thao Thac Thanh Nguyen
Name and title of main supervisor:	Professor Xiaoming Li
In which chapter is the manuscript/published work?	Chapter 3
What percentage of the manuscript/published work was contributed by the student?	70%

Describe the contribution that the student has made to the manuscript/published work:
Thao is the main author of this paper, and while her superviors have made substantial contributions, reflected through co-authorship, the paper is essentially the work of Thao. She has contributed to conceptualization, methodology applied, data circulation, software, original draft writing, and revisions. The supervisors contributed to the paper by providing critical comments and insightful advices on the research subject, and revising the paper.

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CHAPTER FOUR

Does the U.S. export inflation? Evidence from the dynamic inflation spillover between the U.S. and EAGLEs

Chapter 4 presents the third essay of the thesis. Employing the recently developed time-varying parameter vector autoregression (TVP-VAR)-based connectedness approach, this essay investigates the dynamic inflation spillover between the U.S. and the nine emerging and growth-leading economies (EAGLEs). The results of inflation spillover analysis reveal whether the inflation spillover between emerging markets and the U.S. depends on the emerging countries' economic characteristics. Further, the study also examines the changes of spillover behavior between the sample economies under extremely inflationary conditions using quantile-based connectedness measures. Finally, an investigation of the drivers of inflation spillovers among the system is conducted.

4.1 Introduction

Rising inflation rate has been a global concern over the last two years. As the globalization increases interconnectedness of the world economies, global factors like the stimulus package in response to the COVID-19 pandemic, the pandemic-induced global supply disruptions, and the rising energy prices triggered by Russia's invasion of Ukraine have led to an increase in domestic inflation rates across the globe in 2022. In advanced economies, inflation rate peaked at 9.4% in December 2022, the highest level recorded in several decades.[29] However, the inflationary challenge is not limited to developed countries alone; it is also posing a significant threat to emerging and developing countries. In fact, the International Monetary Fund projects an average inflation rate of 9.9% for emerging countries in 2022. These countries are feeling the pinch more acutely due to their lower average household income, a larger portion

[29] See, Consumer Prices, OECD-Updated: 7 February 2-23.

of household budgets allocated to food and energy consumption, and less flexibility to adjust their fiscal and monetary policies.[30]

Central banks worldwide have a critical mandate: to maintain domestic price stability by controlling inflation at a target rate. However, the struggle against hyperinflation rates in 2022 has left many wondering why central bank actions have not been sufficient. One potential culprit for this could be the international inflation spillover effect. If the spillover effect of international inflation on domestic consumer prices is significant, national central banks may not have complete control over domestic inflation rates. Thus, a thorough examination of international inflation spillover is essential for monetary authorities to make informed policy decisions that can absorb the spillover effect and monitor domestic inflation rates. Despite the fact that emerging markets are more vulnerable to global inflationary pressures,[31] previous studies on the inflation spillovers mainly focus on developed economies (e.g., Jordan, 2016; Tiwari et al., 2019; Wen et al., 2021; Elsayed et al. 2021; Pham and Sala, 2022). Our study aims to fill this gap by investigating the dynamics and the role of the U.S. in inflation shock spillover between the U.S. and emerging markets. We also explore how the inflation spillover effect changes in extreme inflationary periods. As the dominant reserve currency in central banks of emerging countries for many decades has been the U.S. dollar, [32] high inflation and monetary policy decisions in the U.S. should have significant interactions with emerging countries' domestic inflation rates. Our study sheds light on these crucial issues and provides valuable insights for policymakers worldwide.

[30] See, https://www.weforum.org/agenda/2022/02/explainer-how-is-inflation-hitting-low-income-households-in-developing-nations
[31] See Figure 4.1 for the display of the higher inflation rates in emerging markets compared to the developed markets.
[32] Data comprised from 149 reporting countries provided by the International Monetary Fund shows that as in the 2nd quarter of 2022, the U.S. dollar accounted for 59% of the central bank reserves. See, https://crsreports.congress.gov/product/pdf/IF/IF11707

To this end, we adopt the time-varying parameter vector autoregressive (TVP-VAR)-based connectedness framework introduced by Antonakakis et al. (2020) and quantile-based connectedness method by Ando et al. (2022) to investigate the inflation spillover effect between the U.S. and EAGLE countries at both conditional mean and tails of inflation distributions. The TVP-VAR-based connectedness method derives the connectedness measures of Diebold and Yilmaz (2012, 2014) within the underlying TVP-VAR model. Since the estimation of TVP-VAR circumvents the problem of loss of valuable observation, it is appropriate for short sample data such as inflation data.[33] This advantage of TVP-VAR model motivates us to measure connectedness index based on the baseline framework TVP-VAR. Our sample emerging markets include Brazil, China, India, Indonesia, South Korea, Mexico, Russia, Turkey, and Taiwan (the so-called EAGLE group). On one hand, these emerging countries are major players in the world economy and their contributions to global GDP will soon bypass the contributions of G7 countries.[34] Also, except Taiwan, all these countries belong to G-20, implying that they would meet regularly to coordinate their economic and financial policies. On the other hand, the U.S. maintains the strong trade linkage with the emerging markets of EAGLE group. This is reflected in the ratio of imports from EAGLE to the total imports of the U.S., which is around 44.82%.[35] Meanwhile, the ratio of exports to the U.S makes up an average of 4.73% of the GDP of EAGLE group in 2020.[36] This implies that the international factors are significant determinants of the consumer price indexes of the U.S. and EAGLE countries.

Further, our study answers an important question of whether the U.S. is a net exporter (importer) of inflation to (from) emerging economies. This is the question left over in the extant

[33] Our sample period is relatively long, ranging between 1991M1 to 2022M2. However, as the inflation data is monthly data, the number of observations in each country's inflation time-series stands at only 375, which is relatively short compared to other studies on connectedness using daily data.
[34] https://www.pwc.com/gx/en/world-2050/assets/pwc-the-world-in-2050-full-report-feb-2017.pdf
[35] See Figure 4.2, available at: https://oec.world/en/profile/country/usa?yearlyTradeFlowSelector=flow1
[36] See Figure 4.3.

literature. We conjecture two channels that determine the role of the U.S. in the inflation spillover effects with emerging economies. First, the U.S. acts as a transmitter of inflation shocks because central banks in emerging markets tend to accommodate their monetary policy to the Fed's policies in an attempt to keep its exports competitive in terms of the U.S. dollar. Specifically, when the Fed loosens its monetary policy, the U.S. dollar becomes weaker, making the imports from emerging nations to the U.S. more expensive. While many emerging economies are dependent on the U.S. as the largest exporting destination, these countries should devaluate their own currencies to hold their exports' prices competitive. Then, this devaluation would lead to inflation in developing countries. In this way, a higher inflation rate in the U.S. could spill to emerging markets through the synchronization of monetary policies. In fact, numerous studies find evidence of the U.S. monetary policy spillovers to emerging markets' policies (e.g., Chen et al., 2014; Anaya et al., 2017; and Bräuninga and Ivashina, 2020). We term this channel as the "*monetary policy channel*". This channel supports the role of inflation exporter of the U.S. to emerging markets.

In reverse, higher inflation rates in emerging markets could increase the U.S. import prices, hence influencing the U.S. inflation in both direct and indirect ways. This helps explain why the U.S. would be an inflation importer from emerging markets (Tootell, 1998). Since many foreign goods prices are included in the calculation of the U.S. Consumer Price Index, the import prices could directly affect the U.S domestic inflation. Further, the inflation of foreign good prices can exert an indirect effect on the U.S. inflation if those foreign goods are important inputs to the U.S. goods production. Increases in the foreign goods prices used as inputs, particularly permanent changes in these prices, lead to increasing production costs, which in turn boost the prices of goods and services made in the U.S. We term this channel as the "*consumption channel*". This channel explains the role of inflation importer of the U.S. from emerging markets.

The results of the TVP-VAR-based connectedness show that there is a moderate degree of inflation spillover effects between the U.S and EAGLES. The inflation spillover effects not only vary over time but also exhibit an upward trend over the sample period, indicating a greater interdependence in terms of inflation among the selected countries. This increasing interdependence possibly reflects higher economic and monetary integration between the countries.[37] Our finding is in line with recent evidence reported by Elsayed et al. (2021). Further, the average connectedness results also reveal that over the sample period, South Korea, India, and Mexico are the most crucial net transmitters of inflation shocks. On the contrary, Russia, Indonesia, and Turkey are the most important net inflation shock receivers. Intriguingly, we find that the magnitude of inflation spillover effects between an emerging market with the U.S. depends on country-specific characteristics. Specifically, we point out that inflation spillover effects with the U.S. are more pronounced for the emerging economies with higher openness, the net oil-importing emerging markets, and the emerging markets following free-float exchange rate regimes.

Regarding the role of the U.S. in this inflation relationship, our average connectedness measure unveils that on average the U.S. is a net importer of inflation from the block of emerging countries. This role of inflation shock receiver of the U.S suggests that the *"consumption channel"* plays a dominant role in shaping the inflation transmission between the U.S. and EAGLEs. Meanwhile, the time-varying analysis shows that the role of the U.S. was not static, but changing between net importer and net exporter of inflation during the research period. Interestingly, the net pairwise spillover analysis further reveals that the U.S. role as net receiver or net transmitter of inflation shocks also varies across emerging markets. While the U.S. is net importer of inflation shocks from South Korea, India, China, and

[37] For instance, according to the World Trade Organization (WTO), total merchandise trade values in the world have increased fourfold from above USD 5,000 trillion in 2000 to more than USD 22,000 trillion in 2020. Source: https://stats.wto.org/dashboard/merchandise_en.html.

Indonesia, the country is net exporter of inflation spillover from Taiwan, Turkey, Mexico, Russia, and Brazil.

Given that the shock transmissions in financial markets tend to be more significant during the period of extreme market conditions (e.g., Bouri et al., 2021a; Bouri et al., 2021b; among others), we augment our analysis to examine the inflation spillover effects in extreme inflationary times by adopting quantile-based connectedness framework proposed by Ando et al. (2022). The results of upper-quantile- based connectedness reveal that while the spillover effects are moderate at the conditional mean of inflation distribution, they increase significantly when there are large positive shocks of inflation. Furthermore, the U.S. continues to be a net receiver of extremely positive inflation shocks from the EAGLEs.

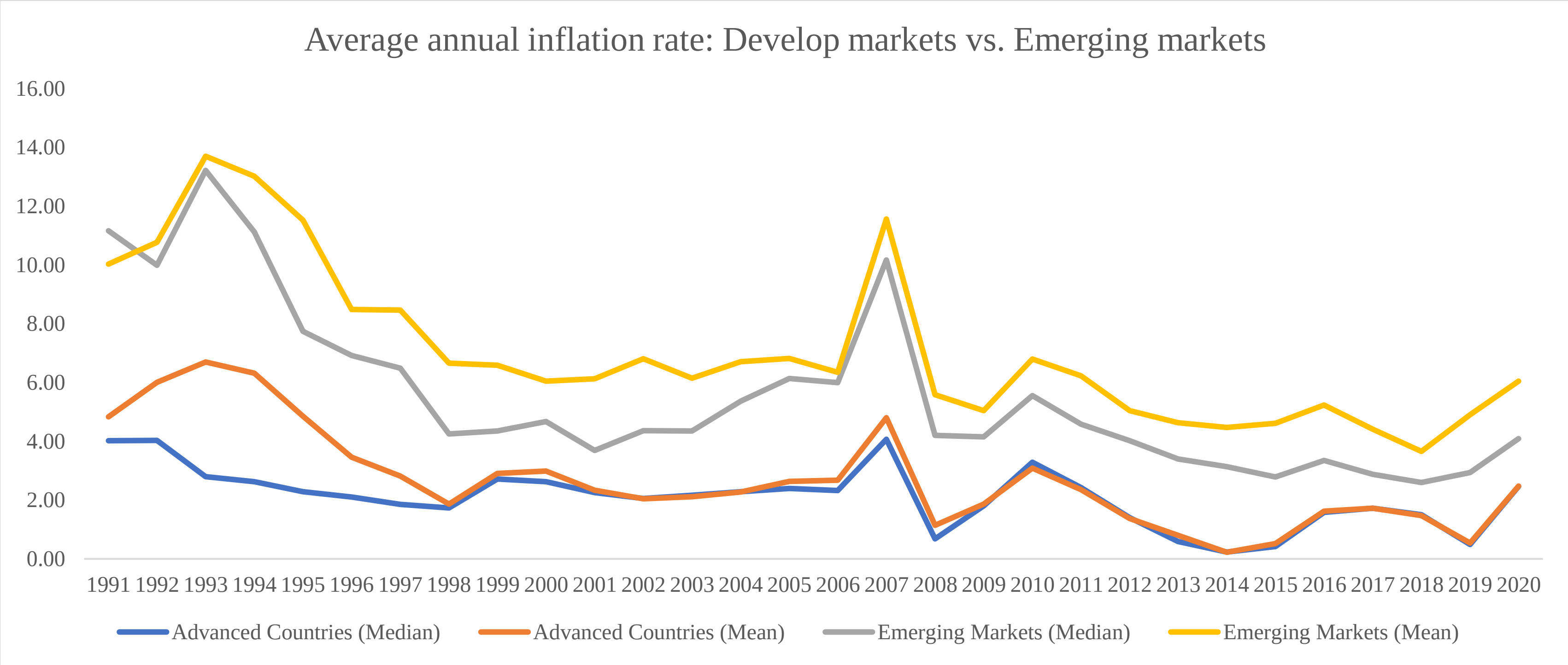
Turning to the drivers of time-varying inflation effect, we investigate the determinants of the spillover effect measured by the TVP-VAR-based connectedness using a comprehensive set of explanatory variables. We find robust evidence that both the inflation spillover from the U.S. to emerging markets and the inflation spillover from emerging markets to the U.S. are positively linked to the strength of the U.S. dollar, the economic policy uncertainty in emerging markets, and the U.S. export or import to and from emerging economies.

Our study contributes to the extant literature in several ways. First, this study is the first attempt to examine the dynamics of inflation spillover effect between the U.S. and the EAGLE countries over a long period. The countries in our sample represent a majority part of the world GDP and their economic shares are continued to increase in the future. As a result, a comprehensive understanding of the inflation spillover effects among these countries is highly valuable to policymakers and investors in both the U.S. and emerging economies. Second, compared to previous studies on inflation interconnectedness, our study employs newly developed connectedness frameworks, which are deemed more suitable to low-frequency and short data such as inflation. The previous studies of Halka and Szafranek (2016), Tiwari et al.

(2019), Istiak et al. (2021), Wen et al. (2021), Elsayed et al. (2021), Pham and Sala (2022) have used the connectedness methodologies by Diebold and Yilmaz (2012, 2014) and/or Barunik and Krehlik (2018). These methodologies, however, suffer the problems of loss of data and subjectivity bias in choosing the rolling-window length, which are all avoided by using the TVP-VAR connectedness measures. Third, we identify the main transmitters/receivers of inflation shock spillover and their dynamic transitions, focusing on the role of the U.S. in the system as its economic policies are highly influential and could exert significant impacts on other economies. This way, our study would answer whether the U.S. is the net exporter (importer) of inflation to (from) EAGLEs. Fourth, our study goes further to examine whether the spillover effects are more pronounced during the highly inflationary environment by applying the quantile-based connectedness approach. This question is relevant as a low to moderate domestic inflation rate is considered pro-economic growth and might not have significant implications to policymakers and investors. Meanwhile, investors and policymakers should be more concerned when domestic inflation rate is high and more susceptible to global factors. Finally, we provide a comprehensive analysis of the drivers of the international inflation spillover effect, which has not yet addressed in the extant literature.

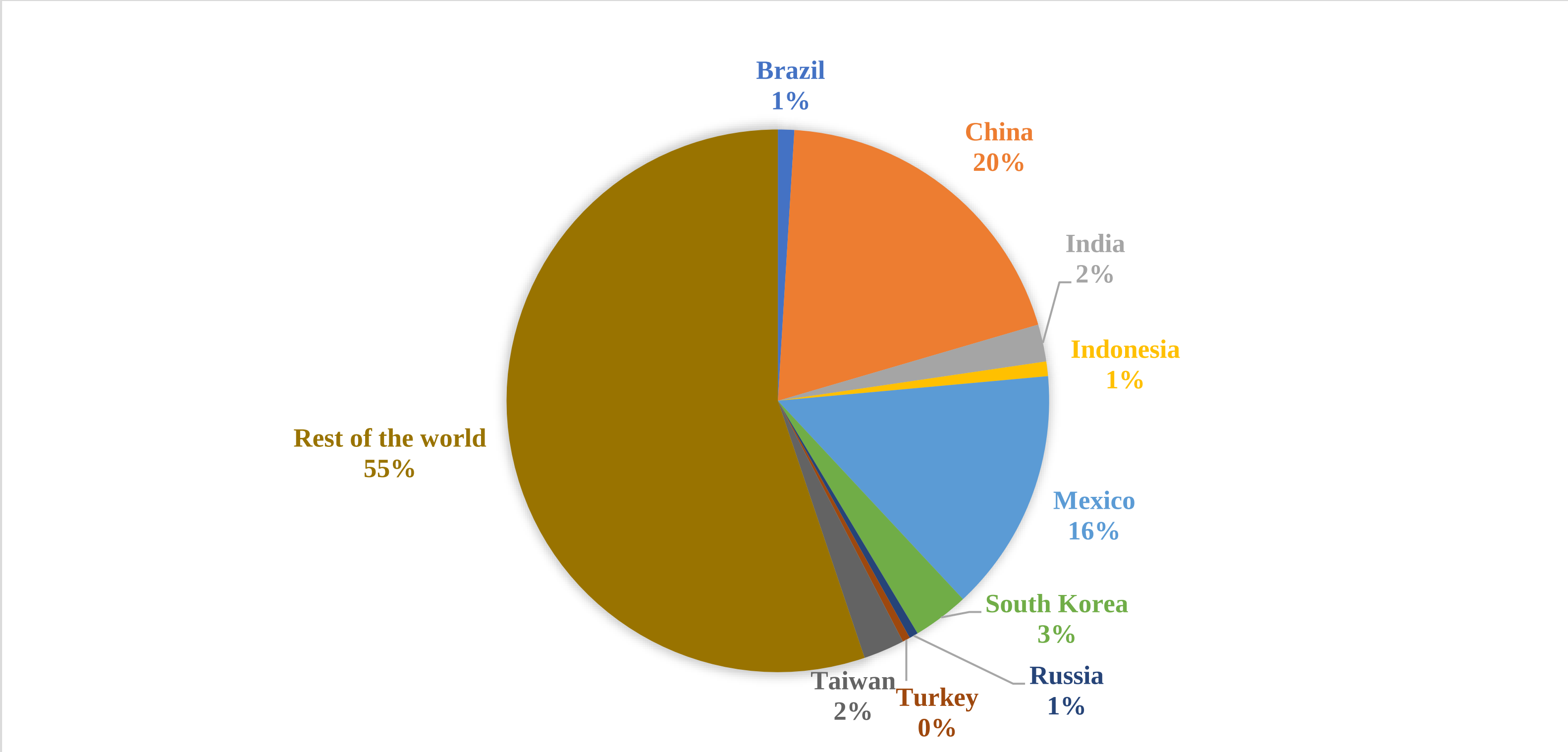
The remainder of the study is organized as follows. Section 4.2 provides a brief review of the related literature. Section 4.3 presents a description of the models employed in this study. Section 4.4 presents the data used. Section 4.5 illustrates and discusses the empirical results. Section 4.6 conducts robustness checks. Section 4.7 concludes.

Figure 4.1 Average annual inflation rates: Developed markets vs. Emerging markets



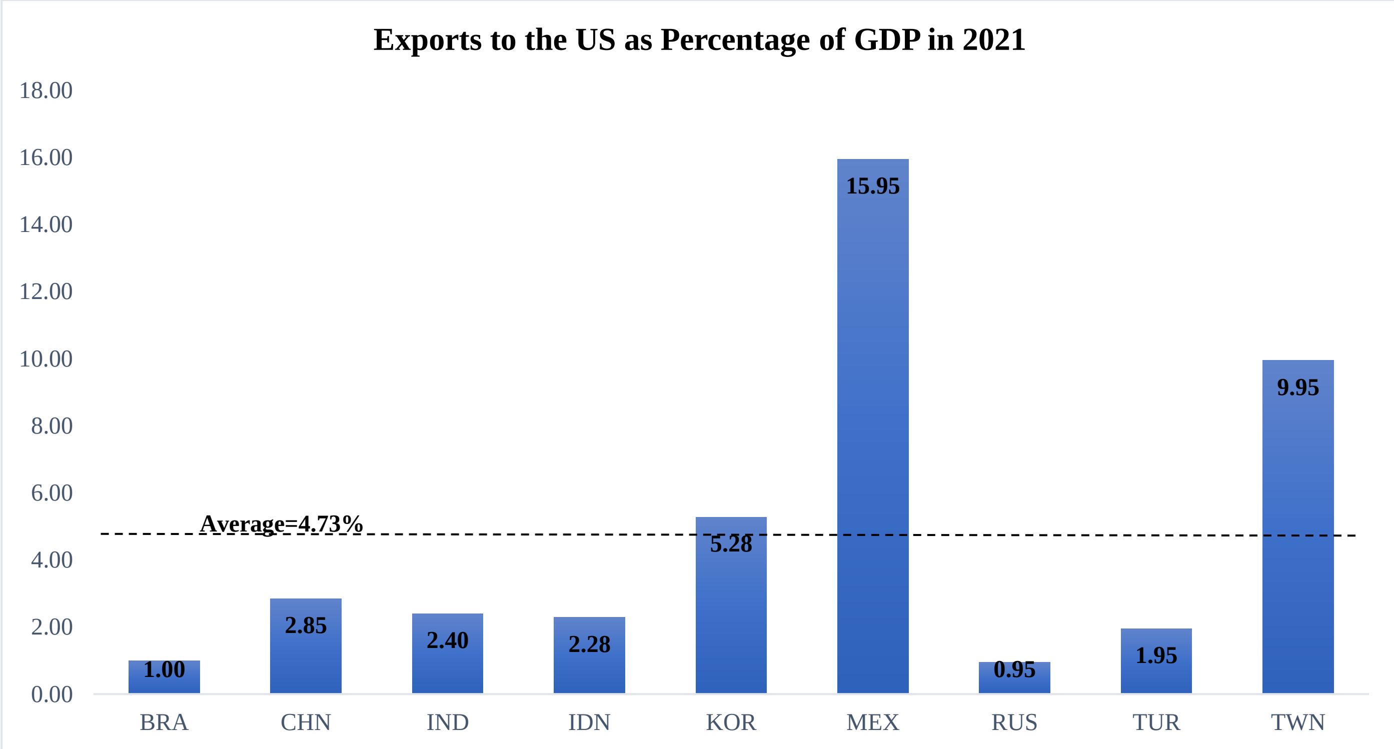
Notes: This figure displays the movement of inflation rates across Developed markets and Emerging Markets between 1991M1 and 2022M2. The data is sourced from World Bank database, prepared by Ha et al. (2021).

Figure 4.2 Contributions of EAGLEs to the U.S. imports in 2020



Notes: This figure shows the contributions of the selected emerging markets to the total U.S. imports in 2020.

Figure 4.3 Exports to the U.S. as percentage of emerging markets' GDP



Notes: This figure shows the contribution of the exports to the U.S. as percentage of GDP of the selected emerging markets: Brazil (BRA), China (CHN), IND (India), Indonesia (IDN), South Korea (KOR), Mexico (MEX), Russia (RUS), Turkey (TUR), and Taiwan (TWN).

4.2 Literature review

Our study is related to two strands of literature. The first strand is the literature on the inflation integration (e.g., co-movement and spillover). There are numerous studies that documents that inflation rates across countries tend to converge and co-move. For instance, Kočenda and Papell (1997) and Lopez and Papell (2012) find that inflation converges in the European Union. Similarly, Nusair and Kisswani (2015) document a nonlinear convergence of inflation rates of ASEAN countries to the inflation rates in the US and Japan. Besides, Tiwari et al. (2015) and Tiwari et al. (2016) employ the continuous wavelet approach to investigate the co-movement in inflations in G-7 and European countries, respectively. Both papers document that the inflation correlations are dynamic and vary across different time-frequencies. In an attempt to explore the underlying causes of the inflation convergence or co-movement, Ciccarelli and Mojon (2010) show that inflations of 22 OECD countries co-move and this co-movement is largely explained by common risk factors such as business cycle. In a similar vein, Aastveit et al. (2016) and Hakkio (2010) confirm that common external shocks and international factors contribute significantly to explaining the local inflation rates.

The inflation rates are not only co-move but could also spill from one country to another through international trade linkage (Tootell, 1998; Bernanke, 2007; Auer and Saure, 2013), commodity prices (Ciccarelli and Mojon, 2010), synchronization of monetary policies (Tiwari et al., 2015), and input linkage (Auer et al., 2019). In this direction, various studies have examined the magnitude and the direction of inflation spillover across countries, with a predominant focus on developed ones. Halka and Szafranek (2016) employ the Diebold and Yilmaz's (2012) connectedness measures to investigate the spillover of several measures of inflation between European Union and small open economies in Europe. They find that the spillover effects vary across different inflation measures and the euro area is the net inflation diffuser in most cases. Tiwari et al. (2019) employ the Diebold and Yilmaz's (2012) and

Barunik and Krehlik's (2018) connectedness frameworks to analyse the inflation spillover in Euro-area countries. Other researchers turn to the inflation spillover among G-7 countries and/or the interaction between oil prices and inflation rates (e.g., Istiak et al., 2021; Wen et al., 2021; Elsayed et al. 2021; Pham and Sala, 2022). For instance, Pham and Sala (2022) find a significant level of inflation connectedness among G-7 countries and this connectedness intensifies in periods of common economic turmoil. Elsayed et al. (2021) explore the role of oil inflation in the inflation network of G-7 countries and document that that oil is a net transmitter of inflation shocks. Hall et al., (2023) investigate the drivers and spillover effects of inflation among the U.S., the Euro area, and the United Kingdom. It is noteworthy that in all cited studies above, the U.S. acts as a net diffuser of inflation shocks.

Our study is also related to a strand of literature that explore the impacts of the U.S. macroeconomic factors on the emerging markets. As discussed in the introduction, inflation can spill from the U.S. to emerging markets through the *"monetary policy channel"*. In this channel, an expansionary monetary policy in the US can lead to a loosening monetary policy in emerging markets as the emerging economies aim to keep its exports to the U.S. competitive. Indeed, there are various studies that have confirmed the spillovers from the U.S. monetary policy to the rest of the world, including emerging markets (e.g., Maćkowiak, 2007; Chen et al., 2014; Bowman et al., 2015; Tillmann, 2016; Anaya et al., 2017; Tillmann et al., 2019; and Bräuning and Ivashina, 2020; among others). For instance, Chen et al. (2014) find that central banks in emerging economies reacts accordingly to monetary policy shocks from the U.S. Their reactions, however, vary, depending on several factors including the fundamentals of the recipient countries and the unconventional or conventional monetary policy in the U.S. Anaya et al. (2017) examine the impacts of unconventional monetary policy in the U.S. on several macro-economic indicators of emerging markets. They find that in response to an expansionary U.S. shock, both policy (e.g., short-term) interest rates and lending rates in emerging markets decrease. In addition, an expansionary U.S. shock leads to an appreciation of emerging currencies versus the U.S. dollar and higher economic growth in emerging markets. More recently, Bräuning and Ivashina (2020) reveal that U.S. easing monetary policy contributes to increasing the volume of loans from developed countries to emerging economies, hence, playing a significant role in the formation of credit cycles in emerging markets.

Our study extends the literature by investigating the inflation spillover effect between the U.S and EAGLES at both conditional mean and tails of inflation distributions. We also contribute to the literature of the U.S. macroeconomic factors' effects on emerging markets by scrutinizing the role of the U.S. in the inflation shock transmission with the emerging markets.

4.3 Methodologies

Our study examines the international spillover effect of inflation rates between the U.S. and EAGLE countries at both mean and tails of conditional distributions. To explore the dynamic transmission of inflation shocks at the conditional mean among the selected countries, we employ the connectedness measures derived from the time-varying parameter vector autoregressive model (TVP-VAR). Antonakakis et al. (2020) develop the dynamic connectedness framework within the base model TVP-VAR which is introduced by Koop and Korobilis (2014). The advantage of the TVP-VAR-based connectedness approach is that its result avoids the subjectivity bias caused by window length selection as in traditional rolling-window VAR approach (Diebold and Yilmaz, 2012). More importantly, the TVP-VAR-based connectedness measures are considered an appropriate method for low-frequency datasets as there is no loss of observations in computing connectedness measures. Then we go further to measure the spillover of extreme inflation shocks by applying the quantile-based connectedness framework of Ando et al. (2022). So, now we present our two econometric methodologies in subsection 4.3.1 and 4.3.2.

4.3.1 TVP-VAR-based connectedness

We consider a stationary TVP-VAR(p) of m assets with the optimal lag order p estimated by the Bayesian Information Criterion (BIC). The TVP-VAR(p) is specified as follows,

$$y_t = \sum_{j=1}^{p} \beta_{j,t} y_{t-j} + \varepsilon_t \qquad \varepsilon_t | \mathrm{I}_{t-1} \sim N(0, \boldsymbol{\Sigma}_t) \tag{4.1}$$

where y_t is the $m \times 1$ vector of monthly inflation rates for m sample countries, and $\beta_{j,t}$ is the jth $m \times m$ time-varying autoregressive coefficient matrices, ε_t is the $m \times 1$ vector residual.

The value of the lagged variables can be written in a $mp \times 1$ matrix form as $Z'_t \equiv I \otimes (y'_{t-1}, \dots, y'_{t-p})$, where $\otimes$ denotes the Kronecker product. We vectorize the time-varying coefficients as $\theta_t \equiv vec\left(\left[\beta_{1,t}, \dots, \beta_{p,t}\right]'\right)$. Then Eq. (4.1) can be rewritten as follows,

$$y_t = Z'_t \theta_t + \varepsilon_t \tag{4.2}$$

The TVP-VAR coefficients evolve following the assumed law of motion which is a random walk as,

$$\theta_t = \theta_{t-1} + v_t \qquad v_t | \mathrm{I}_{t-1} \sim N(0, \xi_t) \tag{4.3}$$

where the vector error terms $\varepsilon_t \sim N(0, \boldsymbol{\Sigma}_t)$ and $v_t \sim N(0, \xi_t)$ in the Eq. (4.1) and (4.2) are not serial correlated; ε_t and v_t are $m \times 1$ and $m^2 p \times 1$ dimensional vector; the time-varying variance-covariance matrices $\boldsymbol{\Sigma}_t$ and ξ_t are $m \times m$ and $m^2 p \times m^2 p$ dimensional matrices, respectively. I_{t-1} represents all available information at (t-1). The algorithm for estimation of the time-varying parameters of the TVP-VAR model bases on Kalman filter estimation with forgetting factors following the spirit of Koop and Korobilis (2014). After estimating the time-varying parameters, to drive the connectedness indexes within the underlying TVP-VAR, we transform the Eq. (4.2) into an infinite moving average representation based on the Wold representation theorem as follows,

$$y_t = \sum_{k=0}^{\infty} A_{kt}\varepsilon_{t-k} \tag{4.4}$$

where A_{kt} is determined as,

$$A_{kt} = \begin{cases} 0 & \text{for } k < 0; \\ I_m & \text{for } k = 0; \\ \beta_{1,t}A_{k-1,t} + \cdots + \beta_{p,t}A_{k-p,t} & \text{for } k > 0 \end{cases}$$

The time-varying coefficients A_{kt} of the vector moving average (VMA) and the time-varying variance-covariance matrices $\boldsymbol{\Sigma}_t$ are used to compute the generalized forecast error variance decomposition (GFEVD) (Koop et al., 1996, Pesaran and Shin, 1998). Then the dynamic connectedness measures of Diebold and Yilmaz (2012) are developed upon the GFEVD. Our focus is on the *H*-step ahead error variance in forecasting variable i that is due to shocks to variable j. Mathematically, it can be computed as follows,

$$\varphi_{ij,t}(H) = \frac{S_{jj,t}^{-1}\sum_{t=1}^{H-1}(e_i' A_{h,t}\Sigma_t e_j)^2}{\sum_{t-1}^{H-1} e_i' A_{h,t}\Sigma_t A_{h,t}' e_i} \tag{4.5}$$

and normalized as follows,

$$\tilde{\varphi}_{ij,t}(H) = \frac{\varphi_{ij,t}(H)}{\sum_{j=1}^{m}\varphi_{ij,t}(H)} \tag{4.6}$$

where $\tilde{\varphi}_{ij,t}^{g}$ denotes the *H*-step ahead GFEVD of the variable *i*th attributable to shocks to variable *j*th, Σ_t is the variance-covariance matrix of vector error terms ε_t, and $S_{jj,t}$ is the *j*th diagonal element of the matrix Σ_t, and e_i is the selection vector with one for the *i*th element and zero otherwise. Note, $\sum_{j=1}^{m}\tilde{\varphi}_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{m}\tilde{\varphi}_{ij,t}(H) = m.$

Based on the computed GFEVD, we derive the total spillover index (TSI) of the network following the connectedness framework of Diebold and Yilmaz (2012) as,

$$TSI_t(H) = \frac{\sum_{i,j=1,i\neq j}^{m}\tilde{\varphi}_{ij,t}(H)}{m} \times 100 \tag{4.7}$$

First, we are interested in the spillovers *FROM* variable i to all others defined as,

$$DSI_{i\to j}(H) = \frac{\sum_{j=1,i\neq j}^{m} \tilde{\varphi}_{ji,t}(H)}{\sum_{i,j=1}^{m} \tilde{\varphi}_{ji,t}(H)} \times 100 = \frac{\sum_{j=1,i\neq j}^{m} \tilde{\varphi}_{ji,t}(H)}{m} \times 100 \tag{4.8}$$

Second, we compute the spillovers *TO* variable i from all others defined as,

$$DSI_{j\to i}(H) = \frac{\sum_{j=1,i\neq j}^{m} \tilde{\varphi}_{ij,t}(H)}{\sum_{j,i=1}^{m} \tilde{\varphi}_{ij,t}(H)} \times 100 = \frac{\sum_{j=1,i\neq j}^{m} \tilde{\varphi}_{ij,t}(H)}{m} \times 100 \tag{4.9}$$

Third, we calculate the net spillover from variable *i* to all others as,

$$NSI_{i,t}(H) = DSI_{i\to j}(H) - DSI_{j\to i}(H) \tag{4.10}$$

The sign of the net spillover index illustrates if variable *i* is driving the network ($NSI_{i,t}(H) > 0$) or driven by the network ($NSI_{i,t}(H) < 0$).

Finally, we break down the net total spillover index to examine the bidirectional relationships by computing the net pairwise directional spillover (NPDS) from variable *i* to variable *j* as,

$$NPDS_{ji,t}(H) = \frac{\tilde{\varphi}_{ji,t}(H) - \tilde{\varphi}_{ij,t}(H)}{m} \times 100 \tag{4.11}$$

4.3.2 The quantile connectedness

Our study also employs the quantile connectedness framework, developed by Ando et al. (2022) to measure the dynamic inflation spillover effects between the U.S. and the EAGLE emerging markets at the *upper* tail of the conditional distributions of inflation series. The results of upper quantile connectedness unveil the changes in spillover behavior during the extreme inflationary periods. This quantile-based connectedness framework estimates a VAR system at a given conditional quantile by quantile regression, and then derive the connectedness indices of Diebold and Yilmaz (2012) based on the underlying quantile VAR model.

Consider a VAR system of *m* assets with the optimal lag order *p* estimated using the Bayesian Information Criteria (BIC), the VAR model at τ th conditional quantile can be estimated by equation-by-equation quantile regression as follows:

$$y_t = \mathcal{B}_{0(\tau)} + \sum_{\ell=1}^{p} \mathcal{B}_{\ell(\tau)} y_{t-\ell} + e_{t(\tau)} \tag{4.12}$$

where $\tau \in (0,1)$ is a given quantile index, y_t is the $m \times 1$ vector of inflation series for m sample countries, $\mathcal{B}_{0(\tau)}$ is the $m \times 1$ vector of intercepts and $e_{t(\tau)}$ is the $m \times 1$ vector residual at τ th quantile. $\mathcal{B}_{\ell(\tau)}$ is the ℓth $m \times m$ autoregressive parameter matrix at τ th quantile.

The single equation of (4.12) estimated by equation-by-equation quantile regression is specified as follows,

$$y_{jt} = \mathcal{B}_{j(\tau)}^{\top} z_t + e_{jt(\tau)} \tag{4.13}$$

where $j = 1, 2, ..., m$ and z_t represents $(mp+1) \times 1$ vector of all regressors including the intercept, $\mathcal{B}_{j(\tau)}$ is the estimated corresponding autoregressive coefficients at τ th quantile.

Assuming that the residuals adhere to the conditional quantile restriction $Q_\tau(e_{jt(\tau)} \mid z_t) = 0$, then following Koenker and Xiao (2006), the τ th conditional quantile function of y_{jt} can be specified as,

$$Q_\tau\left(y_{jt} \middle| z_t\right) = \mathcal{B}_{j(\tau)}^{\top} z_t \tag{4.14}$$

Given a value of quantile τ , following the work of Koenker and Hallock (2001), the autoregressive coefficients $\mathcal{B}_{j(\tau)}$ can be estimated by solving the problem,

$$\min_{\mathcal{B}_{j(\tau)}} \sum_{t=1}^{T} (\tau - \boldsymbol{I}[y_{jt} \leq \mathcal{B}_{j(\tau)}{}_{j(\tau)}^{\top} z_t])(y_{jt} - \mathcal{B}_{j(\tau)}^{\top} z_t) \tag{4.15}$$

where $\boldsymbol{I}[\bullet]$ is the indicative function taking the value of 1 when $y_{jt} \leq \mathcal{B}_{j(\tau)}^{\top} z_t$ and 0 otherwise, and T is number of observations in the sample.

To derive the connectedness indices of Diebold and Yilmaz (2012) within the quantile VAR framework, we re-write the Eq. (4.12) as an infinite moving average representation as follows,

$$y_t = \mu_{(\tau)} + \sum_{k=1}^{\infty} A_{k(\tau)} e_{t-k(\tau)} \tag{4.16}$$

where $\mu(\tau)$ and $A_k(\tau)$ are determined as,

$$\mu_{(\tau)} = (I_m - \mathcal{B}_{1(\tau)} - \cdots - \mathcal{B}_{p(\tau)})^{-1} \mathcal{B}_{0(\tau)}$$

$$A_{k(\tau)} = \begin{cases} 0 \text{ for } k < 0; \\ I_m \text{ for } k = 0; \\ \mathcal{B}_{1(\tau)} A_{k-1(\tau)} + \cdots + \mathcal{B}_{p(\tau)} A_{k-p(\tau)} \text{ for } k > 0 \end{cases}$$

Following the approaches of Diebold and Yilmaz (2012), the coefficients of vector moving average are used to compute the generalized forecast error variance decomposition (GFEVD) of the *i*th variable in y_t caused by shocks to other variables for a forecast horizon *H* at τth quantile as,

$$\theta_{ij(\tau)}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_{h(\tau)} \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} e_i' A_{h(\tau)} \Sigma A_{h(\tau)}' e_i} \tag{4.17}$$

where $\theta_{ij(\tau)}(H)$ represents the contribution of the *j*th variable to the variance of *h*-step-ahead forecast error of the variable *i*th, Σ is the variance matrix of vector error terms, σ_{jj} denotes the *j*th diagonal element of the Σ matrix, and e_i is the selection vector with one for the *i*th element and zero otherwise. Each entry of the variance decomposition matrix is normalized as follows,

$$\tilde{\theta}_{ij(\tau)}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{m} \theta_{ij}(H)} \tag{4.18}$$

Using the GFEVD, we compute at the given quantile four connectedness measures. First, the total spillover index (*TSI*) at τth quantile is:

$$TSI(\tau) = \frac{\sum_{i,j=1;i\neq j}^{m} \tilde{\theta}_{ij(\tau)}(H)}{m} \times 100 \tag{4.19}$$

The directional spillover index received by variable i from all other variables in the system at τth quantile is computed as:

$$DSI_{i.(\tau)} = \frac{\sum_{j=1;i\neq j}^{m} \tilde{\theta}_{ij(\tau)}}{m} \times 100 \tag{4.20}$$

In reverse, directional spillover index transmitted by variable i to all other variables at τth quantile is defined as:

$$DSI_{.i(\tau)} = \frac{\sum_{j=1;i\neq j}^{m} \widetilde{\theta}_{ji(\tau)}}{m} \times 100 \tag{4.21}$$

The net spillover from variable i to all other variables j at τth quantile is defined as,

$$NDSI_{i(\tau)} = DSI_{.i(\tau)} - DSI_{i.(\tau)} \tag{4.22}$$

4.4 Data and preliminary analysis

4.4.1 Sample and data

Our data comprises of two parts. First, we collect the monthly headline consumer price index (CPI) from the World Bank database to proxy for the inflation in the U.S. and EAGLEs. This database is prepared by Ha et al. (2021) and provides a comprehensive set of inflation measures for up to 196 countries over the period of 1970-2022. Our sample data, however, ranges from 1991M1 to 2022M2 as most data for the selected emerging markets started in 1990. The monthly inflation rate is then calculated as the log difference series of the CPI.

Our study also uses a wide range of macro-economic variables, international trade data, and uncertainty measures to investigate their roles in driving the inflation spillover effects. The macro-economic variables and international trade data are gathered from the DataStream. Different uncertainty measures are collected from https://www.policyuncertainty.com/.

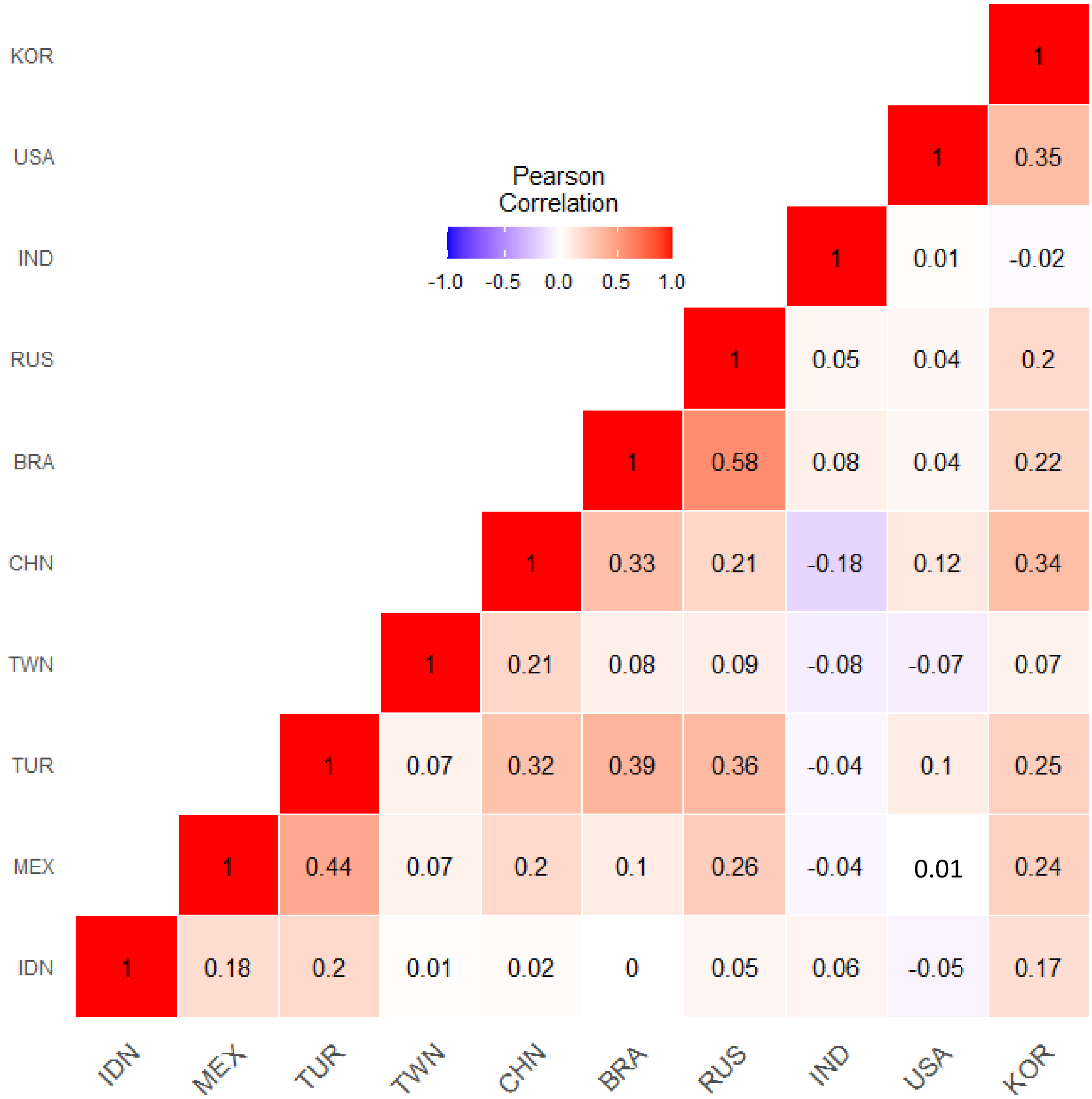
4.4.2 Descriptive analysis

Table 4.1 shows the summary statistics for the monthly inflation rates of the selected countries. As can be seen, the average monthly inflation for all countries is positive over the sample period. The number is particularly high for Russia (3.74%), Brazil (3.48%), and Turkey (2.35%) as these countries have experienced a period of hyperinflation in early 1990s. On the contrary, East Asian emerging countries including Taiwan, South Korea, and China have relatively low level of inflation. The U.S. has an average monthly inflation rate of 0.20%, which is lower than most of the selected emerging markets. This is not surprising as high inflation rates are more common in emerging markets than in developed countries. Pertaining to the skewness, only the U.S. has a negative number, indicating that deflation is not uncommon in the U.S. Conversely, the positive skewness of all emerging countries suggests that sudden extreme positive inflation shocks are frequent in these countries. Further, the U.S. and most of emerging markets (except China and India) are subject to high possibility of extremely low and high inflation, based on their leptokurtic distributions (i.e., kurtosis greater than 3). This characteristic implies the need to move beyond the mean-based connectedness framework and capture the spillover behavior at tails of conditional distribution when modelling the inflation spillover effects between the selected countries.

The last three rows of Table 4.1 present the diagnostic tests of inflation series. First, the Jarque-Bera statistics significantly reject the null hypothesis of normal distribution for all countries. Second, the results of augmented Dickey-Fuller (ADF) tests are statistically significant and reject the null hypothesis of a presence of a unit root in inflation time series, indicating the stationarity in all cases. Finally, the Ljung-Box Q statistics up to 10 lags suggest that there is significant autocorrelation in all inflation series.

Figure 4.1 illustrates the pairwise correlation matrix of the inflation series. There are two remarks standing out from here. First, most of the pairwise correlation coefficients (36/45) are positive, which indicates that inflation tends to co-move across the countries in the sample. It is observable that the highest positive correlation coefficient (0.58) belongs to the pair of two large oil-exporting countries, namely, Brazil (BRA) and Russia (RUS). On the contrary, the most negative correlation coefficient (-0.18) is given to the pair of China (CHN) and Indonesia (IDN). Second, the U.S. inflation rate is positively correlated with each of the selected emerging markets, except Indonesia (IDN) and Taiwan (TWN). However, these correlations are relatively low (below 0.12 for all cases). In particular, the inflation rate in the U.S. has the highest correlations with those of China (CHN) (0.12) and Turkey (TUR) (0.1).

Figure 4.4 Inflation Correlation Matrix between Countries



Notes: This figure shows the pairwise correlation coeffcients of the inflation series among the selected countries.

Table 4.1 Descriptive statistics

	USA	BRA	CHN	IND	IDN	KOR	MEX	RUS	TUR	TWN
Mean	0.20	3.48	0.32	0.58	0.68	0.26	0.68	3.74	2.35	0.13
Variance	0.11	76.82	0.79	0.68	1.53	0.20	0.70	200.94	7.58	0.66
Skewness	-0.869	3.068	0.944	0.385	5.033	0.971	3.483	13.747	2.367	0.346
Kurtosis	4.909	8.619	2.036	2.261	34.708	3.290	20.700	226.369	9.649	2.041
JB	422***	1,744***	120***	88.8***	20,351***	227***	7,433***	810,316***	1,799***	72.3***
ADF	-138.3***	-13.04***	-204.2***	-167.7***	-108.8***	-172.3***	-40.0***	-167.2***	-84.3***	-435.1***
Q(10)	103***	1,515***	109***	72.1***	298***	76.1***	651***	83.4***	463***	22.3***
N. of Obs.	363	363	363	363	363	363	363	363	363	363

Notes: This table reports the descriptive statistics of monthly inflation of the U.S. and the selected emerging markets between 1991M1 and 2022M2, covering monthly observations. JB statistics indicates the Jarque-Bera test for the normality of sample data. ADF test represents the unit root test. Q(10) represents the Ljung-Box Q-statistics up to the 10^{th} order autocorrelation. *** denotes the cases where the null hypothesis of no autocorrelation (for LB Q test), and normal distribution (for JB test), and a presence of a unit root (for ADF test) is rejected at the 1% significance level.

4.5 Empirical results and discussion

We provide the comprehensive understanding of the inflation spillover between the U.S. and EAGLEs in five subsections. In subsection 4.5.1, we discuss the static inflation spillover results between sample countries at the conditional mean using TVP-VAR-based connectedness approach. Subsection 4.5.2 reports and discusses the dynamics of the mean-based inflation spillover. Subsection 4.5.3 examines the heterogeneous inflation spillover effects across countries based on their fundamental characteristics. Subsection 4.5.4 investigates the changes of inflation spillover behavior in extreme inflationary times by moving to the average connectedness at upper tails (i.e., upper quantile) of the inflation distributions. Lastly, subsection 4.5.5 analyses the drivers of the inflation spillover measures.

4.5.1 The average TVP-VAR-based inflation spillover results

We generate the 20-step-ahead generalized forecast error variance decomposition based on the estimated coefficients of the underlying TVP-VAR model as in Eq. (4.5). Then, the GFEVD used to compute the connectedness indexes by Diebold and Yilmaz (2012) to measure the inflation spillover effect at the conditional mean between the selected countries, as reported in Table 4.2. As the results of the TVP-VAR-based connectedness approach are time-varying, each entry reported in the table is the average figure of the connectedness time series over the sample period between 1991M1 and 2022M2. There are several key findings standing out from the table. First, we find that the total spillover index (TSI) of the whole system is moderate at 18.83%, implying that on average 18.83% of the forecast error variance of a country's inflation is explained by inflation shocks from all other countries. This figure is significantly lower than the inflation spillover in G-7 countries, which has been documented to be around 40-50% (e.g., see Istiak et al., 2021; Wen et al., 2021; Elsayed et al. 2021; Pham and Sala, 2022). Thus, the inflation spillover effects between the U.S. and emerging markets are less pronounced than those between developed markets. In other words, emerging markets seem to be quite resilient to external inflation shocks. The "*Spillover from others*" column provides more insights into the resilience of a specific country to external inflation shocks. Specifically, we find that Brazil (9.98), India (12.22), and Taiwan (13.7) receive the least inflation shocks from others, implying these countries' inflation rates are mostly driven by their domestic factors, rather than impacted by other countries' inflation. On the flip side, Turkey (27.85%), China (25.57%), and the U.S. (25.39%) are most vulnerable to inflation shocks from other countries.

Second, the "*Spillover to others*" row indicates that the South Korea (32.42%) along with China (25.83%), Turkey (25.19%), and the U.S. (25.04%) diffuses most inflation shocks to other countries. As shown in the "KOR" column, the U.S. (11.99%) and China (6.89%) are most affected by inflation shocks transmitted from the South Korea. In the "USA" column, it is observable that inflation shocks in the U.S. influence hardly the South Korea (7.66%) and Taiwan (4.89%) while their impacts on Brazil (0.28%) and Indonesia (0.34%) are negligible. The higher inflation spillover effects among the U.S., South Korea, and China can be explained by the fact that these countries are close trading partners. Particularly, the U.S. is the second largest trading partner of the South Korea in terms of both exports and imports.[38] On the other hand, China is the most significant importer from South Korea and the largest exporters to the U.S.[39] On the contrary, the "Spillover to others" indexes of Russia (6.37%) and Indonesia (6.9%) point out that those countries are less influential on other countries' inflation.

Third, regarding the net spillover index (NSI), we find that South Korea (10.15%), India (6.27%), and Mexico (4.09%) are strongest net transmitters of inflation shocks with the high positive net spillover indexes. In the opposite direction, Russia (-10.59%) and Indonesia (-7.5%) are the largest net receivers of the inflation shocks. Interestingly, we find that the U.S.

[38] See, e.g., https://wits.worldbank.org/CountrySnapshot/en/KOR.
[39] See, https://wits.worldbank.org/countrysnapshot/en/CHN

is a net receiver of inflation shocks from the EAGLEs during the sample period, with its net spillover index being marginally negative at -0.35%. This important finding suggests that for the whole sample period, the "*consumption channel*" would have been more influential than the *"monetary policy channel"* in shaping the role of the U.S. as the net inflation importer from emerging markets.

Table 4.2 Average TVP-VAR connectedness measures

	USA	BRA	CHN	IND	IDN	KOR	MEX	RUS	TUR	TWN	*Spillover from others*
USA	74.62	0.07	3.71	5.34	0.37	11.99	0.65	0.32	0.7	2.25	25.39
BRA	0.28	90.02	2.27	0.12	0.02	0.92	0.53	2.29	3.26	0.28	9.98
CHN	3.14	2.28	74.43	4.12	0.49	6.89	2.45	0.19	3.3	2.7	25.57
IND	3.73	0.41	3.27	87.78	0.4	1.56	0.55	0.4	0.51	1.38	12.22
IDN	0.34	0.09	0.95	2.05	85.6	5.75	1.35	0.22	3.52	0.14	14.4
KOR	7.66	0.79	4.38	1.6	2.37	77.73	3.54	0.3	1.1	0.52	22.27
MEX	1.49	0.28	3	0.94	1.14	1.01	79.99	0.77	9.5	1.88	20.01
RUS	1.06	5.55	0.37	1.66	0.12	1.95	3.46	83.04	2.48	0.31	16.96
TUR	2.44	2.9	3.79	1.06	1.44	1.78	11.03	1.53	72.15	1.86	27.85
TWN	4.89	0.3	4.09	1.59	0.54	0.57	0.55	0.35	0.82	86.3	13.7
Spillover to others	25.04	12.67	25.83	18.49	6.9	32.42	24.1	6.37	25.19	11.32	
NSI	-0.35	2.69	0.26	6.27	-7.5	10.15	4.09	-10.59	-2.65	-2.38	
TSI	18.83										

Notes: Results are based on the TVP-VAR-based connectedness framework with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

To gain more insights into the role of the U.S. in this network inflation connectedness, we report the net pairwise directional spillover index (NPDS) of the U.S. with each emerging country in Table 4.3. The NDPS of the U.S. with an emerging country is calculated as the difference between the directional spillover from the U.S. to that emerging country and the directional spillover from the emerging country to the U.S. as specified in Eq. (4.11). While in general the U.S. is the importer of inflation shocks from the sample emerging markets as a group, the NPDS of the U.S. in Column (3) of Table 4.3 indicate that the role of the U.S. varies across the emerging countries. Specifically, the U.S. is the net receiver of inflation spillover from South Korea (KOR), India (IND), China (CHN), and Indonesia (IDN) whereas it is the net transmitter of inflation shocks to Taiwan (TWN), Turkey (TUR), Mexico (MXN), Russia (RUS), and Brazil (BRA). Among the net inflation shock diffusers to the U.S., South Korea (KOR) emerges as the most important one as shown by the NPDS of the U.S. with the South Korea ($NPDS_{KOR,USA}$) of -4.33%. The South Korea's inflation shocks contribute 11.99% to the inflation innovations in the U.S. while it receives 7.66% in return. Besides South Korea, India (IDN) and China (CHN) are other important net shock transmitters to the U.S. with the $NPDS_{IDN,USA}$ and $NPDS_{CHN,USA}$ of -1.61% and -0.57%, respectively. The significant roles of these countries in transmitting inflations shocks to the U.S. might be explained by the *"consumption channel"*, given the fact that China, India, and South Korea are consistently among the top 15 largest exporting countries[40] to the U.S. and the U.S. usually has trading deficit with these countries.[41] On the opposite direction, Taiwan (TWN), Turkey (TUR), and Mexico (MXN) are the three largest net receivers of inflation spillover from the U.S. with the $NPDS_{TWN,USA}$, $NPDS_{TUR,USA}$, $NPDS_{MXN,USA}$ of 2.64%, 1.74%, and 0.84%, respectively. The

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[40] Source: https://wits.worldbank.org/CountryProfile/en/Country/USA/Year/2020/TradeFlow/EXPIMP

[41] In every year between 1991 and 2021, China and India consistently have had trading surplus with the U.S. (Source: https://www.census.gov/foreign-trade/balance/c5700.html#1991 and https://www.census.gov/foreign-trade/balance/c5330.html). South Korea has had trading surplus with the U.S. in all years since 1991, except three years (1995, 1996, and 1997) (Source: https://www.census.gov/foreign-trade/balance/c5800.html).

strong transmission of inflation shocks from the U.S. to Taiwan and Mexico is understandable because these countries' GDP are highly dependent on their exporting activities to the U.S.,[42] leading the impact of the U.S. monetary policy more pronounced in these countries. This explanation is supported by several studies that examine the impact of the U.S. monetary policy on emerging markets. For instance, Bowman et al. (2015) reveal that a monetary policy shock that lowers the U.S. 10-year yields by 25 bps could reduce Mexican bond yields up to 30 bps. Chadwick (2019) empirically finds that monetary easing in the U.S. causes the local currency of Taiwan to be depreciated. Moreover, in case of Turkey, since the country's economy is highly dollarized, its macroeconomic variables are substantially vulnerable to outside shocks, including inflation shocks from the U.S. (e.g., Pınar Ardıç and Selçuk, 2006; Metin-Özcan and Us, 2007; Arellano and Heathcote, 2010; Sui et al., 2021).

Table 4.3 Net pairwise directional spillover index (NPDS) of the U.S. with each emerging market

j	Spillover effect from the US to the emerging market j ($\tilde{\varphi}^{g}_{j,USA,t}$) (1)	Spillover effect from the emerging market j to the US ($\tilde{\varphi}^{g}_{USA,j,t}$) (2)	Net pairwise inflation spillover index of the U.S. ($NPDS_{j,USA}$) (3)=(1)-(2)
BRA	0.28	0.07	0.21
CHN	3.14	3.71	-0.57
IND	3.73	5.34	-1.61
IDN	0.34	0.37	-0.03
KOR	7.66	11.99	-4.33
MEX	1.49	0.65	0.84
RUS	1.06	0.32	0.74
TUR	2.44	0.7	1.74
TWN	4.89	2.25	2.64
Total	25.04	25.39	-0.35

Notes: Results are based on the TVP-VAR-based connectedness framework with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition. NPDS is calculated as in Eq. (4.11).

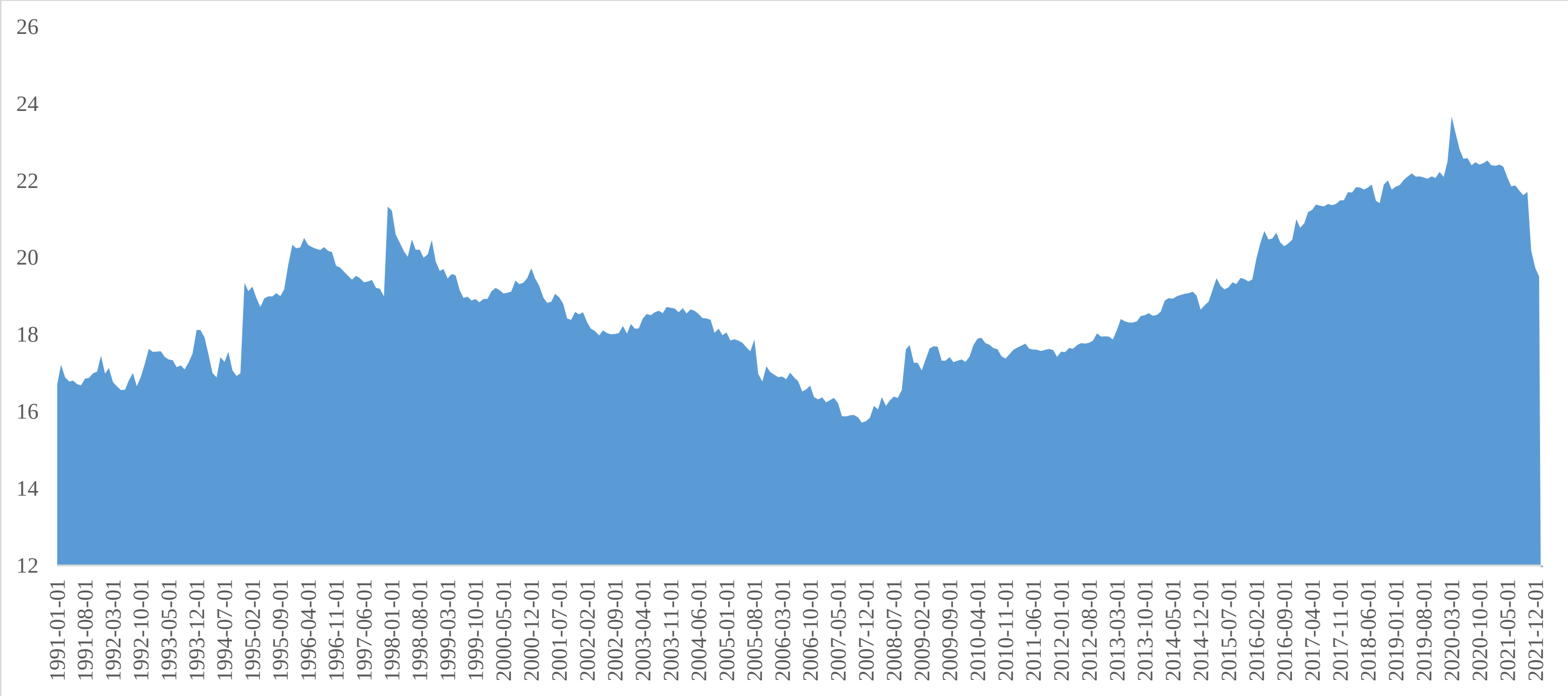
[42] Exports to the U.S. account for 9.95% and 15.95% of Taiwan's and Mexico's GDP in 2021, respectively. See, Figure 4.3.

4.5.2 The time-varying TVP-VAR-based inflation spillover results

Given that the inflation spillover effects should be different at some points of time, in this subsection, we describe and discuss the time-varying spillover effect measured at the conditional mean of inflation distributions. Figure 4.5 presents the time-varying total spillover index (TSI) of the network. Two outstanding remarks emerge from our reported results. First, despite some fluctuations, there is upward trend in the spillovers during the research period. In particularly, the TSI has increased from around 17% in 1991 to more than 23% in 2020. This uptrend of TSI might be the result of the increasing global trade[43] as well as the amplification of common global factors (Bean, 2006; Borio and Filardo, 2007), which strengthens the economic interdependence between countries. Second, the spillovers tend to spike during periods of economic turmoil, such as the Mexican crisis of 1994-1995, the Asian Financial Crisis 1997-1998, the Global Financial Crisis 2008-2009, and the early of the COVID-19 pandemic in February and March of 2020.

[43] Please see, e.g., https://data.worldbank.org/indicator/NE.TRD.GNFS.ZS

Figure 4.5 TVP-VAR dynamic total spillover index

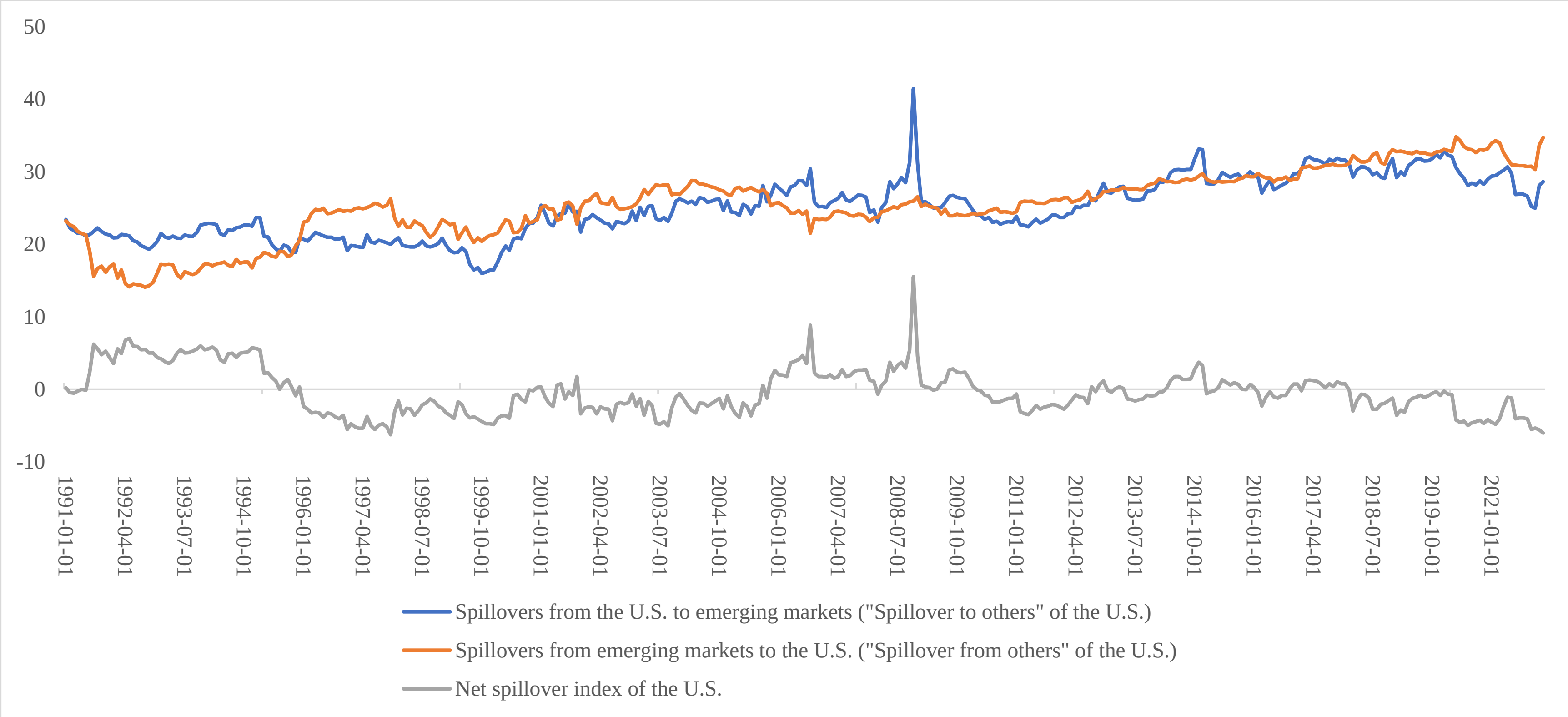


Notes: Results are based on a TVP-VAR-based connectedness framework with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

Considering the changing role of the U.S. in the dynamic network inflation spillovers, we plot the "*Spillover to others*", "*Spillover from others*", and the "Net Spillover Index" of the U.S. over the sample period in Figure 4.6. The blue line indicates the "*Spillover to others*" of the U.S., implying the spillovers from the U.S. to all emerging markets ($DSI_{US \to EME}$). The orange line denotes the "*Spillover from others*" of the U.S., displaying the spillovers from all emerging markets to the U.S. ($DSI_{EME \to US}$). The grey line shows the "Net Spillover Index" of the U.S. We point out three significant findings from the results of the U.S spillover indexes. First, both the blue and orange lines exhibited increasing trends over time, implying that the inflation interdependence between the U.S. and emerging markets has risen steadily. On the one hand, impact of the U.S. inflation on emerging markets' inflation rates became stronger over time. On the other hand, the inflation rate in the world's largest economy was also more and more dependent on inflation innovations in emerging markets. Second, although the U.S. acts as a net receiver of inflation shocks as evidenced by the average results of spillovers in Table 4.2, the dynamics of the Net Spillover Index (e.g., grey line) of the U.S. indicates that the U.S. role switched between net reciever and net transmitter of inflation shocks. Notably, during the period 1994-2003, when many emerging markets exhibited economic crisis or financial turmoil, the group of emerging markets was the net transmitter of shocks to the U.S.[44] Conversely, during the Global Financial Crisis (2007-2009), triggered by the sub-prime mortgage crisis in the U.S., the country acted as the net transmitter of inflation shocks to emerging economies.

[44] These events include crises in Mexico (1995); Asian economies (1997); Russia (1998); Brazil (1998); Argentina (2001); and Turkey (2001-2002). See more details in Williamson (2004).

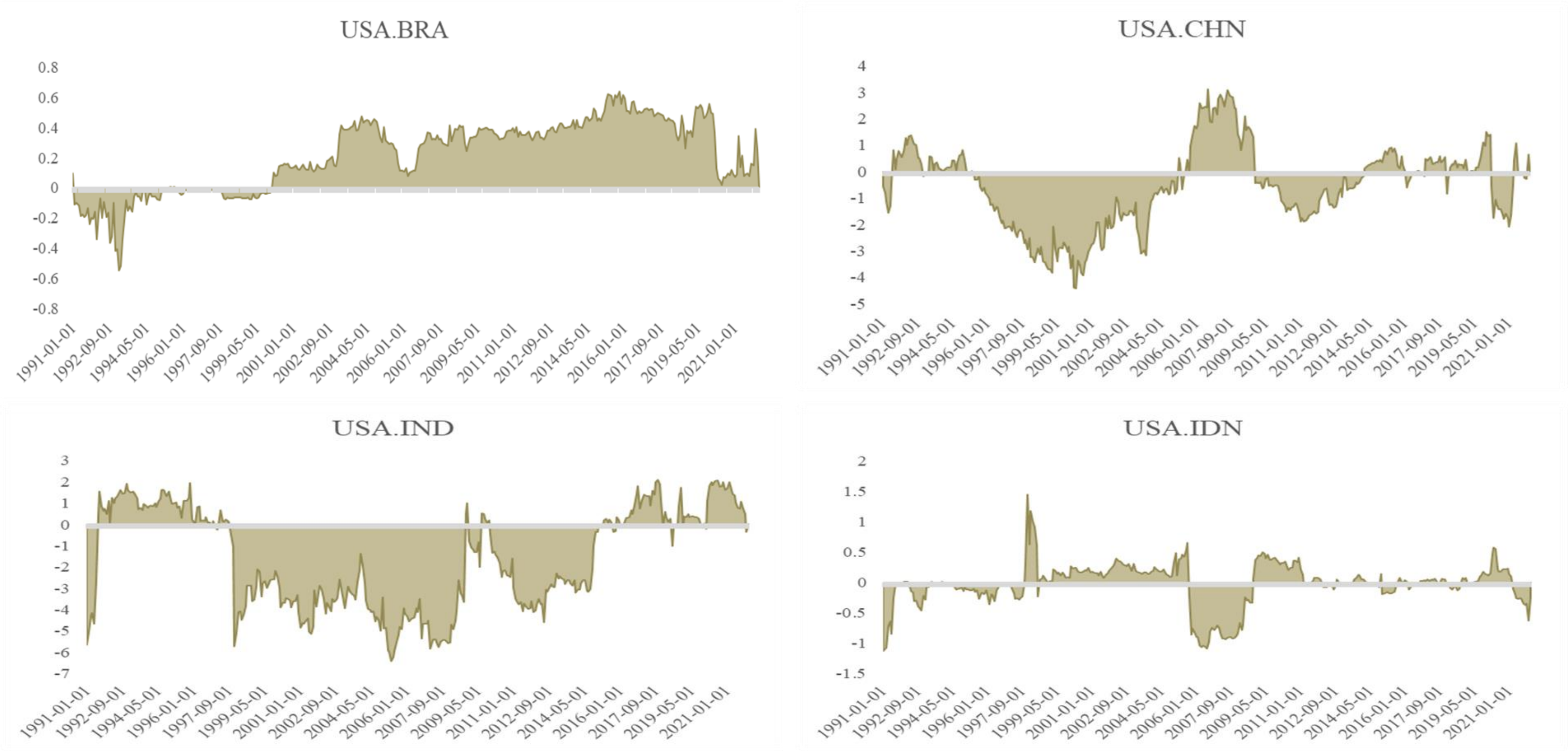
Figure 4.6 Inflation spillover measures of the U.S.

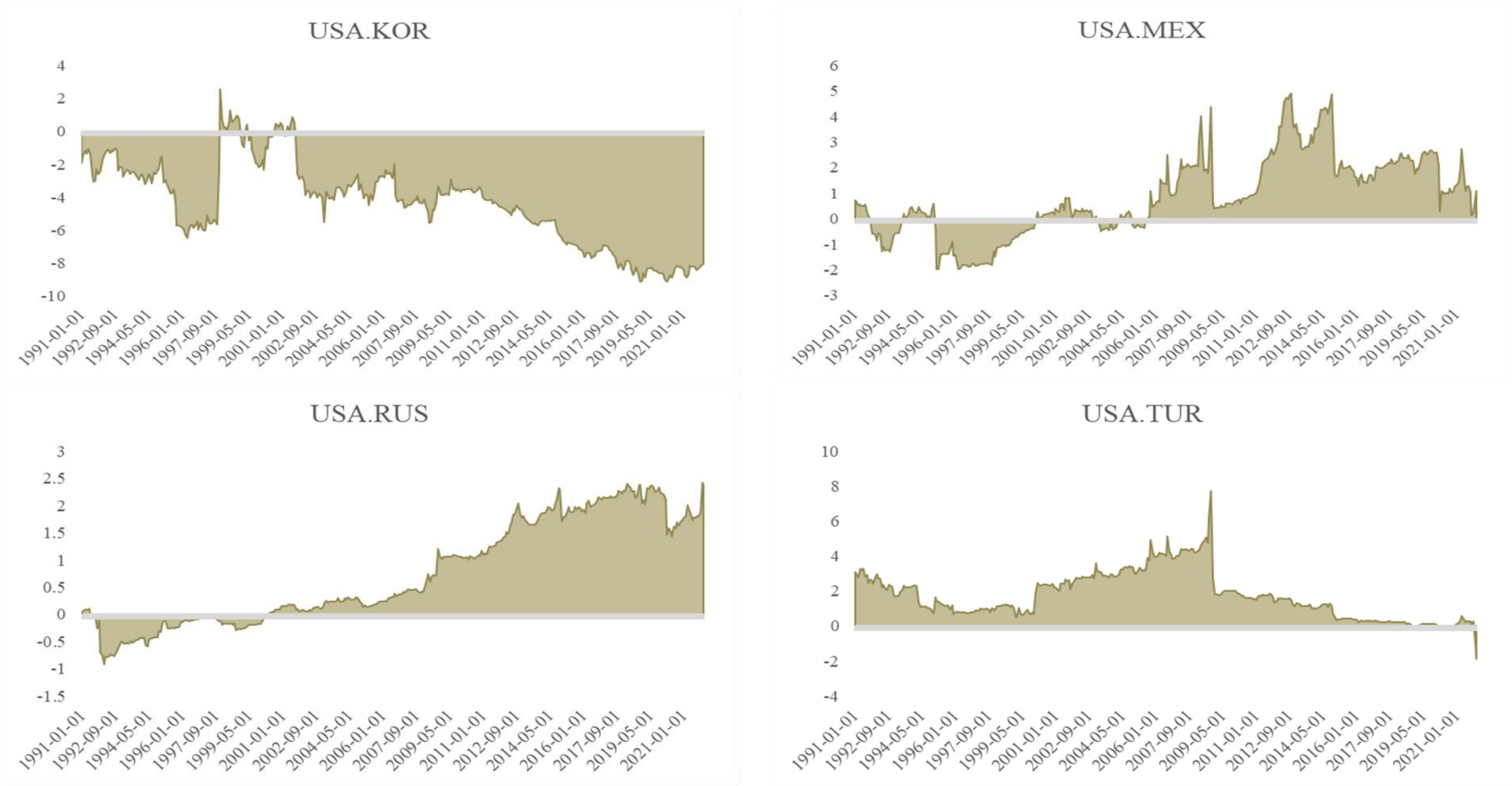


Notes: Results are based on the TVP-VAR-based connectedness framework with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

To uncover the bilateral spillover effects, we further plot the net pairwise directional spillover index (NPDS) of the U.S. with each emerging country in Figure 4.7. Similar to the net spillover index, a reading above (below) 0 of the net pairwise spillover index of the U.S. indicates the country is the net transmitter (receiver) of shocks to (from) the emerging market. First, it is observable that for most the sample period, the U.S. is the net transmitter of inflation shocks to Brazil, Russia, Turkey, and Taiwan, and net receiver of shocks from South Korea. The other countries including China, India, Indonesia, and Mexico switched between net receiver and net transmitter of shocks from (to) the U.S. more frequently. Second, the trend of the net position is also noteworthy. The increasing trend of the NPDS of the U.S. suggests that Brazil, Mexico, and Russia are more and more vulnerable to inflation shocks from the U.S. while the reverse finding applies for Taiwan. It is noticeable that the NPDS index between the U.S. and South Korea became more negative over time, implying the influence of the Asian country's inflation on the U.S. was magnifying. The trend of the net position for other emerging markets is less apparent as their indices experienced more fluctuations.

Figure 4.7 Time-varying net pairwise directional spillover (NPDS) of the U.S. with each emerging country




USA.KOR
USA.MEX
USA.RUS
USA.TUR
1991-01-01
1992-09-01
1994-05-01
1996-01-01
1997-09-01
1999-05-01
2001-01-01
2002-09-01
2004-05-01
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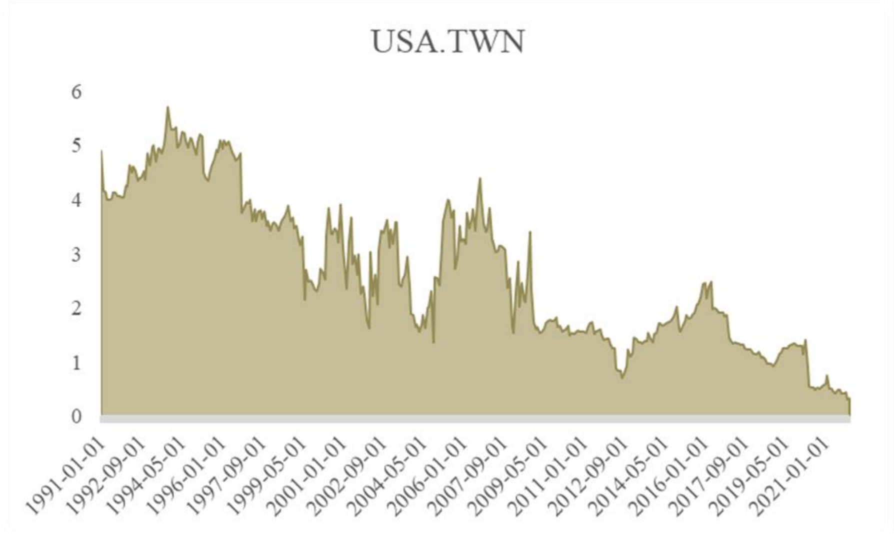
2019-05-01
2021-01-01



Notes: Results are based on the TVP-VAR-based connectedness framework with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

4.5.3 Do emerging country's characteristics matter?

In this subsection, we explore whether the inflation spillover effects between the U.S. and emerging markets might depend on the fundamental characteristics of the emerging countries. These characteristics include the country's exposure to international trade, the oil-exporting or importing status, and the exchange rate regime. The rationale for each characteristic is discussed in the following paragraphs.

First, international trade is considered an important channel through which inflation can spill from one country to another one (Tootell, 1998). As such, as a country's exposure to international trade is large, we expect its inflation spillover effects with other countries will be more pronounced.

Second, as oil is the global most important commodity, various studies find evidence that a change in oil prices is the key determinant of inflation rates and contributes to the inflation synchronization across countries (e.g., Barsky and Kilian, 2004; Jacquinot et al., 2009; Gómez-Loscos et al., 2011; Elsayed et al. 2021; Wen et al. 2021; among others). More importantly, the inflation of both oil-exporting and oil-importing countries is positively affected by oil prices (e.g., Filis and Chatziantoniou, 2014). On the one hand, it is apparent that oil price increases could cause cost-push inflation in oil-importing markets. On the other hand, oil price increases could lead to demand-side inflationary pressures in oil-exporting countries as their governments tend to increase spending thanks to higher oil-related revenues. As the cause of inflation is diverse, Filis and Chatziantoniou (2014) further show that the positive effect of oil price increases on inflation endures longer in oil-importing countries than in oil-exporting countries. Based on these discussions and given the fact the U.S. is a net oil-importing country, we expect that the inflation spillover between the U.S. and oil-importing countries should be greater than that between the U.S. and oil-exporting countries.

Third, exchange rate regime is also an important determinant of how a country's central bank reacts to inflation shocks and controls inflation (e.g., Bleaney, 2000). When a country sticks to a free-floating exchange rate regime, its central bank will follow more accommodating policies. As a result, the central bank under floating regime can accept more volatile and high inflation rates. Supporting this argument, numerous studies have provided evidence that inflation rates are lower under fixed regimes than floating regimes (e.g., Bleaney and Francisco, 2007; Giannellis and Koukouritakis, 2013; Husain et al., 2005). Moreover, inflation shocks under floating regimes usually take longer time to die out, which causes inflation to last longer – a phenomenon known as persistent inflation (e.g., Dornbusch, 1982; Alogoskoufis and Smith, 1991; Obstfeld, 1995). In light of these evidence, we conjecture that inflation spillover effects are more pronounced between the U.S. and emerging markets that follow ultimately free-floating exchange rate regimes.

To examine the impacts of these country-specific characteristics on the inflation spillover, we classify the nine emerging markets into two groups based on their exposure to international trade, oil-exporting (importing) status, and exchange rate regime, respectively. First, using the Openness Index in 2018 as proxy for a country's exposure to international trade, we group the emerging countries into two groups of low openness (including Brazil, China, India, Indonesia, and Russia) and high openness (Korea, Mexico, Turkey, and Taiwan). Second, based on the net oil-importing (exporting) character, the emerging markets are divided into net oil-exporting countries (Brazil, Russia, and Mexico) and net oil-importing economies (China, India, Indonesia, South Korea, Turkey, and Taiwan). Finally, based on the latest report on exchange rate regime classification from International Monetary Fund (2022),[45] the countries classified as fixed peg or managed floating regimes in the report are divided into low

[45] See, International Monetary Fund. 2022. Annual Report on Exchange Arrangements and Exchange Restrictions 2021.

floating regimes (Russia, China, India, and Taiwan), while the currencies defined as floating or free-floating exchange rates are considered high floating systems (South Korea, Brazil, Indonesia, Mexico, and Turkey). The detailed characteristics of each country are provided in Table A.4.1 of Appendix A.4.1.[46]

In order to examine how the inflation spillover effects between the U.S. and emerging market differ depending on the characteristics of emerging markets, we next employ the block connectedness technique proposed by Greenwood-Nimmo et al. (2016)[47] to decompose the total spillover effects among the sample countries in Table 4.2 into block aggregations of connectedness as reported in Table 4.4. Panel A Table 4.4 reports two block aggregations of connectedness: (1) the U.S. and the group of low openness countries; and (2) the U.S. and the group of high openness countries. Each entry in the panel shows the portion of inflation spillover from the column variable to the row variable as percentages of the total inflation spillover effects of the system. It is shown that the group of emerging countries with more economic openness have greater inflation interconnectedness with the U.S. than the other group. In particular, the directional inflation spillover from "High openness" countries to the U.S. stands at 1.559%, whereas the figure of "Low openness" group is just 0.981%. In a similar vein, directional inflation spillover from the U.S. to "High openness" group is 1.648%, which is nearly twice the number from the U.S. to "Low openness" markets. These figures are in line with our conjecture that countries, which are exposed more to international trade would have more inflation interdependence with the U.S.

In Table 4.4 Panel B, two groups of interest are oil-exporting and oil-importing countries. The figures suggest that the inflation interdependence between the U.S. and oil-importing group are much stronger than the inflation transmission between the U.S. and oil-

[46] Note, the countries that have undergone complex changes in their exchange rate policies during our research period are classified based on their exchange rate regimes for the majority of the sample time.
[47] The technique is presented in detail in Appendix A.4.2.

exporting markets. Specifically, the directional spillover index from oil-exporting countries to the U.S. is 0.104%, which is substantially lower than the spillover index from oil-importing group to the U.S. (2.436%). Similarly, oil-exporting economies seem to be more resilient to inflation shocks from the U.S. than oil-importing countries, as evidenced by the directional spillover index from the U.S. to these two groups of 0.283 % and 2.22%, respectively. This finding supports our above prediction.

Finally, in Table 4.4 Panel C, we consider the role of foreign exchange regime. We find that compared to countries with low floating exchange regime, countries with high floating exchange regime exhibit stronger inflation interconnectedness with the U.S. In details, “Low floating” group both receives and transmits lower portions of inflation shocks from and to the U.S. than “High floating” group. The directional spillover index of “Low floating” group to and from the U.S. are 0.974% and 0.827%, respectively, whereas these figures for “High floating” group are 1.566% and 1.676%, correspondingly. This evidence highlights the role of foreign exchange regime in determining the inflation spillover effects. As emerging markets following managed floating or pegged exchange rate regime are more concerned with inflation and tend to control inflation more closely, their inflation rates are less interrelated with outside inflation shocks from the U.S.

Table 4.4 The importance of emerging market's specific characteristics

Panel A. Low-openness vs. high-openness

	USA	Low openness	High openness
USA	7.462	0.981	1.559
Low openness	0.855	44.814	4.329
High openness	1.648	3.316	35.033

Panel B. Oil-exporting vs. oil-importing

	USA	Oil-exporting	Oil-importing
USA	7.462	0.104	2.436
Oil-exporting	0.283	26.593	3.123
Oil-importing	2.22	2.923	54.853

Panel C. Foreign exchange regime (Low floating vs. high floating)

	USA	Low floating	High floating
USA	7.462	0.974	1.566
Low floating	0.827	34.509	4.663
High floating	1.676	3.359	44.961

Notes: Results are initially based on the TVP-VAR-based connectedness framework with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition. Then, the block connectedness framework of Greenwood-Nimmo et al. (2016) is applied to compute the inflation spillover measures between groups.

4.5.4 Inflation spillover effects during highly inflationary environment (The quantile-based inflation connectedness results)

Another important but unanswered question in extant literature of inflation synchronization or spillover is whether the international inflation spillover is more pronounced during the period of high inflationary pressures (e.g., hyperinflation). To address this raised question, we employ the quantile connectedness,[48] proposed by Ando et al. (2022), to examine the inflation spillover effects at the upper tails of the conditional distributions, where the inflation rates are at extremely positive levels.

Table 4.5 Panel A, B, C, and D present the results of quantile connectedness estimated for four upper quantiles, which are 80%, 85%, 90%, and 95%, respectively. There are three striking findings from here. First, the total spillover index (TSI) increases as the quantile moves further to upper tails. The TSIs are 47.18%, 56.51%, 68.77%, and 77.15% at upper quantiles of 80%, 85%, 90% and 95%, respectively. Notably, these figures are substantially higher than the average TSI (18.83%) at the conditional mean of distributions using the TVP-VAR-based connectedness approach, as shown in Table 4.2. This indicates that the transmission of inflation shocks between the selected countries significantly intensifies when inflationary shocks are extremely high. Second, the U.S. remains the net importer of inflation shocks from emerging markets at the upper tails, as shown by the consistent negative "Net Spillover Index" of the U.S. in all cases. This lend further supports that the *"consumption channel"* is dominant in shaping the inflation interdependence between the world's largest economy and emerging countries. Third, it can be seen that at the extremely positive inflation environment, some emerging markets turn from net receiver to net transmitter of shocks and vice versa. Specifically, countries such as Taiwan and Turkey act as net shock receivers in normal

[48] To be consistent with the TVP-VAR connectedness framework's results in subsection 5.1, we employ a 20-step forecast head (h=20) and lag order of 1 (p=1) in the quantile VAR model.

condition (Table 4.2) but become net shock diffusers in the extreme inflationary conditions (all panels in Table 4.5). On the other hand, India role changes from net shock transmitter to net shock receiver. Finally, it is noteworthy that China, South Korea, and Mexico consistently continue to be net transmitters of inflation shocks in the system while Russia's role as net shock receiver is unchanged.

Table 4.5 Inflation spillover effects across various upper quantiles

Panel A. At quantile=80%

	USA	BRA	CHN	IND	IDN	KOR	MEX	RUS	TUR	TWN	*Spillover from others*
USA	45.96	1.18	7.78	8.59	3.14	16.08	6.2	0.14	5.27	5.67	54.04
BRA	1.55	77.14	6.79	2.58	0.57	1.47	2.02	1.1	3.74	3.03	22.86
CHN	5.43	7.9	34.1	5.02	4.61	13.1	9.44	1.2	10.32	8.89	65.9
IND	10.28	1.95	4.02	53.73	6.8	7.99	5.23	0.63	3.61	5.75	46.27
IDN	2.75	0.57	3.53	4.66	54.59	7.06	9.2	0.3	13.23	4.12	45.41
KOR	12.12	1.21	12.52	5.18	8.64	40.21	9.67	0.04	4.53	5.88	59.79
MEX	4.44	0.66	9.46	3.14	5.99	6.81	45.38	2.26	14.58	7.27	54.62
RUS	0.19	6.46	1.32	0.53	0.83	0.31	1.99	84.42	3.32	0.61	15.58
TUR	3.66	6.04	12.6	3.77	4.39	7.43	14.24	0.4	39.89	7.58	60.11
TWN	6.32	2.08	11.18	4.91	4.04	7.21	5.2	0.14	6.15	52.77	47.23
Spillover to others	46.75	28.06	69.2	38.37	39	67.46	63.19	6.21	64.76	48.8	
NSI	-7.3	5.2	3.3	-7.9	-6.4	7.66	8.57	-9.36	4.65	1.57	
TSI	47.18										

Panel B. At quantile = 85%

	USA	BRA	CHN	IND	IDN	KOR	MEX	RUS	TUR	TWN	*Spillover from others*
USA	37.27	2.03	8.33	10.16	4.77	16.14	7.6	0.31	5.65	7.74	62.73
BRA	2.35	65.02	10.51	3.87	1.24	2.39	2.89	0.45	6.06	5.22	34.98
CHN	5.77	8.26	26.47	7.03	5.17	12	10.27	1.89	13.14	10	73.53
IND	10.9	2.26	5.75	44.43	8.2	9.22	6.4	0.7	4.66	7.49	55.57
IDN	4.73	0.99	6.21	6.11	42.63	10.47	11.12	0.42	11.78	5.55	57.37
KOR	12.81	1.48	12.32	7.48	8.8	33.55	10.03	0.11	6.09	7.34	66.45
MEX	6.02	1.14	11.61	5.97	6.92	9.49	33.66	1.66	14.6	8.92	66.34
RUS	0.62	5.4	2.17	1.2	2.14	0.97	2.86	78.66	3.87	2.11	21.34

TUR	5.06	5.17	14.05	6.09	5.03	8.32	15.22	0.44	31.51	9.1	68.49
TWN	8.46	2.97	12.44	6.83	4.89	8.75	6.28	0.75	6.91	41.72	58.28
Spillover to others	56.71	29.72	83.38	54.73	47.16	77.74	72.67	6.74	72.76	63.47	
NSI	-6.01	-5.26	9.85	-0.84	-10.21	11.29	6.33	-14.61	4.27	5.19	
TSI	56.51										

Panel C. At quantile=90%

	USA	BRA	CHN	IND	IDN	KOR	MEX	RUS	TUR	TWN	*Spillover from others*
USA	28.07	1.68	8.81	11.23	8.19	15.12	10.08	0.43	7.52	8.87	71.93
BRA	4.42	50.67	10.85	6.16	3.32	4.33	5.37	0.36	8.41	6.1	49.33
CHN	7.68	6.48	20.05	6.84	8.62	12.44	11.76	0.22	16.04	9.87	79.95
IND	10.88	2.48	6.22	34.38	10.16	9.6	9.71	1	6.44	9.14	65.62
IDN	7.33	1.25	8.27	9.24	24.26	12.58	14.53	0.38	14.31	7.85	75.74
KOR	11.43	2.11	12.63	7.41	8.97	24.39	11.68	3.07	9.59	8.73	75.61
MEX	5.83	1.03	7.88	7.44	10.36	9.93	25.18	11.23	12.77	8.34	74.82
RUS	2.56	4.49	5.07	5.08	6.55	5.13	9.46	50.05	6.76	4.87	49.95
TUR	6.52	3.64	13.06	5.47	9.78	11.09	15.39	0.51	25.29	9.25	74.71
TWN	9.99	2.62	10.46	8.71	7.79	10.22	9.92	1.95	8.37	29.97	70.03
Spillover to others	66.63	25.77	83.25	67.58	73.73	90.44	97.91	19.15	90.22	73.02	
NSI	-5.3	-23.56	3.29	1.96	-2.02	14.83	23.08	-30.8	15.51	2.99	
TSI	68.77										

Panel D. At quantile = 95%

	USA	BRA	CHN	IND	IDN	KOR	MEX	RUS	TUR	TWN	*Spillover from others*
USA	16.1	2.86	9.59	11.69	11.86	12.08	13.29	1.71	11.81	9.01	83.9
BRA	4.7	36.87	12.31	6.36	4.01	5.69	6.63	3.47	11.35	8.6	63.13
CHN	6.25	7.07	15.54	8.13	8.19	10.44	12.38	5.77	14.96	11.27	84.46
IND	9.87	3.25	8.17	25.17	12.05	9.28	9.49	6.4	6.07	10.25	74.83

IDN	7.99	1.38	8.68	8.44	23.92	12.71	14.32	0.26	15.27	7.01	76.08
KOR	10.24	3.61	13.14	8.23	9.44	19.35	11.23	3.95	11.01	9.81	80.65
MEX	6.61	1.39	10.06	5.48	8.75	9.69	25	2.7	20.66	9.68	75
RUS	4.3	10.53	12.04	7.69	7.35	6.82	9.45	19.62	10.82	11.37	80.38
TUR	6.2	3.57	12.65	3.05	8.35	11.42	18.66	0.36	27.99	7.76	72.01
TWN	6.83	5.65	12.47	8.44	7.57	8.95	10.39	10.84	9.94	18.91	81.09
Spillover to others	62.99	39.31	99.11	67.54	77.56	87.07	105.84	35.48	111.88	84.75	
NSI	-20.91	-23.82	14.65	-7.29	1.49	6.42	30.83	-44.9	39.87	3.67	
TSI	77.15										

Notes: Results are based on the quantile VAR-based connectedness approach with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

4.5.5 Drivers of the time-varying inflation spillover effects

Our previous results in subsection 4.5.2 show that the inflation spillover between the U.S. and emerging countries exhibits significant variations and highly volatile behavior. Consequently, there is a necessity to examine the key drivers of these fluctuations. The comprehensive understanding of the drivers of inflation transmission is of great importance to investors and policymakers when considering their portfolio allocation and forecasting inflation to propose efficient and timely macroeconomic policies. In this subsection, we explore the determinants of the inflation spillover effects between the U.S. and emerging markets by estimating the following models,

$$DSI_{US\to EME,t} = \beta_0 + \beta_1 USMPU_t + \beta_2 USTPU_t + \beta_3 DXY_t + \beta_4 VIX_t + \beta_5 FFR_t + \beta_6 WTI_t + \beta_7 OVX_t + \beta_8 EMEPU_t + \beta_9 US\_EXP_t + \varepsilon_t \quad (4.23)$$

and

$$DSI_{EME\to US,t} = \gamma_0 + \gamma_1 USMPU_t + \gamma_2 USEPU_t + \gamma_3 DXY_t + \gamma_4 VIX_t + \gamma_5 FFR_t + \gamma_6 WTI_t + \gamma_7 OVX_t + \gamma_8 EMEPU_t + \gamma_9 US\_IMP_t + \epsilon_t \quad (4.24)$$

where $DSI_{US\to EME}$ *and* $DSI_{EME\to US}$ denote the directional spillover index from the U.S. to emerging markets, and the directional spillover index from emerging markets to the U.S., respectively; β_0 and γ_0 are intercepts; $\beta_i, \gamma_i | i = 1, \ldots, 9$ are the sets of estimated coefficients; ε_t is the residual term.

There are nine selected explanatory variables including: (1) $USMPU$ is the natural logarithm of the monetary policy uncertainty index in the U.S. introduced by Husted et al. (2020); (2) $USTPU$ is the natural logarithm of the U.S. trade policy uncertainty index from Baker et al. (2016); (3) DXY is natural logarithm of the U.S. dollar index; (4) VIX is the CBOE implied volatility index of the S&P 500 index; (5) FFR is the Fed's fund rate; (6) WTI is the natural logarithm of WTI crude oil spot price; (7) OVX is the volatility of WTI crude oil measured by its standard deviation of returns during one month; (8) $EMEPU$ is the average economic policy uncertainty index of six emerging markets in the sample;[49] (9) US_EXP is the natural logarithm of the U.S. exports (in USD billion) to the emerging markets used as a regressor in Eq. (4.23) while US_IMP is the natural logarithm of the U.S. imports (in USD billion) from the emerging markets included as an explanatory variable in Eq. (4.24). The time-varying fluctuations of the trade balance between the U.S. and EAGLEs are displayed in Figure A.4.3 of the Appendix A.4.3.

The first seven explanatory variables in Eqs. (4.23) and (4.24) reflect several factors that possibly affect the inflation shock transmission between the U.S. and emerging markets. First, we include four important variables to account for the change in macro-economic conditions in the U.S. including $USMPU$, $USTPU$, DXY, and FFR. The U.S. monetary policy uncertainty ($USMPU$) and trade policy uncertainty ($USTPU$) represent key policy uncertainties in the U.S. The variations in these variables encompass the risks of changes in monetary and trade policies of the U.S.,[50] which are well regarded as important drivers of inflation integration between the U.S. and other countries. This statement is implicitly grounded on open-economy macroeconomic theories. For example, chapter 11 of the textbook Macroeconomics (Carlin and Soskice, 2015, Oxford University Press) presents a simple 2-bloc model with which to analyse how a permanent demand shock in bloc A (causing A's inflation to rise) can spill over to bloc B (causing B's inflation to rise). The demand shock can arise from changes in monetary policy and/or trade policy in block A. The analysis involves several economic variables such as interest rates, real exchange rates, inflation rates, national output, trade balance (imports and exports), and so on. The insight provided by that theoretical model is that changes in monetary policy and/or trade policy as demand-side policies could become important drivers of inflation transmission between two blocs of countries. Policy uncertainties are also documented to be

[49] These countries are Brazil, China, India, South Korea, Russia, and Mexico. The data on the economic policy uncertainty index is unavailable for Turkey, Taiwan, and Indonesia.
[50] The construction of the U.S. economic policy uncertainty index includes the uncertainty relating to trade policies as a component. See, Baker et al. (2016).

an important driver of inflation in empirical studies (Istrefi and Piloiu, 2014; Balcilar et al., 2017). For instance, Istrefi and Piloiu (2014) find that both long- and short-term inflation expectations are vulnerable to policy-related uncertainty shocks. Their results indicate a positive relationship between long-term inflation expectations and policy uncertainty. In addition, the US dollar index (DXY) is included in the equations as it also matters to the U.S. inflation and trade balance. According to Cecchetti et al. (2000), the U.S. dollar index can be used to predict the U.S. inflation rates, however, its credibility might vary depending on certain macroeconomic conditions. Concerning to the impact of the U.S. dollar index on the U.S. trade balance, various studies such as Cushman (1987), Yousefi and Wirjanto (2003), and Hunt and Rebucci (2005) indicate the U.S. dollar appreciation deteriorates the U.S. trade balance and vice versa.[51] Besides these roles, the U.S. dollar is also considered a safe haven for emerging stock markets (Wen and Cheng, 2018) and a high level of the U.S. dollar might intensify the spillover effects across financial markets (Batten et al., 2019; Saeed et al., 2021; and Bouri, et al., 2021b). The last U.S. variable included in these equations is the Fed's fund rate (FFR), which accounts for the short-term interest rates and the Fed's monetary policy stance. Because the U.S. monetary policy can spillover to emerging markets (e.g., Maćkowiak, 2007; Chen et al., 2014; Bowman et al., 2015; Anaya et al., 2017; and Bräuning and Ivashina, 2020; among others), inflationary pressures caused by loosening monetary policy in the U.S. can transmit to the emerging markets as well.

In addition to the five U.S. market indicators, we include the WTI crude oil price (WTI) and the oil volatility index (OVX) to proxy for the general price level and uncertainty in global commodity markets. A high level of global commodity prices might be an explanation for global inflation integration as it directly affects the aggregate supply by raising production

[51] These findings are consistent with the traditional external trade channel which implies that when the U.S. dollar appreciates against another country's currency, the products of that country become more competitive relative to U.S. products, thereby fostering its exports and output.

costs (e.g., inflation triggered from supply side). Further, as the world's most crucial commodity, numerous studies have shown that oil prices affected inflation rates in both developed and emerging markets (Cuñado and de Gracia, 2003; Farzanegan and Markwardt, 2009; and Zhao et al. 2016; among others). Finally, we take in the policy uncertainty in emerging markets by adding the average economic policy uncertainty index ($EMEPU$) of six emerging markets including Brazil, China, India, South Korea, Russia, and Mexico. The last variable in Eq. (4.23) is the exports from the U.S. to emerging markets (US_EXP) accounting for the critical role of international trade on the inflation spillover effects. In Eq. (4.24), the U.S. imports from emerging economies (US_IMP) is the last regressor accounting for the effect of international trade on inflation shock transmission.

One could concern that balance of payment could be a potential driver of inflation shock transmission as it could affect the vulnerability of emerging markets' monetary policies to the US monetary policies. By definition, balance of payment includes capital account and current account. Current account, in turn, includes the impact of trade balance, which is partly considered in our paper through the bilateral trade between the US and emerging market. More importantly, the data on balance of payments for emerging markets from IMF database is only available on a quarterly or yearly basis (https://data.imf.org/regular.aspx?key=62805742), so we cannot include this variable in our models to explain the inflation shock transmission.

We estimate Eqs. (4.23) and (4.24) using the feasible generalized least square (FGLS). The estimated coefficients and their corresponding standard errors are reported in Table 4.6. The regression results yield several remarkable findings. First, the adjusted R-squared of the both models are relatively of 63.4% and 79.6%, respectively, suggesting that both models have ability to explain the variation of the spillover measures. The statistical significance of the F-statistics further corroborates this conclusion.

Pertaining to the inflation spillover from the U.S. to emerging markets, we find that the $DSI_{US \to EME}$ is positively correlated with the $USTPU$ (1.029) and the DXY (4.962) while insignificantly affected by the $USMPU$. These figures indicate that transmission of inflation shocks from the U.S. to emerging economies is higher when there are more uncertainties regarding the U.S. trade policies and the U.S. dollar exhibits the appreciations in its value. Meanwhile, the U.S. monetary policy uncertainty exerts no significant impact on the inflation spillover of the U.S to other countries. In addition, consistent with our expectation, inflation spillover effects from the U.S. tend to be more pronounced when the Fed expands its monetary policy as evidenced by the negative and statistically significant coefficient of FFR (-0.282). Regarding the impact of global commodity market, we find that the $DSI_{US \to EME}$ is higher when oil price is elevated and more volatile, as shown by significant positive coefficient of WTI (5.078). As oil prices have significant effect on inflation, high oil price uncertainty might induce more inflation uncertainty. In turn, inflation would rise with inflation uncertainty (Golob, 1994; Jiranyakul and Opiela, 2010). This would help explain why oil price uncertainty might lead to higher inflation and inflation spillover effects. Finally, the coefficients of $EMEPU$ and US_EXP are both positive and statistically significant, standing at 0.007 and 5.973, respectively. These numbers suggest that emerging markets receives more inflation shocks from the U.S. when their policy-related uncertainty are high and when they import more from the U.S. Notably, a 1 percent increase in the U.S. export to emerging markets causes a 5.973% increase in the $DSI_{US \to EME}$.

Concerning the directional inflation spillover effects from emerging markets to the U.S., we reveal that only four out of nine selected explanatory variables statistically and significantly explain the variation of $DSI_{EME \to US}$, including the dollar index (DXY), the WTI, the EMEPU and the US_IMP. In particular, the U.S. dollar index continue to have a positive effect on the $DSI_{EME \to US}$ as shown by its coefficient of 7.12. This positive relationship is consistent with our conjecture about the role of a strong US dollar as a booster of the U.S. imports from emerging markets. It is also in line with recent evidence from Batten et al. (2019), Saeed et al. (2021), and Bouri, et al. (2021) that the strengthening of the U.S. dollar is associated with more interconnectedness of global financial markets. Contrary to our expectation, the coefficient of WTI is negative and statistically significant (-2.46), implying that the increasing oil prices exert an attenuating impact on the inflation spillover from emerging markets to the U.S. Besides, the impacts of the emerging markets' economic policy uncertainty ($EMEPU$) and the U.S. imports from emerging markets (US_IMP) are consistent with our expectations. The coefficient of EME_EPU is 0.015, implying that an 1% increase in the $EMEPU$ leads to an 0.015% increase in the $DSI_{EME\rightarrow US}$. In a similar vein, the coefficient of US_IMP (13.143) suggests that an 1% increase in the U.S. imports from emerging markets induces an 13.143% increase in the $DSI_{EME\rightarrow US}$.

Table 4.6 Drivers of directional inflation spillover effects

	$DSI_{US\rightarrow EME}$ (1)	$DSI_{EME\rightarrow US}$ (2)
USMPU	0.204	-0.337
	[0.288]	[0.249]
USTPU	1.029^{***}	0.096
	[0.342]	[0.299]
DXY	4.962^{***}	7.12^{***}
	[1.751]	[1.547]
FFR	-0.282^{***}	-0.011
	[0.082]	[0.072]
WTI	5.078^{***}	-2.46^{**}
	[1.318]	[1.183]
OVX	0.004^{*}	-0.0001
	[0.002]	[0.002]
EMEPU	0.007^{**}	0.015^{***}
	[0.004]	[0.003]
US_EXP	5.973^{***}	
	[1.431]	
US_IMP		13.143^{***}
		[0.966]
Constant	-34.072^{***}	-63.81^{***}
	[7.295]	[6.389]
Adjusted-R^2	0.634	0.796
N. Obs.	363	363
F-statistics	80.53^{***}	180.45^{***}

Notes: This table presents the estimated coefficients and their standard errors (in bracket) of Eqs. (4.23) and (4.24) using the Generalized Feasible Least Square (GFLS), where *DSI* is based on a TVP-VAR-based connectedness with a 20-step forecast ahead. The *DSI* is defined in Eqs. (4.8) and (4.9). ***, ** and * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively.

4.6 Robustness checks

One concern might be that our results are driven by the choice of the number of *h*-step forecast ahead used to calculate the time-varying inflation spillover measures. To address this concern, we re-estimate the inflation spillover measures in this study using *10*-step and *30*-step forecast ahead as robustness checks for our key empirical findings. We first report the average spillover measures in Table A.4.4 of Appendix A.4.4. As shown in both panels of the appendix, the U.S. remains the net receiver of inflation shocks from the EAGLES with the net spillover index (NSI) of the U.S. in Panels A and B being -1.5% and -0.82%, respectively. In addition, the role of other countries as net exporter or net importer of inflation spillover effects in the network is consistent with our base results in Table 4.2. We further plot the time-varying TSI using various *h*-step forecast ahead in Figure A.4.5 of Appendix A.4.5. It is observable that the evolvements of these connectedness indices are very close to those of our main analysis in Figure 4.5. Overall, these results of the robustness tests add more credence to our key empirical findings in this study.

4.7 Conclusion

Rising inflation has been a major concern in global economic policy over the last one to two years. Our study highlights that government authorities should not only focus on the domestic inflation rate, but also consider inflation shock spillover from outside as well as its determinants when making economic policy decisions. Our study focuses on the role of the U.S. in international inflation transmission and investigates how this role changes during the research period.

To this end, we use data in the U.S. and the nine EAGLES countries between January 1991 and February 2022 to examine the inflation spillover effects among these nations at both normal and extreme conditions. First, we find that the total inflation spillover index among the sample countries stays at a considerable level of nearly 19% in the normal condition. More importantly, the U.S. inflation rate tends to be more connected with the countries which are more opened, or are net oil-importing, or follow the free-floating exchange rate regime.

Second, our study provides evidence that the total inflation spillover of the sample system is much more severe, soaring up to 70% in an extreme inflationary period (e.g., inflation surge). This finding highlights the necessity take into consideration the inflation spillover effect when estimating a country's inflation to design appropriate response policy. Since we may not return to the era of a steady inflation rate of 2-3% in the next five years, it has become even more important to keep a close eye on international inflation spillover effects in order to better monitor domestic inflation rates.

Third, our static connectedness results show that the U.S. is a net importer of inflation shocks from the emerging countries regardless of the measures at the conditional mean or tails of conditional distributions. However, the net pairwise inflation spillover indexes of the U.S. with each emerging market reveal that the role of the U.S. varies across emerging markets and fluctuates over time. On the one hand, China, India, and South Korea are the largest net transmitters of inflation shocks to the U.S., which is consistent with the large and frequent trade deficit situation of the U.S. with these countries, following the explanation mentioned in the *"consumption channel"*. On the other hand, as GDP growth rates of Taiwan and Mexico are substantially dependent on their exports to the U.S., these countries are the most important net receivers of inflation shocks from the U.S., supporting the *"monetary policy channel"*.

Finally, the investigation of inflation spillovers' determinants reveals that the U.S. dollar is among the strongest drivers of the inflation shock transmission, along with the bilateral trade between the U.S. and EAGLES, and the EPU in the emerging markets. While the effect of the emerging markets' EPU on the inflation spillover is relatively small in terms of magnitude, hence, leading to less interest, the economic significance of the U.S. dollar and bilateral trade deserve more attention. These findings are as expected due to the importance of bilateral trade between the U.S. and EAGLES, and the fact that central banks of these emerging countries have maintained a large portion of their reserves in the U.S. dollars for several decades. More importantly, our finding of the critical role of the U.S. dollar as the inflation shock driver further justifies the recent actions of central banks to protect the domestic currencies by decreasing the U.S. dollar in their reserves.[52]

[52] See, https://www.nytimes.com/2022/10/27/business/strong-dollar-global-economy.html

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the student and the student's main supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the student's contribution as indicated below in the Statement of Originality.

Student name:	Thao Thac Thanh Nguyen
Name and title of main supervisor:	Professor Xiaoming Li
In which chapter is the manuscript/published work?	Chapter 4
What percentage of the manuscript/published work was contributed by the student?	60%

Describe the contribution that the student has made to the manuscript/published work:
Thao is the main author of this paper, and while her superviors have made substantial contributions, reflected through co-authorship, the paper is essentially the work of Thao. She has made contributions to methodology applied, data circulation, original draft writing, and revisions. The supervisors contributed to the paper by providing critical comments, insightful advices, supervision, and revising the paper. Additionally, this paper also benefits from the contributions of an external co-author, Dr. Son Duy Pham, who has made critical contributions to conceptualization, software and revising the paper.

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CHAPTER FIVE

Conclusion of the Thesis

This chapter concludes the thesis by summarizing the key findings and implications of each essay in section 5.1. The future areas of research are discussed in section 5.2.

5.1 Main findings and implications

5.1.1 Essay One (Chapter Two)

The increasing volatile property in the oil market has magnified the transmission of oil volatility shocks to oil-dependent currency markets. This has sparked the interest among FX market participants about whether the volatility connectedness among oil-dependent currencies changes if the oil market enters a state of high volatility. The knowledge of oil-volatility-dependent FX connectedness, therefore, could serve as an empirical base to design a dynamic FX strategy that can improve the benefits of FX diversifications and help with formulating hedging strategies.

The first essay of the thesis develops the VHAR(Q)-DCC-GARCH-based connectedness measures to investigate the high-frequency volatility connectedness between oil-exporting and oil-importing currencies under different states of the oil market's volatility. There are several key findings from this essay can be outlined as follows. First, the average cross-group connectedness between oil-exporting and oil-importing currencies is moderate, and mainly comes from the short-run transmission of volatility shocks from the oil-exporting group to the oil-importing group. Second, this cross-group FX connectedness tends to be more pronounced when the oil market switches from a low-volatility to a high-volatility regime. Finally, in this network connectedness, the oil-exporting currencies consistently act as volatility shock transmitters regardless of different oil volatility regimes.

The findings of this essay deliver an important implication for FX portfolio managers in terms of asset allocation and risk management. As the results of this essay show that the regime switching of the oil market volatility from a low state to a high state significantly intensifies the volatility connectedness between oil-dependent currencies, the diversification benefit of an FX portfolio engaging in both oil-exporting and oil-importing currencies should decline in response to this regime switch. Accordingly, FX traders who hold both oil-exporting and oil-importing exchange rates should keep close eyes on the information of the oil market's volatility to actively adjust the portfolio weights. This oil-regime-dependent FX trading could help FX portfolio managers better manage their portfolio risk and improve their portfolios' risk-adjusted returns.

5.1.2 Essay Two (Chapter Three)

The disruptions in Russian gas supplies, trigged by the conflict between Russia and Ukraine, have had detrimental impacts on European economies, and posed a significant threat to the European corporate debt market. This motivates a thorough investigation of the relationship between European corporate credit default swap (CDS) markets and the natural gas market. Thereby, the second essay of the thesis examines the causal relationship and the dynamic pattern of the return connectedness between European CDSs and natural gas.

This essay presents several significant findings. First, decomposing the return shocks in the sample markets into positive shocks and negative shocks, the Granger Causality tests among these components of shocks show that the shocks in the natural gas market significantly positively Granger cause the shocks in European sectoral CDS markets. By contrast, the opposite direction of the causality is negative. Second, the results of mean-based- and quantile-based-connectedness point out that the cross-market spillover of average shocks among the system is moderate, but there is a significant strengthening of spillover effects for extreme large positive and negative shocks, suggesting increased interdependence among these markets under extreme conditions. Third, in this return connectedness, the gas market plays the dominant role of a return shock absorber regardless of whether the connectedness measured at the conditional mean or tails of return distributions. Fourth, the analysis of time-varying return connectedness shows that the high degrees of this return connectedness are all driven by various financial market uncertainties. Finally, this essay quantifies the magnifying effect of the Russian-Ukrainian war on return shock transmission between European CDS markets and the gas market.

These findings have important implications for investors and policymakers. First, they can use the insights into the causal linkages and consider the type of shocks when making decisions about their positions in these markets or when formulating stabilizing policy. Second, recognizing that the return shock propagation is stronger in extreme events, investors and policymakers should extend their analyses beyond average shock transmission to capture the spillover effects of extreme large shocks for more-informed-decision making. Finally, as the war's duration remains uncertain, this study timely informs investors and policymakers to take into consideration the amplifying effect of the war on return shock transmission to better manage their portfolio risk and maintain financial stability in the European area.

5.1.3 Essay Three (Chapter Four)

Continuing the topic of measuring financial spillover risk as discussed in the previous two essays, the third essay of the thesis turns to examine the spillover effect of inflation rates between the U.S. and nine emerging and growth-leading economies (EAGLEs). This issue has gained significant interest in recent times since global economies have experienced rising inflation rates over the last one to two years.

This study relies on the low-frequency and short sample data (i.e., monthly inflation rates), so the investigation of inflation spillover is conducted using the TVP-VAR-based connectedness framework. The essay reveals several key findings. First, the average inflation spillover index is moderate under normal conditions, but significantly intensifies under extreme inflationary periods. Second, the inflation rates of the U.S. tend to be more connected with those of the emerging countries which have higher openness, or are net oil-importers, or follow free-floating exchange rate regimes. Third, on average, the U.S. predominantly acts as an importer of inflation shocks from the system of emerging markets. However, this role of the U.S. varies over time and among different emerging markets, switching between being a net importer and net exporter of inflation shocks. Finally, this research identifies that the value of the U.S. dollar, along with bilateral trade between the U.S. and EAGLEs, and the Economic Policy Uncertainty (EPU) in emerging markets are key determinants of inflation shock transmission between these countries.

There findings carry several important implications for policymakers and regulators. First, the increased spillover effect of extreme inflation shocks underscores the need to take into consideration the information of inflation spillover, particularly under hyperinflationary conditions, when formulating response policies to effectively monitor domestic inflation rates. Second, policymakers in both the U.S. and emerging countries should pay close attention to the factors driving inflation spillover effects, such as the characteristics of specific emerging markets, the emerging markets' EPU, the bilateral trade dynamics, and the value of the U.S. dollar. This knowledge enables them to enact informed policies aimed at safeguarding their currencies.

5.2 Future areas of research

The three essays in my thesis have conducted comprehensive investigations into the dynamics of spillover effects across various asset classes. This thesis has primarily focused on how financial spillover effects evolve during extreme economic conditions, such as financial crises, pandemics, or geopolitical events, as well as the determinants of interconnectedness. Understanding the dynamic spillover effects during these critical times can provide valuable insights for risk management and policymaking. Notably, the studies in my thesis have utilized diverse newly developed econometric methodologies. These methods go beyond the mean-based connectedness framework to consider connectedness at different quantiles of distributions, particularly the extreme lower and upper quantiles. Further, the VHAR(Q)-DCC-GARCH-based connectedness framework introduced in the first essay is specifically designed for high-frequency measures of volatility. It has demonstrated its effectiveness in addressing the biases of realized volatility estimation caused by long-memory behavior and measurement errors. While high-frequency analysis allows for real-time monitoring and prompt responses to spillover events, making it particularly relevant for traders and regulators, the research on connectedness based on high-frequency data is limited in the existing literature. So, there is potential for future empirical research to employ this methodology to study high-frequency spillover effects among other asset classes. An additional area for prospective research is to extend the HAR model by incorporating additional regressors to account for leverage effects, jumps or nonlinear effects in realized volatility timeseries. Using extensions of the multivariate HAR model as the baseline function in computing connectedness could help confirm the robustness of empirical connectedness results.

The second essay of this thesis has documented the significant intensifying effect of the Russian-Ukrainian war on return connectedness between the European credit markets and natural gas market. This calls for future research to consider the role of sanctions, trade tensions, or other geopolitical factors in propagating financial shocks. Additionally, other promising research areas could include studying the effectiveness of various policy interventions, such as central bank actions and regulatory measures, in mitigating financial spillovers. Such research would inform policymakers about timely responses.

The final essay of this thesis investigates the spillover effects in inflation rates between the U.S. and emerging markets. The results highlight the significant inflation spillovers, and these effects are determined by the economic characteristics of emerging countries, bilateral trade relationships, and the value of the U.S. dollar. Future studies may expand the inflation spillover analyses using time-frequency analysis techniques, such as wavelet analysis, to investigate how inflation spillover effects vary across different time scales. This approach can help identify short-term and long-term transmission channels.

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APPENDICES

The thesis comprises several appendices, specifically designed as follows: Appendix A.2.1 to A.2.7, used in Chapter 2; Appendix A.3.1 to A.3.4, provided for Chapter 3; Appendix A.4.1 to A.4.5, provided for Chapter 4.

Appendix A.2.1
The DCC-GARCH Model

We employ the standard DCC model of Engle (2002) to model the vector of residuals ε_t obtained from the VHAR(Q) model in Eq. (2.2) of the study presented in Chapter 2 as follows:

$$\varepsilon_t = H_t^{1/2} z_t \tag{2.1A}$$

$$z_t \sim NID\ (0, I)$$

where $z_{it} = \varepsilon_{it} / \sqrt{h_{it}}$ are standardized residuals that have mean zero and variance one for each series; ε_t is vector of error term ($m\times 1$) obtained from the VHAR(Q) model; H_t is conditional variance covariance matrix $m\times m$ of vector error term.

The conditional variance covariance matrix of vector of error term, H_t, is modelled by DCC-GARCH (Engle, 2002) with two-step method as follows,

$$\varepsilon_t \sim N(0, H_t)$$
$$\boldsymbol{H_t} = \boldsymbol{D_t}\, \boldsymbol{R_t}\, \boldsymbol{D_t} \tag{2.2A}$$

where $D_t = diag\ (h_{1,t}^{1/2}, \ldots, h_{m,t}^{1/2})$**,** D_t is the $(m \times m)$ diagonal matrix of conditional standard deviations, with conditional variances $h_{i,t}$ (i = 1, …, m) are defined by GARCH(1,1):

$$h_{i,t} = \omega_i + \alpha_{i,1}\epsilon_{i,t-1}^2 + \gamma_{i,1}h_{i,t-1} \tag{2.3A}$$

and R_t is the $m\times m$ conditional correlation matrix of standardized residuals, $z_{it} = \varepsilon_{it} / \sqrt{h_{it}}$, and can be estimated as,

$$E_{t-1}(z_t \acute{z}_t) = D_t^{-1} H_t D_t^{-1} = R_t$$

$$R_t = diag\left(q_{11,t}^{-\frac{1}{2}}, \dots, q_{mm,t}^{-\frac{1}{2}}\right) Q_t \; diag\left(q_{11,t}^{-\frac{1}{2}}, \dots, q_{mm,t}^{-\frac{1}{2}}\right) \quad (2.4A)$$

where the $m \times m$ symmetric positive definite matrix $Q_t = (q_{ij,t})$ follows the correlation equation as:

$$Q_t = (1 - a - b)\bar{Q} + a \, z_{t-1} \acute{z}_{t-1} + b \, Q_{t-1} \quad (2.5A)$$

with $\bar{Q}$ = E $[z_t \acute{z}_t]$ stands for the $m \times m$ unconditional variance matrix of z_t, and a and b are non-negative scalar parameter satisfying $a + b < 1$.

The conditional variance covariance matrix of vector of error term (ε_t), H_t, is estimated by the DCC-GARCH based on maximizing the log likelihood estimation approach under t-distribution assumption. Using the two-step method, the set of parameters including ($\omega_i, \alpha_i, \gamma_i |$ i = 1, …, m) are estimated by GARCH(1,1) in Eq. (2.3A) and the correlation coefficients (a,b) are estimated by the DCC model in Eq. (2.5A).

Appendix A.2.2
The block connectedness in the VHAR(Q) model

We construct the block aggregation scheme[53] of Greenwood-Nimmo et al. (2016) and within the underlying VHAR(Q) process. First, we re-normalize the h-step-ahead *(m×m)* connectedness matrix $\boldsymbol{C}^{(h)}$ among oil-dependent currencies (*m* is the number of considered foreign exchange spot markets) as in Eq. (2.6A). The connectedness matrix $\boldsymbol{C}^{(h)}$ is estimated using the generalized forecast error variance decomposition introduced by Diebold and Yilmaz (2012) as shown in section 2.3.2.

$$\underset{(m \times m)}{\boldsymbol{C}_R^{(h)}} = m^{-1}\,\boldsymbol{C}^{(h)} = \; m^{-1}\begin{bmatrix} \tilde{\theta}_{1\leftarrow 1}^{(h)} & \tilde{\theta}_{1\leftarrow 2}^{(h)} & \cdots & \tilde{\theta}_{1\leftarrow m}^{(h)} \\ \tilde{\theta}_{2\leftarrow 1}^{(h)} & \tilde{\theta}_{2\leftarrow 2}^{(h)} & \cdots & \tilde{\theta}_{2\leftarrow m}^{(h)} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{\theta}_{m\leftarrow 1}^{(h)} & \tilde{\theta}_{m\leftarrow 2}^{(h)} & \cdots & \tilde{\theta}_{m\leftarrow m}^{(h)} \end{bmatrix} \tag{2.6A}$$

Each element of re-normalized matrix *m*×*m* $\boldsymbol{C}_R^{(h)}$ represents the proportion of h-step-ahead *FEV* of the total system is attributed to the spillover effect from variable *j* to variable *i*.

Second, we aggregate the re-normalized connectedness matrix $\boldsymbol{C}_R^{(h)}$ based on block structure of 2 groups: (1) oilexporting group *"ox"* and (2) oil-importing group *"om"* as follows,

$$\boldsymbol{C}_R^{(h)} = \begin{bmatrix} B_{ox\leftarrow ox}^{(h)} & B_{ox\leftarrow om}^{(h)} \\ B_{om\leftarrow ox}^{(h)} & B_{om\leftarrow om}^{(h)} \end{bmatrix} \tag{2.7A}$$

Given the *m* variables of vector realized variance of foreign exchange spot markets RV_t = ($RV_{CAD,t}, RV_{NOK,t}, RV_{MXN,t}, RV_{EUR,t}, RV_{GBP,t}, RV_{JPY,t}, RV_{SGD,t}$), four blocks of connectedness $\boldsymbol{B}^{(h)}$ are constructed as follows,

[53] Greenwood-Nimmo, Nguyen & Rafferty (2016) introduce an alternative approach which is derived from the generalized connectedness index by Diebold and Yilmaz (2012) to aggregate the connectedness matrix based on a defined block structure. This innovative method allows the block connectedness among any desired groups of variables to be directly evaluated, enhancing the flexibility of Diebold and Yilmaz framework in satisfactorily capturing group-level connectedness at a defined level of aggregation of connectedness structure.

$$\underset{(3\times4)}{\boldsymbol{B}_{ox\leftarrow om}^{(h)}} = m^{-1}\begin{bmatrix} \tilde{\theta}_{RV_{CAD}\leftarrow RV_{EUR}}^{(h)} & \tilde{\theta}_{RV_{CAD}\leftarrow RV_{GBP}}^{(h)} & \tilde{\theta}_{RV_{CAD}\leftarrow RV_{JPY}}^{(h)} & \tilde{\theta}_{RV_{CAD}\leftarrow RV_{SGD}}^{(h)} \\ \tilde{\theta}_{RV_{NOK}\leftarrow RV_{EUR}}^{(h)} & \tilde{\theta}_{RV_{NOK}\leftarrow RV_{GBP}}^{(h)} & \tilde{\theta}_{RV_{NOK}\leftarrow RV_{JPY}}^{(h)} & \tilde{\theta}_{RV_{NOK}\leftarrow RV_{SGD}}^{(h)} \\ \tilde{\theta}_{RV_{MXN}\leftarrow RV_{EUR}}^{(h)} & \tilde{\theta}_{RV_{MXN}\leftarrow RV_{GBP}}^{(h)} & \tilde{\theta}_{RV_{MXN}\leftarrow RV_{JPY}}^{(h)} & \tilde{\theta}_{RV_{MXN}\leftarrow RV_{SGD}}^{(h)} \end{bmatrix} \quad (2.8A)$$

$$\underset{(4\times3)}{\boldsymbol{B}_{om\leftarrow ox}^{(h)}} = m^{-1}\begin{bmatrix} \tilde{\theta}_{RV_{EUR}\leftarrow RV_{CAD}}^{(h)} & \tilde{\theta}_{RV_{EUR}\leftarrow RV_{NOK}}^{(h)} & \tilde{\theta}_{RV_{EUR}\leftarrow RV_{MXN}}^{(h)} \\ \tilde{\theta}_{RV_{GBP}\leftarrow RV_{CAD}}^{(h)} & \tilde{\theta}_{RV_{GBP}\leftarrow RV_{NOK}}^{(h)} & \tilde{\theta}_{RV_{GBP}\leftarrow RV_{MXN}}^{(h)} \\ \tilde{\theta}_{RV_{JPY}\leftarrow RV_{CAD}}^{(h)} & \tilde{\theta}_{RV_{JPY}\leftarrow RV_{NOK}}^{(h)} & \tilde{\theta}_{RV_{JPY}\leftarrow RV_{MXN}}^{(h)} \\ \tilde{\theta}_{RV_{SGD}\leftarrow RV_{CAD}}^{(h)} & \tilde{\theta}_{RV_{SGD}\leftarrow RV_{NOK}}^{(h)} & \tilde{\theta}_{RV_{SGD}\leftarrow RV_{MXN}}^{(h)} \end{bmatrix} \quad (2.9A)$$

$$\underset{(3\times3)}{\boldsymbol{B}_{ox\leftarrow ox}^{(h)}} = m^{-1}\begin{bmatrix} \tilde{\theta}_{RV_{CAD}\leftarrow RV_{CAD}}^{(h)} & \tilde{\theta}_{RV_{CAD}\leftarrow RV_{NOK}}^{(h)} & \tilde{\theta}_{RV_{CAD}\leftarrow RV_{MXN}}^{(h)} \\ \tilde{\theta}_{RV_{NOK}\leftarrow RV_{CAD}}^{(h)} & \tilde{\theta}_{RV_{NOK}\leftarrow RV_{NOK}}^{(h)} & \tilde{\theta}_{RV_{NOK}\leftarrow RV_{MXN}}^{(h)} \\ \tilde{\theta}_{RV_{MXN}\leftarrow RV_{CAD}}^{(h)} & \tilde{\theta}_{RV_{MXN}\leftarrow RV_{NOK}}^{(h)} & \tilde{\theta}_{RV_{MXN}\leftarrow RV_{NOK}}^{(h)} \end{bmatrix} \quad (2.10A)$$

$$\underset{(4\times4)}{\boldsymbol{B}_{om\leftarrow om}^{(h)}} = m^{-1}\begin{bmatrix} \tilde{\theta}_{RV_{EUR}\leftarrow RV_{EUR}}^{(h)} & \tilde{\theta}_{RV_{EUR}\leftarrow RV_{GBP}}^{(h)} & \tilde{\theta}_{RV_{EUR}\leftarrow RV_{JPY}}^{(h)} & \tilde{\theta}_{RV_{EUR}\leftarrow RV_{SGD}}^{(h)} \\ \tilde{\theta}_{RV_{GBP}\leftarrow RV_{EUR}}^{(h)} & \tilde{\theta}_{RV_{GBP}\leftarrow RV_{GBP}}^{(h)} & \tilde{\theta}_{RV_{GBP}\leftarrow RV_{JPY}}^{(h)} & \tilde{\theta}_{RV_{GBP}\leftarrow RV_{SGD}}^{(h)} \\ \tilde{\theta}_{RV_{JPY}\leftarrow RV_{EUR}}^{(h)} & \tilde{\theta}_{RV_{JPY}\leftarrow RV_{GBP}}^{(h)} & \tilde{\theta}_{RV_{JPY}\leftarrow RV_{JPY}}^{(h)} & \tilde{\theta}_{RV_{JPY}\leftarrow RV_{SGD}}^{(h)} \\ \tilde{\theta}_{RV_{SGD}\leftarrow RV_{EUR}}^{(h)} & \tilde{\theta}_{RV_{SGD}\leftarrow RV_{GBP}}^{(h)} & \tilde{\theta}_{RV_{SGD}\leftarrow RV_{JPY}}^{(h)} & \tilde{\theta}_{RV_{SGD}\leftarrow RV_{SGD}}^{(h)} \end{bmatrix} \quad (2.11A)$$

where (4×4) $\boldsymbol{B}_{om\leftarrow om}^{(h)}$ and (3×3) $\boldsymbol{B}_{ox\leftarrow ox}^{(h)}$ define the within-group connectedness matrices; (3×4) $\boldsymbol{B}_{ox\leftarrow om}^{(h)}$ and (4×3) $\boldsymbol{B}_{om\leftarrow ox}^{(h)}$ represent the cross-group connectedness matrices. Each element of block connectedness $\boldsymbol{B}^{(h)}$ is obtained from re-normalized forecast error variance decomposition (Diebol & Yilmaz, 2012).

Correspondingly, we can compute the within-group spillover effect of each group and the cross-group spillover effect for each of groups as follows,

$$\boldsymbol{W}_{ox\leftarrow ox}^{(h)} = \boldsymbol{e}_k' \, \boldsymbol{B}_{ox\leftarrow ox}^{(h)} \, \boldsymbol{e}_k \quad (2.12A)$$

$$\boldsymbol{W}_{om\leftarrow om}^{(h)} = \boldsymbol{e}_n' \, \boldsymbol{B}_{om\leftarrow om}^{(h)} \, \boldsymbol{e}_n \quad (2.13A)$$

$$\boldsymbol{W}_{ox\leftarrow om}^{(h)} = \boldsymbol{e}_k' \, \boldsymbol{B}_{ox\leftarrow om}^{(h)} \, \boldsymbol{e}_n \quad (2.14A)$$

$$\boldsymbol{W}_{om\leftarrow ox}^{(h)} = \boldsymbol{e}_n' \, \boldsymbol{B}_{om\leftarrow ox}^{(h)} \, \boldsymbol{e}_k \quad (2.15A)$$

with $\boldsymbol{e}_k$ and $\boldsymbol{e}_n$ are vectors of ones dimension (3×1) and (4×1).

We define the aggregate within-group spillover index ($WSI^{(h)}$), aggregate cross-group spillover index ($CSI^{(h)}$), and the net spillover index (*NSI*) of each group as follows,

$$WSI^{(h)} = \boldsymbol{W}^{(h)}_{ox\leftarrow ox} + \boldsymbol{W}^{(h)}_{om\leftarrow om} \quad \text{and} \quad CSI^{(h)} = \boldsymbol{W}^{(h)}_{ox\leftarrow om} + \boldsymbol{W}^{(h)}_{om\leftarrow ox} \tag{2.16A}$$

where $WSI^{(h)} + CSI^{(h)} = 1$

$$NSI^{(h)}_{om\leftarrow ox} = \boldsymbol{W}^{(h)}_{om\leftarrow ox} - \boldsymbol{W}^{(h)}_{ox\leftarrow om} \tag{2.17A}$$

$$NSI^{(h)}_{ox\leftarrow om} = \boldsymbol{W}^{(h)}_{ox\leftarrow om} - \boldsymbol{W}^{(h)}_{om\leftarrow ox} \tag{2.18A}$$

Appendix A.2.3
The Markov-Switching Autoregressive (MS-AR) model

We specify the MS-AR with two regimes to account for the possible non-linearities of crude oil return process as follows,

$$r_t = \alpha_{s_t} + \sum_{k=1}^{p} \gamma_{k,s_t} r_{t-k} + \omega_t \qquad (2.19A)$$

$$\omega_t \sim \text{i.i.d.} N(0, \sigma_{s_t}^2)$$

where r_t represents the crude oil return, computed as the difference in the log of the crude oil prices. The lag order p in Autoregressive model is decided by the lowest Akaike Information Criterion (AIC). $s_t = 1$ or 2 denotes the unobserved state variable, with $s_t = 1$ indicating the low volatility regime of oil market, and $s_t = 2$ defining the high volatility regime of oil market. The conditional variance in low volatility regime is smaller than in the high volatility regime, meaning that the market is more stable in low volatility regime ($\sigma_{s_t=1}^2 < \sigma_{s_t=2}^2$).

We employ the simple two-state, first-order Markov process by Hamilton (1990) to model the unobserved state variable, s_t, with the transition probabilities matrix defined as,

$$P = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}$$

with $Pr(s_t = 1|s_{t-1} = 1) = p_{11}$; $Pr(s_t = 2|s_{t-1} = 1) = p_{12} = 1 - p_{11}$; $Pr(s_t = 1|s_{t-1} = 2) = p_{21}$; $Pr(s_t = 2|s_{t-1} = 2) = p_{22} = 1 - p_{21}$

To estimate MS-AR model, we follow Hamilton (1990) to derive the joint density of r_t, s_t and s_{t-1} conditional on past information I_{t-1} as follows,

$$\text{f}(r_t, s_t, s_{t-1}|I_{t-1}) = f(r_t|s_t, s_{t-1}, I_{t-1})\Pr[s_t, s_{t-1}|I_{t-1}] = \qquad (2.20A)$$

$$\frac{1}{\sqrt{2\pi\sigma_{s_t}^2}} \exp\left(-\frac{\left(r_t - \alpha_{s_t} - \sum_{k=1}^{p} \gamma_{k,s_t} r_{t-k}\right)^2}{2\sigma_{s_t}^2}\right) \Pr[s_t, s_{t-1}|I_{t-1}]$$

Then we have the marginal density function of r_t derived from Eq. (2.20A),

$$f(r_t|I_{t-1}) = \sum_{s_t=1}^{2}\sum_{s_{t-1}=1}^{2} f(r_t, s_t, s_{t-1}|I_{t-1}) \tag{2.21A}$$

$$= \sum_{s_t=1}^{2}\sum_{s_{t-1}=1}^{2} f(r_t|s_t, s_{t-1}, I_{t-1})\mathrm{Pr}[s_t, s_{t-1}|I_{t-1}]$$

Then we can derive the log likelihood from Eq. (2.21A) as follows,

$$\ln L = \sum_{t=1}^{T} \ln\left(\sum_{s_t=1}^{2}\sum_{s_{t-1}=1}^{2} f(r_t|s_t, s_{t-1}, I_{t-1})\mathrm{Pr}[s_t, s_{t-1}|I_{t-1}]\right) \tag{2.22A}$$

$$= \sum_{t=1}^{T} \ln\left(\sum_{s_t=i=1}^{2} \frac{1}{\sqrt{2\pi\sigma_{s_t}^2}} \exp\left(-\frac{\left(r_t - \alpha_{s_t} - \sum_{k=1}^{p}\gamma_{k,s_t} r_{t-k}\right)^2}{2\sigma_{s_t}^2}\right)\left(\sum_{j=1}^{2} p_{ji}\,\mathrm{Pr}[s_{t-1} = j, |I_{t-1}]\right)\right)$$

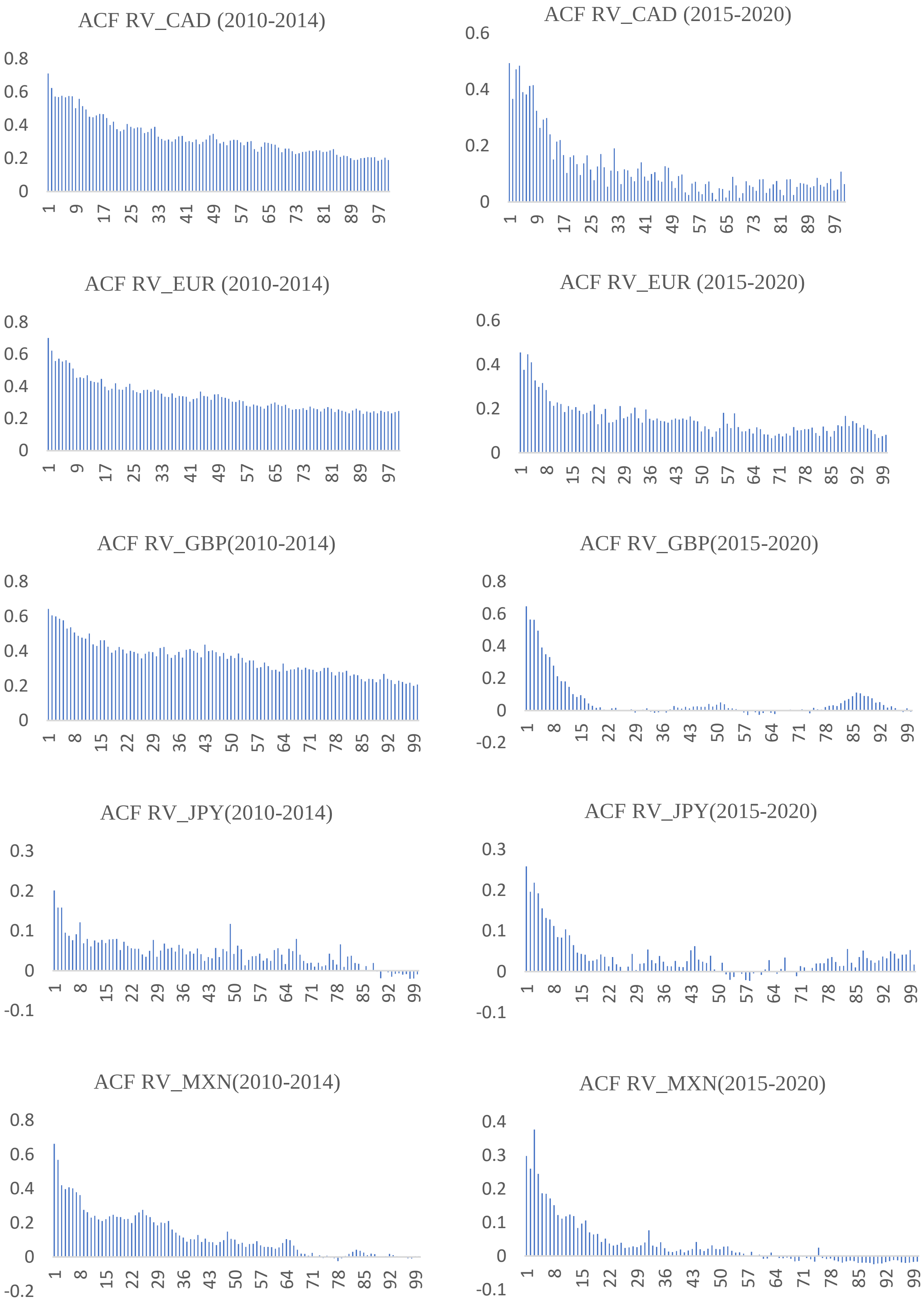
where

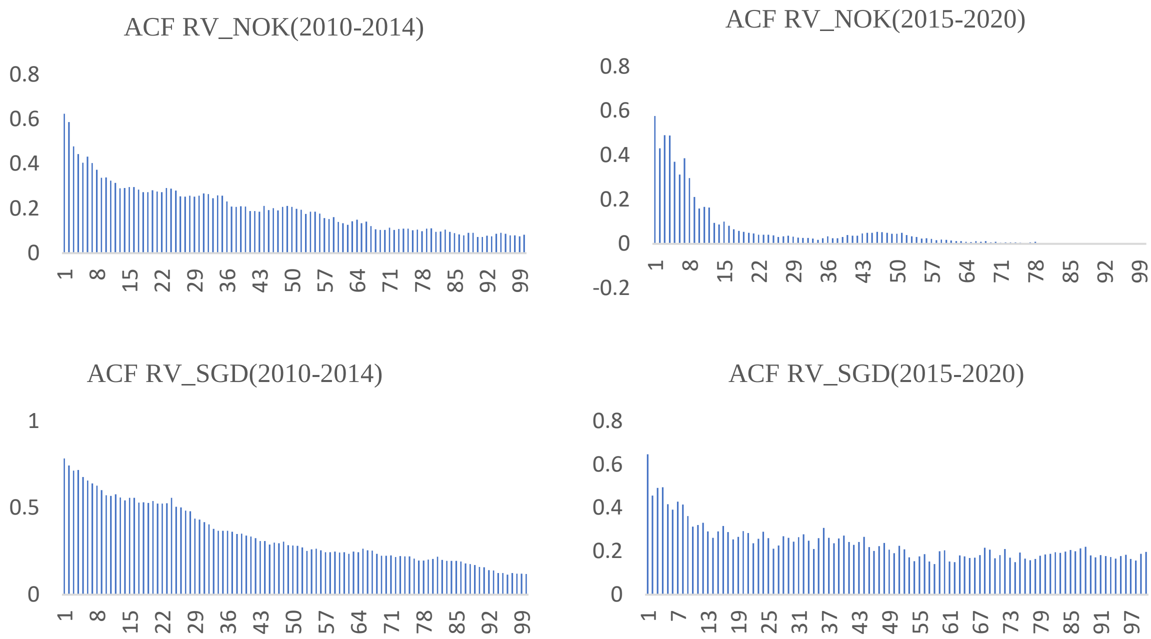
$\mathrm{Pr}[s_t = i, s_{t-1} = j|I_{t-1}] = \mathrm{Pr}[s_t = i, |s_{t-1} = j]\mathrm{Pr}[s_{t-1} = j, |I_{t-1}] = p_{ji}\,\mathrm{Pr}[s_{t-1} = j, |I_{t-1}]$;

I_{t-1} denotes the information set available at time $t-1$; with $i, j = 1, 2$. The MS-AR model can be estimated by maximizing the likely-hood function in Eq. (2.22A) by the filtering procedure of Hamilton (1990) and followed by the algorithm of Kim (1994) to calculate the smoothed probabilities of each regime.

Appendix A.2.4

Figure A.2.4 The autocorrelogram of realized volatility series of seven selected oil-dependent currencies from lag 1 to lag 100





Note: These figures show the autocorrelation function of seven sample exchange rates for the period of relatively stable oil prices (2010-2014) and the period of highly volatile oil prices (2015-2020). For the period from 2010 to 2014, the hyperbolic slow decays in their auto-correlogram indicate the long-memory characteristic in realized volatility of these currencies.

Appendix A.2.5

Table A.2.5 The effect of oil's high-volatility regime on FX connectedness measures

	Cross-market spillover index	Spillover to others						
	CSI	CAD	EUR	GBP	JPY	MXN	NOK	SGD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Oil_High_Vol_Pro	0.002*	0.002*	-0.009*	0.0001	-0.004*	0.021**	0.008***	0.002**
	(1.88)	(1.92)	(-1.77)	(0.14)	(-1.91)	(2.45)	(4.26)	(2.44)
VIX	0.002***	0.002***	-0.022***	-0.0004	0.006***	0.002	0.023***	0.001***
	(6.08)	(6.04)	(-13.18)	(-1.36)	(6.95)	(0.92)	(11.02)	(2.97)
GPR	0.0001***	0.00003	0.0005***	-0.0001**	0.0001	0.0001	-0.0003***	0.00003*
	(2.77)	(1.24)	(3.27)	(-2.15)	(1.22)	(0.84)	(-2.84)	(1.86)
USD	0.002***	-0.001***	-0.018***	0.003***	-0.002***	0.012***	0.017***	-0.001***
	(6.10)	(-3.01)	(-9.46)	(13.14)	(-2.81)	(5.43)	(10.37)	(-3.26)
FFR	-0.01***	-0.01***	0.14***	0.003	0.0003	-0.009	-0.177***	-0.008***
	(-4.75)	(-5.35)	(10.40)	(1.03)	(0.04)	(-0.56)	(-16.29)	(-6.93)
Intercept	0.38***	0.19***	3.34***	-0.11***	0.28***	0.01	-1.15***	0.10***
	(13.97)	(5.70)	(14.07)	(-5.05)	(3.90)	(0.06)	(-5.77)	(4.72)
N. Obs.	2,188	2,188	2,188	2,188	2,188	2,188	2,188	2,188
Adj. R-squared	0.0808	0.1515	0.4208	0.1137	0.0594	0.0528	0.5257	0.1985
F-statistics	39.39***	79.02***	318.45***	57.06***	28.61***	25.37***	485.29***	109.23***

Note. This table reports the estimated results of the models represented in Eq. (2.12) and Eq. (2.13) to evaluate the effects of the high oil volatility regime on the cross-group connectedness among seven sample oil-dependent currencies and the "Spillover to others" index of each currency with the main regressor being the natural logarithm of the estimated probability of oil's high-volatility regime. The reported t-statistics are computed using heteroskedasticity-consistent robust standard errors. ***, ** and * represent that the estimated parameters are statistically significant at 1%, 5% and 10% significance level, respectively.

Appendix A.2.6

Table A.2.6 The results of robustness check: The regression results of the VHAR-X(Q) model

	CAD	EUR	GBP	JPY	MXN	NOK	SGD
$\beta^{CAD,d}$	0.332***	0.068*	-0.060	0.07063	0.37849	0.489***	-0.0088
$\beta^{CAD,w}$	0.00107	-0.0476	-0.092**	0.01648	-0.224	-0.431**	-0.0272
$\beta^{CAD,m}$	0.383***	0.08508	0.228***	-0.0769	-0.4806	-0.2027	0.012
$\beta_{Q}^{CAD,d}$	-140.258***	-26.8915	22.42083	-32.08567	-136.63	-203.654**	4.70897
$\beta^{EUR,d}$	-0.0559	0.333***	-0.0127	-0.1318	0.00467	-0.938***	-0.0117
$\beta^{EUR,w}$	0.201***	0.358***	0.171***	0.22784	0.24377	0.645***	0.070***
$\beta^{EUR,m}$	0.01584	0.352***	-0.0127	0.04037	-0.2063	0.724**	0.0161
$\beta_{Q}^{EUR,d}$	17.43	-66.505*	-1.55435	49.85191	23.655	957.122***	27.7863**
$\beta^{GBP,d}$	-0.0404	-0.0216	0.352***	-0.0744	-0.3077	0.535***	-0.019*
$\beta^{GBP,w}$	0.0789**	0.01411	0.232***	-0.0166	-0.1179	-0.1948	0.01133
$\beta^{GBP,m}$	-0.0219	-0.0925	0.285***	0.14843	0.4562	-0.538**	-0.0345
$\beta_{Q}^{GBP,d}$	15.74512	14.54527	-101.053***	18.43705	83.513	-33.96039	8.382*
$\beta^{JPY,d}$	0.01637	-0.0274	-0.055**	0.549***	0.03797	-0.283***	-0.018**
$\beta^{JPY,w}$	0.00242	-0.0083	-0.046*	0.128**	0.12057	-0.1123	-0.0065
$\beta^{JPY,m}$	0.05134	0.04759	0.104*	0.218**	0.01871	0.550***	0.037***
$\beta_{Q}^{JPY,d}$	3.8472	7.644**	7.873**	-59.279***	9.76605	36.903***	4.756***
$\beta^{MXN,d}$	0.0337***	0.029***	0.068***	0.071***	0.327***	0.333***	0.018***
$\beta^{MXN,w}$	0.00926	0.00315	0.042***	-0.0095	0.307**	0.215***	0.00459

$\beta^{MXN,m}$	-0.052***	-0.0211	-0.037**	-0.0248	0.06744	-0.192***	-0.011**
$\beta_Q^{MXN,d}$	-3.357***	-3.036***	-5.273***	-7.423***	-21.539***	-26.058***	-1.335***
$\beta^{NOK,d}$	0.038***	0.01669	0.02168	0.01882	-0.0582	0.505***	0.00142
$\beta^{NOK,w}$	-0.020*	-0.0041	0.066***	0.00641	-0.0582	0.324***	-0.0071
$\beta^{NOK,m}$	-0.002	-0.043**	-0.139***	-0.110**	-0.0339	-0.1126	-0.0111
$\beta_Q^{NOK,d}$	-14.168***	-6.209**	-14.800***	-9.12051	-18.399	-109.545***	-2.512**
$\beta^{SGD,d}$	-0.0044	-0.191	-0.1464	-0.579**	-0.1314	-1.096***	0.389***
$\beta^{SGD,w}$	0.212**	0.06608	-0.1124	-0.559*	0.23975	-0.5552	0.346***
$\beta^{SGD,m}$	-0.237*	-0.0961	-0.2287	1.018***	-0.8032	-0.4983	0.281***
$\beta_Q^{SGD,d}$	-70.03388	117.498	108.769	723.23767	51.9597	1086.21	29.813
β_{yield}	0.00012***	0.00001***	0.00004*	0.00000	0.00003	-0.00076*	0.00000
β_{US_yield}	0.00003	0.00011***	0.00007*	0.00023	0.00193***	0.00067***	0.00000
β_{Spread}	0.0597**	-0.0425	0.07818*	-0.04234	-0.10274	0.04257	0.00462
β_{VIX}	0.0659***	0.0605***	0.0675***	0.0714***	0.4560***	0.3660***	0.0216***

Note. This table reports the estimated parameters of the extended VHAR-X(Q) model in E.q. (2.14) of the study for seven foreign exchange rates. ***, ** and * indicate that the estimated parameters are statistically significant at the 1%, 5% and 10% level, respectively. The robust standard errors of the estimates are not represented in this table to conserve space. The coefficients for the effects of the stock market are multiplied with 10^5 to get the readable results.

Appendix A.2.7

Table A.2.7 The results of robustness check: The connectedness matrix and block connectedness
Panels A and B of this table report the average of individual currency-level directional connectedness across seven exchange rates and group-level connectedness using the extended VHAR-X(Q) model in E.q. (2.14) of the study as the underlying function to compute connectedness indices.

Panel A. Individual currency-level connectedness

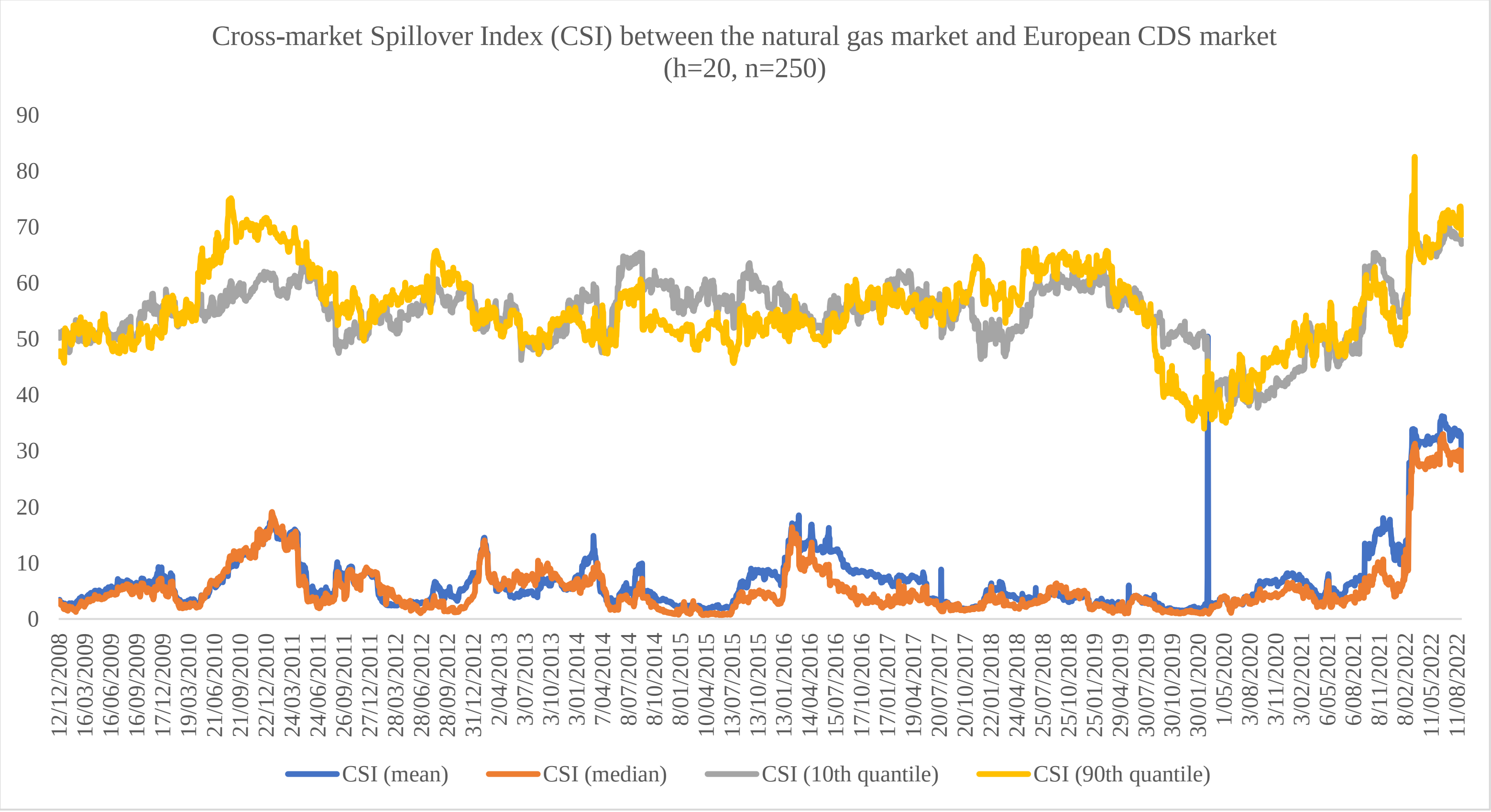
	Oil-exporting currencies			**Oil-importing currencies**				Spillover from others
	CAD	MXN	NOK	EUR	GBP	JPY	SGD	
CAD	27.91%	27.34%	11.10%	23.59%	2.69%	5.99%	1.37%	10.30%
MXN	1.02%	78.35%	8.51%	8.37%	0.98%	2.50%	0.26%	3.09%
NOK	1.17%	15.75%	60.92%	17.96%	0.53%	3.42%	0.25%	5.58%
EUR	1.87%	14.97%	13.16%	60.38%	3.17%	5.59%	0.87%	5.66%
GBP	2.41%	17.12%	10.83%	35.16%	28.57%	4.82%	1.08%	10.20%
JPY	1.74%	19.92%	5.33%	21.40%	2.53%	48.20%	0.87%	7.40%
SGD	4.11%	19.55%	16.47%	17.24%	3.83%	4.23%	34.56%	9.35%
Spillover to others	1.76%	14.06%	9.34%	17.68%	1.96%	3.79%	0.67%	
Net spillover	-8.54%	10.97%	3.76%	12.02%	-8.24%	-3.61%	-8.68%	
Total spillover index	51.59%							

Panel B. Group-level connectedness

	Export	Import
Export	33.15%	9.70%
Import	18.21%	38.93%
Net Export Spillover	8.51%	
Net Import Spillover	-8.51%	
Total within-group spillover	72.08%	
Total cross-group spillover	27.92%	

Appendix A.3.1

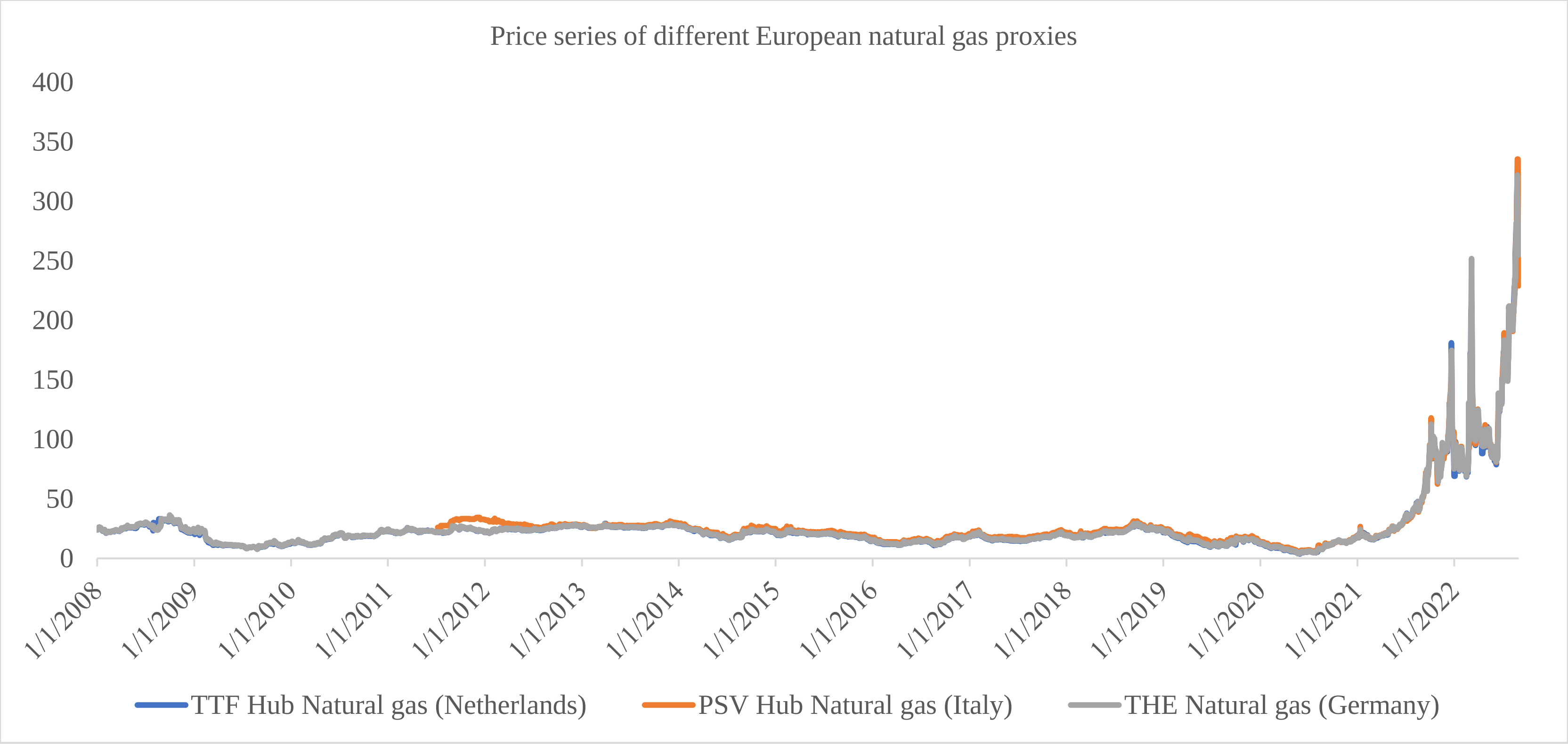
Figure A.3.1 Time-varying cross-market spillover index (CSI) between European natural gas and sectoral CDS markets at different quantiles (h=20, n=250)



Note: This figure shows the time-varying cross-market spillover index (CSI) between the European natural gas and CDS markets at the conditional mean, median, lower tail (10^{th} quantile) and upper tail (90^{th} quantile) of the return distribution using the rolling-window approach with the window length of 250 days (*n*=250) and the number of *h*-step forecast ahead of 20 (*h*=20)**.**

Appendix A.3.2

Figure A.3.2 Dynamics of natural gas prices across different hubs



Note: This graph displays the daily price series of natural gas of three different European natural gas hubs, including the Title Transfer Facility (TTF) (Netherlands), the Punto di Scambio Virtuale (PSV) (Italy), and the Trading Hub Europe (THE) (Germany).

Appendix A.3.3

Table A.3.3 Regression Results of Daily Model in Eq. (3.20) using GFLS

Dep. Variables	CSI (middle)	CSI (lower tail)	CSI (upper tail)
	(1)	(2)	(3)
VSTOXX	0.08***	-0.179***	-0.051**
	(6.97)	(-11.82)	(-2.45)
RET	23.01*	-53.81***	-15.23
	(1.91)	(-3.39)	(-0.70)
OVX	0.057***	0.041***	0.143***
	(9.83)	(5.32)	(13.61)
RFR	-0.551***	-1.882***	-2.935***
	(-4.24)	(-10.99)	(-12.52)
GOPR	0.0004	0.024***	0.015***
	(0.27)	(12.51)	(6.11)
WINTER	1.36***	0.256	-1.22***
	(10.19)	(1.46)	(-5.08)
COVID	0.87	1.41	5.66***
	(1.16)	(1.42)	(4.17)
WAR	25.00***	11.78***	17.03***
	(68.24)	(24.42)	(25.78)
Intercept	5.60***	58.75***	61.10***
	(22.29)	(117.46)	(134.84)
N. Obs.	3,630	3,630	3,630
Adj. R-squared	0.6198	0.3175	0.3115

Note: This table presents the estimated coefficients and their *t*-statistics using daily regression model specified in Eq. (3.20), where *CSI* is computed based on a window length of 200 days and a 10-step forecast horizon. The *CSI* is defined in Eq. (3.19). The Eq. (3.20) is estimated using Generalized Feasible Least Square (GFLS). *VSTOXX* is the expected volatility for the Dow Jones EuroStoxx 50 index; *RET* is proxy for the return of STOXX Europe 50 index; *OVX* is the Chicago Board Options Exchange Crude Oil ETF Volatility index; *RFR* is the European risk-free rate; *GPR* is the geopolitical risk index. *WINTER* is a dummy variable for winter months, which take a value of 1 if the data is in December, January, and February and 0 otherwise. *COVID* is the dummy variable for the COVID-19 pandemic-induce recession period in Europe, which take value of 1 if the data is between January 01, 2020 and June 30, 2020, and 0 otherwise. *WAR* is the binary variable for the war effect, which is equal 1 if the data is between February 24, 2022 and August 31, 2022, and 0 otherwise. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Appendix A.3.4

Table A.3.4 Regression Results of Monthly Model in Eq. (3.21) using GFLS

Dep. Variables	CSI (middle)	CSI (lower tail)	CSI (upper tail)
	(1)	(2)	(3)
VSTOXX	0.141**	-0.137	0.103
	(1.96)	(-1.40)	(0.78)
RET	-11.05	-31.89	0.536
	(-0.36)	(-0.77)	(0.01)
OVX	0.074**	0.012	0.238**
	(2.28)	(0.28)	(3.98)
RFR	-1.44*	-2.29**	-2.78*
	(-1.80)	(-2.11)	(-1.89)
TERMSPR	-0.11	0.478*	-0.384
	(-0.53)	(-1.69)	(-1.01)
DFSPR	-0.192	-0.341	-0.097
	(-1.23)	(-1.60)	(-0.34)
EEPU	0.009	-0.002	0.016
	(1.52)	(-0.22)	(1.42)
GOPR	-0.011	0.027***	0.016
	(-1.49)	(2.69)	(1.23)
WINTER	1.659**	0.422	-0.669
	(2.55)	(0.48)	(-0.56)
COVID	3.094	-2.97	13.60
	(0.60)	(-0.43)	(1.44)
WAR	24.01***	10.29***	15.20***
	(12.48)	(3.93)	(4.30)
Intercept	5.11***	59.12***	58.08***
	(2.92)	(24.80)	(18.03)
N. Obs.	181	181	181
Adj. R-squared	0.6236	0.2903	0.2919

Note: This table presents the estimated coefficients and their *t*-statistics using monthly regression model specified in Eq. (3.21), where *CSI* is computed based on a window length of 200 days and a 10-step forecast horizon. The *CSI* is defined in Eq. (3.19). The Eq. (3.21) is estimated using Generalized

Feasible Least Square (GFLS). *VSTOXX* is the expected volatility for the Dow Jones EuroStoxx 50 index; *RET* is proxy for the return of STOXX Europe 50 index; *OVX* is the Chicago Board Options Exchange Crude Oil ETF Volatility index; *RFR* is the European risk-free rate; *GPR* is the geopolitical risk index. *WINTER* is a dummy variable for winter months, which take a value of 1 if the data is in December, January, and February and 0 otherwise. *COVID* is the dummy variable for the COVID-19 pandemic-induce recession period in Europe, which take value of 1 if the data is between January 01, 2020 and June 30, 2020, and 0 otherwise. *WAR* is the binary variable for the war effect, which is equal 1 if the data is between February 24, 2022 and August 31, 2022, and 0 otherwise. Three monthly exogenous variables added includes: EEPU is the European Economic Policy Uncertainty index; TERMSPR is the difference between Euro area 10-year and 5-year government benchmark bond yields; DFSPR is the spread between ICE BofA Euro High Yield Index Effective Yield and Euro area 10-year government bond yield. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Appendix A.4.1

Table A.4.1 Country-specific characteristics

Country	Openness index 2018	Oil-exporting or -importing	Exchange rate regime
Brazil	28.88	Exporting	Floating
China[54]	37.57	Importing	Fixed peg (before July 2005) Managed floating (after July 2005)
India	43.60	Importing	Managed floating
Indonesia	43.07	Importing	Floating
South Korea	78.99	Importing	Floating
Mexico	80.56	Exporting	Free-floating
Russia	51.58	Exporting	Managed floating
Turkey	62.55	Importing	Floating
Taiwan	101.57	Importing	Managed floating

Notes: This table presents the Openness index, the oil-exporting (importing) status, and the exchange rate regime of the selected emerging markets.

[54] The China's RMB regime evolved from dollar peg to managed floating against a basket of currencies (including the U.S. dollar) in July 2005. The daily trading band of the RMB was widened from +/-0.3% to +/-0.5% in May 2007, +/-1% in April 2012 and +/-2% in July 2021, making the RMB classified as crawl-like arrangement (managed floating regime) as the classification of International Monetary Fund. See, IMF (2019), Evolution of Exchange Rate Management in China, and IMF (2022), Annual Report on Exchange Arrangements and Exchange Restriction 2021.

Appendix A.4.2

Block aggregation of connectedness

To apply the block aggregation of connectedness, let us re-normalize the h-step-ahead (10×10) inflation connectedness matrix $\boldsymbol{C}^{(h)}$ among the U.S. and nine emerging markets EAGLE countries as in Eq. (4.1A). The connectedness matrix $\boldsymbol{C}^{(h)}$ is computed by the generalized connectedness index of Diebold and Yilmaz's (2012) model as shown in section 4.3.1.

$$\underset{(10\times 10)}{\boldsymbol{C}_R^{(h)}} = \frac{1}{10}\,\boldsymbol{C}^{(h)} = \frac{1}{10}\begin{bmatrix} \tilde{\theta}_{1\leftarrow 1}^{(h)} & \tilde{\theta}_{1\leftarrow 2}^{(h)} & \cdots & \tilde{\theta}_{1\leftarrow 10}^{(h)} \\ \tilde{\theta}_{2\leftarrow 1}^{(h)} & \tilde{\theta}_{2\leftarrow 2}^{(h)} & \cdots & \tilde{\theta}_{2\leftarrow 10}^{(h)} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{\theta}_{10\leftarrow 1}^{(h)} & \tilde{\theta}_{10\leftarrow 2}^{(h)} & \cdots & \tilde{\theta}_{10\leftarrow 10}^{(h)} \end{bmatrix} \tag{4.1A}$$

Each element $\tilde{\theta}_{i\leftarrow j}^{(h)}$ of re-normalized connectedness matrix $\boldsymbol{C}_R^{(h)}$ indicates the proportion of h-step-ahead *FEV* of the total system is attributed to the spillover effect from variable j to variable i.

Second, we aggregate the re-normalized connectedness matrix $\boldsymbol{C}_R^{(h)}$ based on the block structure of 3 groups of the U.S., low openness (Brazil, China, India, Indonesia, and Russia), and high openness (South Korea, Mexico, Turkey, and Taiwan) as follows,[55]

$$\boldsymbol{C}_R^{(h)} = \begin{bmatrix} B_{USA\leftarrow USA}^{(h)} & B_{USA\leftarrow Low\ openness}^{(h)} & B_{USA\leftarrow High\ openness}^{(h)} \\ B_{Low\ openness\leftarrow USA}^{(h)} & B_{Low\ openness\leftarrow Low\ openness}^{(h)} & B_{Low\ openness\leftarrow High\ openness}^{(h)} \\ B_{High\ openness\leftarrow USA}^{(h)} & B_{High\ openness\leftarrow Low\ openness}^{(h)} & B_{High\ openness\leftarrow High\ openness}^{(h)} \end{bmatrix} \tag{4.2A}$$

[55] We demonstrate the procedure for Table 4.4 Panel A. Similar process can be applied to compute the block connectedness in Panels B and C of Table 4.4.

The within-group connectedness blocks (i.e., $B^{(h)}_{Low\ openness \leftarrow Low\ openness}$, $B^{(h)}_{High\ openness \leftarrow High\ openness}$, $B^{(h)}_{USA \leftarrow USA}$) represents the connectedness within the countries in the same group while the cross-group connectedness blocks (i.e., $B^{(h)}_{USA \leftarrow Low\ openness}$, $B^{(h)}_{Low\ openness \leftarrow USA}$, $B^{(h)}_{Low\ openness \leftarrow High\ openness}$, $B^{(h)}_{High\ openness \leftarrow Low\ openness}$, $B^{(h)}_{USA \leftarrow High\ openness}$, $B^{(h)}_{High\ openness \leftarrow USA}$) examine the connectedness across two groups and are defined by aggregating the cross-connectedness between all countries of one group and all countries of the other group.

Based on the block aggregation of connectedness, we calculate and report the quantities of the total within-group connectedness and total cross-group connectedness as follows,

$$\boldsymbol{W}^{(h)}_{USA \leftarrow USA} = \boldsymbol{e}_1' \boldsymbol{B}^{(h)}_{USA \leftarrow USA} \boldsymbol{e}_1 \tag{4.3A}$$

$$\boldsymbol{W}^{(h)}_{Low\ openness \leftarrow Low\ openness} = \boldsymbol{e}_2' \boldsymbol{B}^{(h)}_{Low\ openness \leftarrow Low\ openness} \boldsymbol{e}_2 \tag{4.4A}$$

$$\boldsymbol{W}^{(h)}_{High\ openness \leftarrow High\ openness} = \boldsymbol{e}_3' \boldsymbol{B}^{(h)}_{High\ openness \leftarrow High\ openness} \boldsymbol{e}_3 \tag{4.5A}$$

$$\boldsymbol{W}^{(h)}_{USA \leftarrow Low\ openness} = \boldsymbol{e}_1' \boldsymbol{B}^{(h)}_{USA \leftarrow Low\ openness} \boldsymbol{e}_2 \tag{4.6A}$$

$$\boldsymbol{W}^{(h)}_{USA \leftarrow High\ openness} = \boldsymbol{e}_1' \boldsymbol{B}^{(h)}_{USA \leftarrow High\ openness} \boldsymbol{e}_3 \tag{4.7A}$$

$$\boldsymbol{W}^{(h)}_{Low\ openness \leftarrow USA} = \boldsymbol{e}_2' \boldsymbol{B}^{(h)}_{Low\ openness \leftarrow USA} \boldsymbol{e}_1 \tag{4.8A}$$

$$\boldsymbol{W}^{(h)}_{Low\ openness \leftarrow High\ openness} = \boldsymbol{e}_2' \boldsymbol{B}^{(h)}_{Low\ openness \leftarrow High\ openness} \boldsymbol{e}_3 \tag{4.9A}$$

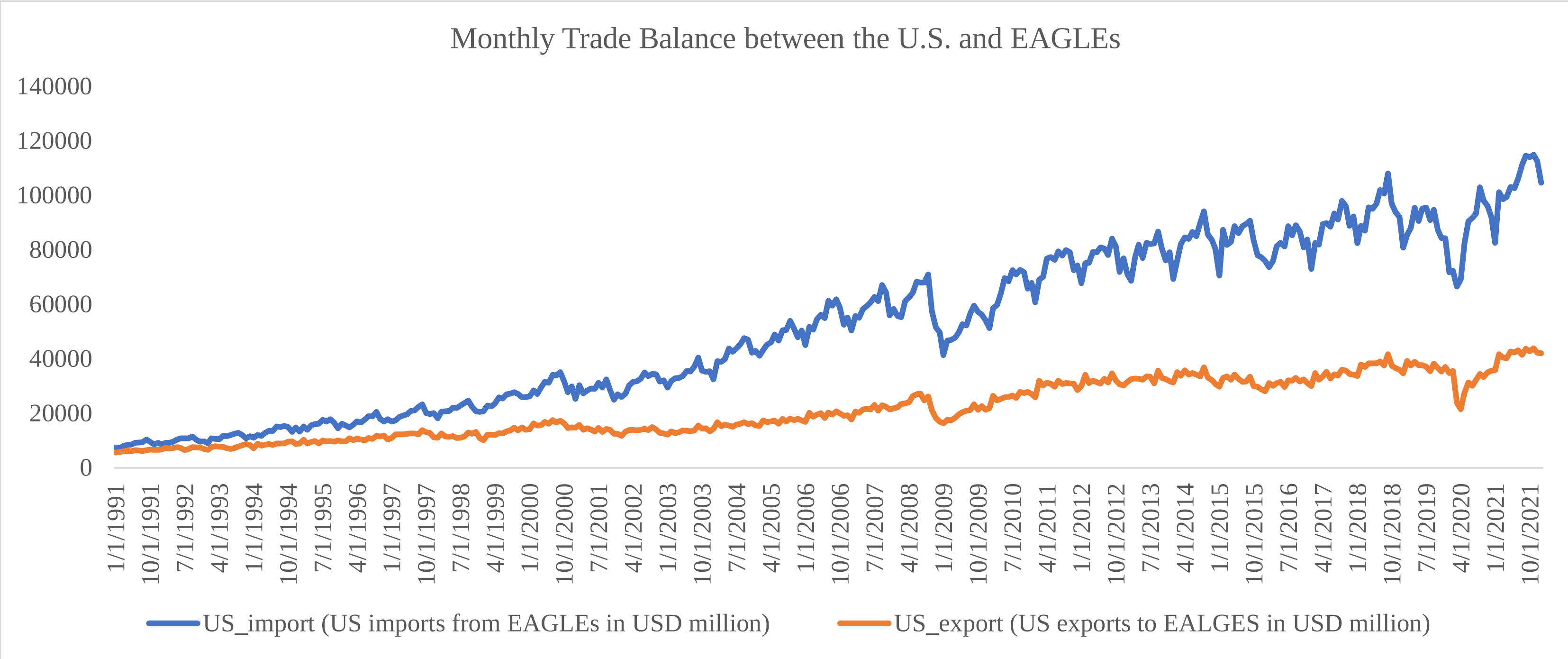
$$\boldsymbol{W}^{(h)}_{High\ openness \leftarrow USA} = \boldsymbol{e}_3' \boldsymbol{B}^{(h)}_{High\ openness \leftarrow USA} \boldsymbol{e}_1 \tag{4.10A}$$

$$\boldsymbol{W}^{(h)}_{High\ openness \leftarrow Low\ opennness} = \boldsymbol{e}'_3\ \boldsymbol{B}^{(h)}_{High\ openness \leftarrow Low\ openness}\ \boldsymbol{e}_2 \tag{4.11A}$$

with $\boldsymbol{e}_1$, $\boldsymbol{e}_2$ and $\boldsymbol{e}_3$ are vectors of ones dimension (1×1), (5×1) and (4×1), respectively.

Appendix A.4.3

Figure A.4.3 Monthly trade balance between the U.S. and EAGLEs



Notes: This figure displays the monthly U.S. imports from the selected emerging markets (the blue line) and the monthly U.S. exports to the selected emerging markets (the orange line). Data is sourced from the Thomson Reuters DataStream.

Appendix A.4.4

Table A.4.4 Robustness check: Inflation spillover tables using different *h*-step forecast ahead

Panel A. Using h=10

	USA	BRA	CHN	IND	IDN	KOR	MEX	RUS	TUR	TWN	*Spillover from others*
USA	75.68	0.07	3.55	4.85	0.39	11.45	0.51	0.35	0.74	2.41	24.32
BRA	0.22	90.01	1.87	0.16	0.04	0.87	0.61	2.56	3.15	0.51	9.99
CHN	3.01	2.51	74.44	4.51	0.36	5.56	2.61	0.24	4.11	2.65	25.56
IND	3.41	0.51	3.14	87.93	0.45	1.68	0.51	0.51	0.61	1.25	12.07
IDN	0.41	0.12	0.87	2.14	85.10	5.55	1.98	0.24	3.41	0.18	14.90
KOR	7.01	0.81	4.65	0.99	2.56	79.25	3.00	0.60	0.88	0.25	20.75
MEX	1.56	0.41	3.15	0.87	1.15	1.12	80.14	0.89	9.15	1.56	19.86
RUS	1.03	5.01	0.51	1.35	0.31	1.51	3.51	84.25	2.01	0.51	15.75
TUR	1.66	2.59	4.10	1.51	1.61	1.35	10.10	1.51	74.11	1.46	25.89
TWN	4.51	0.25	4.15	1.51	0.61	0.61	0.51	0.54	0.61	86.70	13.30
Spillover to other	22.82	12.28	25.99	17.89	7.48	29.70	23.34	7.44	24.67	10.78	
NET	-1.50	2.29	0.43	5.82	-7.42	8.95	3.48	-8.31	-1.22	-2.52	
TSI	18.24										

Panel B. Using h=30

	USA	BRA	CHN	IND	IDN	KOR	MEX	RUS	TUR	TWN	*Spillover from others*
USA	73.38	0.09	3.56	5.51	0.51	12.56	0.71	0.39	0.78	2.51	26.62
BRA	0.24	88.94	2.11	0.51	0.08	1.21	0.74	2.51	3.10	0.56	11.06
CHN	3.11	2.51	72.61	4.61	0.51	6.11	2.66	0.26	5.11	2.51	27.39
IND	3.61	0.56	3.16	86.84	0.60	1.55	0.61	0.67	0.79	1.61	13.16
IDN	0.81	0.24	0.66	1.90	82.92	5.79	2.10	0.91	4.16	0.51	17.08

KOR	8.15	0.60	6.10	1.51	2.88	74.34	3.51	0.89	1.51	0.51	25.66
MEX	2.51	0.51	3.95	0.87	1.51	1.59	77.65	0.91	8.89	1.61	22.35
RUS	1.11	5.25	0.56	1.51	0.48	2.05	3.16	83.39	1.88	0.61	16.61
TUR	1.60	2.51	4.20	1.66	1.69	1.51	10.99	1.21	72.44	2.19	27.56
TWN	4.66	0.41	4.10	1.60	0.55	0.61	0.59	0.55	0.68	86.25	13.75
Spillover to other	25.80	12.68	28.40	19.68	8.81	32.98	25.07	8.30	26.90	12.62	
NET	-0.82	1.62	1.01	6.52	-8.27	7.32	2.72	-8.31	-0.66	-1.13	
TSI	20.12										

Notes: Results in Panel A are based on a TVP-VAR model with lag length of order one (BIC) and a 10-step-ahead generalized forecast error variance decomposition. Results in Panel B are based on a TVP-VAR model with lag length of order one (BIC) and a 30-step-ahead generalized forecast error variance decomposition

Appendix A.4.5

Figure A.4.5 Robustness check: Time-varying TSI using different *h*-step forecast ahead

Notes: This figure display the co-movement of the TSI using 10-step forecast ahead (grey line) and the TSI using 30-step forecast ahead (dashed black line).