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Analysis of sector connectedness within Canadian stock market from an uncertainty perspective

par

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Résumé

Cet mémoire présente une analyse approfondie de la volatilité sectorielle et de l'interconnexion des rendements sur le marché de la Bourse de Toronto (TSX). En utilisant la méthode d'autorégression vectorielle de Diebold et Yilmaz (VAR-DY), ainsi que les méthodes VAR-DY à fenêtre glissante et VAR-DY à paramètres variables dans le temps (TVP-VAR-DY), nous examinons les indices d'interconnexion statique et dynamique. De plus, la méthode Barunik et Krehlik (BK) est utilisée pour analyser les canaux de transmission des débordements de volatilité et de rendement dans différentes bandes de fréquence. De plus, l'impact des événements d'incertitude sur les débordements de risque et de rendement entre les secteurs du marché boursier est examiné en sélectionnant la période de recherche comprenant la vente massive de titres en 2015-2016, le crash des cryptomonnaies en 2018, l'épidémie de COVID-19 en 2020 et la guerre russo-ukrainienne en 2022 à l'aide d'un modèle de régression linéaire avec variable fictive.

Les résultats révèlent des caractéristiques distinctes et des mécanismes de transmission de l'interconnexion de la volatilité et des rendements. Le secteur des services financiers joue un rôle important dans l'interconnexion globale des secteurs de la TSX, indiquant son influence prédominante en matière de transmission. Les débordements de volatilité ont tendance à se produire sur de plus longues périodes, sous l'effet de changements économiques fondamentaux, tandis que les débordements de rendement sont plus rapides et de plus courte durée, souvent influencés par des événements d'actualité propres aux entreprises.

L'analyse de différents événements d'incertitude, tels que la vente massive de titres en 2015-2016, le crash des cryptomonnaies en 2018, l'épidémie de COVID-19 en 2020 et la guerre russo-ukrainienne en 2022, montre leur impact variable sur les différents secteurs du marché boursier canadien. Les secteurs clés tels que l'énergie, les services financiers et l'industrie connaissent une augmentation des débordements de volatilité et de rendement pendant ces événements, reflétant l'interconnexion des marchés financiers, les changements de sentiment du marché et les conditions économiques mondiales.

De plus, l'étude met en évidence l'influence potentielle des événements de marché sur d'autres secteurs tels que la technologie de l'information et les soins de santé, qui présentent également une augmentation des débordements de volatilité et de rendement pendant ces périodes. Des facteurs tels que l'incertitude du marché, les perturbations de la chaîne d'approvisionnement, les fluctuations des devises, les changements de demande et la réévaluation de la tolérance au risque et des stratégies d'investissement contribuent aux effets de débordement observés dans ces secteurs.

Comprendre la nature interconnectée des marchés financiers et le potentiel d'effets de débordement entre les secteurs en réponse aux événements de marché est crucial pour les investisseurs, les décideurs politiques et les participants au marché afin d'évaluer les risques et de prendre des décisions éclairées pendant les périodes de stress ou d'incertitude sur le marché.

Mots-clés

Connexité de la volatilité, connexité des rendements, effet de débordement, événements d'incertitude, méthode VAR-DY, méthode TVP-VAR-DY, méthode BK, régression linéaire à variables fictives

Méthodes de recherche

Méthode VAR-DY, méthode TVP-VAR-DY, méthode BK, régression linéaire à variables fictives

Abstract

This thesis presents an in-depth analysis of sectoral volatility and return connectedness in the Toronto Stock Exchange (TSX) market. By employing the Vector Autoregression Diebold and Yilmaz (VAR-DY) method, as well as the rolling window VAR-DY and Time-Varying Parameter Vector Autoregression Diebold and Yilmaz (TVP-VAR-DY) methods, we investigate static and dynamic connectedness indices. Furthermore, the Barunik and Krehlik (BK) method is utilized to analyze volatility and return spillover transmission channels across different frequency bands. Additionally, the impact of uncertainty events on risk and return spillovers between stock market sectors is examined by selecting the 2015-2016 stock market sell-off, the 2018 cryptocurrency crash, the 2020 COVID-19 outbreak, and the 2022 Russo-Ukrainian War as research time points using a dummy variable linear regression model.

The findings indicate distinct characteristics and transmission mechanisms of volatility and return connectedness. The Financials sector plays a significant role in overall connectedness across TSX sectors, indicating its dominant transmission influence. Volatility spillovers tend to occur over longer time horizons, driven by fundamental economic changes, while return spillovers are faster and more short-term, often influenced by company-specific news events.

Analysis of various uncertainty events, including the 2015-2016 stock market sell-off, the 2018 cryptocurrency crash, the 2020 COVID-19 outbreak, and the 2022 Russo-Ukrainian War, demonstrates their varying impact on different sectors of the Canadian stock market. Key sectors such as Energy, Financials, and Industrials experience in-

creased volatility and return spillovers during these events, reflecting the connectedness of financial markets, shifts in market sentiment, and global economic conditions.

Furthermore, the study highlights the potential influence of market events on other sectors, such as Information Technology and Health Care, which also exhibit increased volatility and return spillovers during these periods. Factors such as market uncertainty, supply chain disruptions, currency fluctuations, changes in demand, and reassessment of risk tolerance and investment strategies contribute to the observed spillover effects in these sectors.

Understanding the interconnected nature of financial markets and the potential for spillover effects across sectors in response to market events is crucial for investors, policymakers, and market participants to assess risks and make informed decisions during periods of market stress or uncertainty.

Keywords

Volatility connectedness, return connectedness, spillover effect, uncertainty events, VAR-DY method, TVP-VAR-DY method, BK method, dummy variable linear regression

Research methods

VAR-DY method, TVP-VAR-DY method, BK method, dummy variable linear regression

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List of acronyms

ADF Augmented Dickey-Fuller

AR AutoRegressive

ARCH AutoRegressive Conditional Heteroskedasticity

ARCH-LM Lagrange Multiplier test for AutoRegressive Conditional Heteroskedasticity

BEKK-GARCH Baba, Engle, Kraft and Kroner GARCH model

BIC Bayesian Information Criterion

BK Barunik and Krehlik

DCC-GARCH Dynamic Conditional Correlation GARCH model

DECO-GARCH Dynamic Equi-correlation GARCH

DY Diebold and Yilmaz

EGARCH Exponential GARCH model

GARCH Generalized AutoRegressive Conditional Heteroskedasticity

GFEVD Generalized Forecast Error Variance Decomposition

GICS Global Industry Classification Standard

GVAR Generalized Vector Autoregression

J.B. Jarque-Bera

Kurt. Kurtosis

NPDC Net Pairwise directional Connectedness

SD Standard Deviation

Skew. Skewness

TCI Total Connectedness Index

TVP-VAR Time-Varying Parameter Vector Autoregression

TVP-VAR-DY Time-Varying Parameter Vector Autoregression Diebold and Yilmaz

TSX Toronto Stock Exchange

VAR Vector Autoregression

VAR-DY Vector Autoregression Diebold and Yilmaz

VMA Vector Moving Average

Preface

This paper aims to investigate the phenomenon of volatility and return spillover effects in financial markets, specifically focusing on the connectedness between different sectors in the stock market. By examining the transmission of shocks, information, and volatility across various markets, this study aims to deepen our understanding of the dynamics and interdependencies within the financial markets. The research shows the patterns, drivers, and implications of volatility and return spillovers. The findings of this study can contribute to the literature on financial market connectedness and offer valuable guidance for investors, policymakers, and researchers in managing the complexities of interconnected financial markets.

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Introduction

List of acronyms

BK Barunik and Krehlik

DY Diebold and Yilmaz

ETF Exchange-Traded Fund

TSX Toronto Stock Exchange

TVP-VAR Time-Varying Parameter Vector Autoregression

TVP-VAR-DY Time-Varying Parameter Vector Autoregression Diebold and Yilmaz

VAR Vector Autoregression

VAR-DY Vector Autoregression Diebold and Yilmaz

From the 2008 subprime crisis to the current "black swan" of the Russo-Ukrainian War in 2022, various adverse phenomena have accompanied these events, particularly the rapid global spread of the financial crisis across countries and markets. The connectedness between financial markets has been identified as the main reason for such events.

As economic globalization continues to progress, trade and investment activities among multiple markets in different countries have become more frequent, leading to deepening connectedness among financial markets. The stock market, being a significant component of the financial market, witnesses increased trading activity across different sectors. Consequently, changes in asset prices in one sector have a noticeable impact on other sectors, resulting in sectoral connectedness.

The connectedness among different sectors in the stock market has led to frequent fluctuations in stock prices, increasing investment risks for investors and systemic risks in the stock market. This, in turn, raises the likelihood of financial crises and affects the stability of financial markets.

In recent years, Canadian stock markets have experienced severe shocks due to major uncertainty events, such as the stock market sell-off in 2015-2016, the cryptocurrency crash in 2018, the COVID-19 epidemic in 2020, and the Russo-Ukrainian War in 2022. During uncertainty events, there has been a notable increase in connectedness among sectors, leading to an acceleration in the spread of risk. Therefore, it is essential to examine how uncertainty events impact risk spillovers and the dynamic network features within stock market sectors.

Traditionally, the approach to studying risk spillover between sectors involves testing the driving and driven relationship using the Granger causality test to determine the spillover effect between two sectors.[1]

For instance, Krause and Tse (2013) examines the return and volatility spillover effects of four exchange-traded funds (ETFs) trading between the US and Canada using the Granger causality test. Although the focus of this study is on sector-specific ETFs, the research explores the spillover effects between US sector ETFs and Canadian sector ETFs in multinational markets, such as the Energy ETF in the United States vs. the Energy ETF in Canada. The study found that the transmission of information in the Financials, Information Technology, Energy, and Materials sectors is unidirectional from the United States to Canada for return series. However, for volatility series, the transmission of information in the Financials and Information Technology sectors is bidirectional, while the Energy and Materials sectors only transmit information unidirectionally from the United States

[1]The Granger causality test is a method for evaluating if a time series can be used to predict another through statistical hypothesis testing. It does not imply that the relationship between the two is causal or that one causes the other.

to Canada.

However, Krause and Tse (2013) did not investigate the spillover effects between different sector ETFs within a single country, such as the Energy and Financials sector ETFs in Canada. Moreover, the Granger causality test used in their study only provides a qualitative assessment of association and cannot quantitatively measure the degree of association between the two sectors. Our study expands the research by examining the spillover effects among various sectors within the Canadian stock market and employs the quantitative-based spillover index framework developed by Diebold and Yilmaz (2012) (DY).

Therefore, this study aims to analyze the sectoral connectedness of the stock market from the perspective of uncertainty shocks. To achieve this goal, we employ the DY spillover index framework, which measures the transmission of volatility and interdependence across financial markets using a vector autoregressive model (VAR) (Diebold and Yilmaz, 2012). The spillover index quantifies the percentage of forecast error variance in one market that can be attributed to shocks from another market, indicating the extent to which shocks in one market affect others.

Our analysis of volatility connectedness involves four steps. As an initial step, we assess the static connectedness of sectors in the Toronto Stock Exchange (TSX) using the Vector Autoregressions Diebold and Yilmaz (VAR-DY) method.

As a second step we study time-varying connectedness using the time-varying volatility spillover index method, which treats all assets as a financial system and examines the changing network-wide characteristics of volatility spillover. The traditional VAR-DY method with rolling windows, as proposed by Diebold and Yilmaz (2012), faces limitations such as sample loss and delayed response to sudden market changes. To address these issues, Antonakakis et al. (2020) introduced the Time-Varying Parameter Vector Autoregressions Diebold and Yilmaz (TVP-VAR-DY) method. This method is based on a time-varying parameter vector autoregressive (TVP-VAR) model and utilizes the multivariate Kalman filter to estimate time-varying parameters. The TVP-VAR-DY method overcomes the drawbacks of the rolling window approach, making it more suitable for analyzing spillover effects with small samples and weakly smooth variables. Moreover, it captures the dynamics of connectedness effects and mitigates the adverse impact of extreme values on parameter estimation. Thus, our analysis focuses on the TVP-VAR-DY method to assess the time-varying volatility connectedness among the 11 economic sectors in the TSX, considering factors such as intensity, direction, and variation. To facilitate comparison and enhance understanding, we compare these results with those obtained from the traditional rolling window VAR-DY method.

Given that the DY framework calculates the total connectedness of variables and lacks the ability to decompose them into different frequencies, Baruník and Křehlík (2018) (BK) proposed the BK frequency spillover indices. These indices build upon the original DY spillover indices and incorporate frequency dimension information. The BK method employs the spectrum representation of variance decomposition to measure connectedness across various frequency bands, enabling the decomposition of total connectedness into short-term, medium-term, and long-term frequencies. This allows for the analysis of the effects of corresponding shocks. Consequently, we employ the BK method to investigate potential transmission channels of volatility spillovers in the TSX market across different frequency bands as a third step in our analysis.

By introducing the VAR-DY, TVP-VAR-DY, and BK connectedness index models, this study addresses the limitations encountered in traditional analysis methods, such as the difficulty of measuring the dynamics of sectoral volatility spillovers within specific frequency bands using conventional correlation analysis.

As a final step, we use these measures of connectedness to analyze four significant events—the 2015-2016 stock market sell-off, 2018 cryptocurrency crash, 2020 COVID-19 outbreak, and 2022 Russo-Ukrainian War—and employed a dummy variable linear regression model to examine the impact of these uncertainty events on risk spillover between stock market sectors. Additionally, we analyzed the TVP-VAR-DY dynamic net pairwise connectedness networks during each period of uncertainty events.

Our methodology is also applied to return connectedness for comparison purposes.

The rest of the paper is structured as follows: the next chapter is the Literature review, chapter 1 describes the methodology used in this paper, chapter 2 provides an overview of the data used, chapter 3 discusses the empirical results and the final chapter concludes the paper.

Literature review

List of acronyms

AR AutoRegressive

ARCH AutoRegressive Conditional Heteroskedasticity

BEKK-GARCH Baba, Engle, Kraft and Kroner GARCH model

BK Barunik and Krehlik

DECO-GARCH Dynamic Equicorrelation GARCH model

DY Diebold and Yilmaz

EGARCH Exponential GARCH model

GARCH Generalized AutoRegressive Conditional Heteroskedasticity

TVP-VAR-DY Time-Varying Parameter Vector Autoregression Diebold and Yilmaz

VAR Vector Autoregression

VAR-DY Vector Autoregression Diebold and Yilmaz

VECM Vector Error Correction Model

0.1 Study of volatility spillover effects

Volatility is widely present in financial markets, and research on this has drawn close attention from market participants and academic researchers at all levels. Volatility is a sign of uncertainty in the stock market. It is a expression of the effectiveness of the stock market. Its existence is a reflection of an incomplete information market (Hameed and Kusnadi, 2006). As the research progresses, scholars begin to focus on the study of volatility spillover effects, which mainly focuses on the study of volatility spillover among different markets, different financial indicators and different sectors.

0.1.1 Volatility spillover effects among stock markets

In recent years, financial crises have become increasingly frequent, making the examination of spillover effects within the financial system, particularly volatility spillover effects among stock markets, an urgent concern.

A significant body of current research is dedicated to understanding the complexities of volatility spillovers across various stock markets. Hung (2019) investigated the daily volatility spillover effects of common stock prices between China and four Southeast Asian countries (Vietnam, Thailand, Singapore, and Malaysia). They employed a VAR model coupled with a bivariate Baba, Engle, Kraft, and Kroner-GARCH (BEKK-GARCH) model.[2] Their study discovered that turbulence in the Chinese market exerts a substantial influence on the other Southeast Asian markets.

Vo and Tran (2020), on the other hand, adopted the augmented EGARCH model to investigate the volatility spillover from the U.S. stock market to the stock markets of the Association of Southeast Asian Nations (ASEAN).[3] Their results demonstrated a pro-

[2]Baba, Engle, Kraft and Kroner-GARCH (BEKK-GARCH) model is proposed by Engle and Kroner (1995). It is a multivariate GARCH model that captures the time-varying conditional correlation between multiple variables. It is widely used in finance to model the volatility and correlation structure of multiple assets. It is an extension of the ARCH and GARCH models, which only focus on modelling the univariate volatility of a single asset. BEKK-GARCH models are used to estimate the time-varying covariance matrix of a multivariate asset return series.

[3]Exponential GARCH model (Nelson, 1991) is a type of ARCH/GARCH model that accounts for asymmetric effects of positive and negative shocks on the volatility of a time series. In traditional GARCH

nounced transmission of volatility from the U.S. stock market to ASEAN stock markets. The process of globalization and financial liberalization further enables the flow of capital across borders. This phenomenon also facilitates volatility spillovers from developed economies to emerging ones.

Finta and Aboura (2020) examined volatility and skewness risk premium spillovers among the U.S., U.K., German, and Japanese stock markets by using the spillover index approach proposed by Diebold and Yilmaz (2012). Their study highlighted how the pattern of risk premium spillovers changes over time. Their findings indicated that cross-market and cross-moment spillovers intensified during periods of financial stress.

0.1.2 Volatility spillover effects among different financial markets

The analysis of volatility spillover effects across various financial markets has become increasingly important, particularly in the context of frequent financial crises. Several works have studied this subject, giving a deep understanding of the connectedness and dynamics of shocks among various financial markets.

One notable study by Diebold and Yilmaz (2012) focused on the daily volatility spillovers among different markets, including U.S. stocks, bonds, foreign exchange, and commodities. Their innovative approach involved the use of a vector autoregressive (VAR) framework (VAR-DY) (Diebold and Yilmaz, 2012) to measure both total and directional volatility spillovers. This method quantified the proportion of total forecast error variance in a market that can be attributed to shocks from other markets, offering valuable information on the degree of connectedness between these markets. Interestingly, their analysis indicated that although significant volatility fluctuations occurred in all four

models, volatility responds equally to both positive and negative shocks. In EGARCH, the conditional variance is modelled as a function of the past squared residuals, with the logarithm of the variance following an asymmetric exponential function of both the past residuals and the past conditional variances. The EGARCH model captures the leverage effect, which means that negative shocks have a greater impact on volatility than positive shocks. This can be especially useful in modelling financial time series, where negative shocks tend to have more severe consequences than positive shocks. The EGARCH model is also useful in forecasting financial time series, as it allows for the incorporation of both volatility clustering and asymmetric effects.

markets, the spillover effects between them remained relatively limited until the outbreak of the global financial crisis in 2007. As the crisis deepened, volatility spillovers surged, especially from the stock market to other markets, with a notable increase following the Lehman Brothers' collapse in September 2008.

In a subsequent study, Antonakakis et al. (2020) extended the VAR-DY spillover index by introducing a time-varying parameter VAR model (TVP-VAR-DY). This innovative framework for analyzing connectedness among financial assets has demonstrated more flexible and robust, particularly regarding time-varying dynamics. It effectively captures the dynamic nature of connectedness effects and minimizes the adverse effects of extreme values on parameter estimation. In this method, they employed the Kalman filter to estimate the time-varying variance-covariance matrix of the model, incorporating the use of decay factors (Koop and Korobilis, 2014). This utilization of the Kalman filter helps in capturing the dynamic nature of parameters associated with volatility spillovers over time. Using multivariate Kalman filters, this framework is less sensitive to outliers. This study continued the exploration of volatility spillover effects in financial markets. However, in this case, the focus shifted to examining the connectedness among various currencies within the foreign exchange market. They applied this methodology to explore the connectedness of the euro (EUR), pound sterling (GBP), Swiss franc (CHF), and Japanese yen (JPY) in the foreign exchange market. Their findings highlighted that the EUR and CHF primarily acted as shock transmitters, while the GBP and JPY served as significant recipients of these shocks. Interestingly, the EUR and CHF drove the GBP and JPY, whereas the GBP drove the JPY between 1990–1997 and 2002–2008. Notably, the EUR and CHF did not transmit shocks to each other.

Tian and Hamori (2016) employed a time-varying parameter structural VAR model with stochastic volatility to investigate the transmission mechanism of cross-market financial shocks in U.S. foreign exchange, stock, bond, and commodity markets. They highlighted two key characteristics of volatility shocks. First, the impact of these shocks developed gradually, often taking five to ten days to reach peak volatility spillover levels. Second, the dynamics of volatility spillovers displayed significant variations over time, with different market types responding to specific, though not all, extreme events.

Aybar et al. (2020) used the spillover index approach proposed by Diebold and Yilmaz (2012) and the methodology of Baruník and Křehlík (2018) to decompose the index into different frequency bands, specifically short-term, medium-term, and long-term dynamics. Their analysis examined the connectedness between the volatilities of commodity convenience yields and zero-interest inflation swap rates. Interestingly, while empirical findings using the Diebold and Yilmaz (2012) methodology suggested a high level of total connectedness across the variables over the entire period, results obtained through the Baruník and Křehlík (2018) approach indicated that this connectedness was primarily evident in the long term.

Some studies have also focused on spillovers between commodity and stock markets. In a study by Kang and Yoon (2019), a multivariate Dynamic Equicorrelation GARCH (DECO-GARCH) model was employed to investigate volatility spillover between Chinese equities and four commodity futures (CSI300 index, aluminum, copper, fuel oil, and natural rubber).[4] Their findings highlighted bidirectional indexes for volatility spillovers between Chinese stock and commodity futures markets. These patterns became especially evident following recent financial crises, emphasizing the strength of spillovers during turbulent periods.

Additionally, Vardar et al. (2018) employed a VAR model combined with the BEKK-GARCH model to examine shock transmission and volatility spillover effects among daily stock market indices for both advanced economies (including the US, the UK, Germany, France, and Japan) and emerging economies (such as China, Turkey, South Africa, South Korea, and India). This analysis also incorporated five major commodity spot prices:

[4]Dynamic Equicorrelation GARCH model, also known as DECO-GARCH, is created by Engle and Kelly (2012). It is a multivariate GARCH model that estimates time-varying correlations between different financial assets. The main feature of the DECO-GARCH model is that it enforces a constraint on the correlation matrix, so that the average correlation equals the average pairwise correlations. This constraint ensures that the estimated correlation matrix is positive definite, which is important for estimating asset return volatility and co-volatility. The DECO-GARCH model is an extension of the Dynamic Conditional Correlation GARCH model, and it has been shown to perform better than other multivariate GARCH models in capturing the complex dynamics of financial markets. It has applications in portfolio optimization, risk management, and asset pricing, among others.

crude oil, natural gas, platinum, silver, and gold, particularly during the period of the 2008 global financial crisis. Their findings demonstrated that the primary trend in both advanced and emerging countries was the bidirectional shock transmission and volatility spillover effects between stocks and commodities. During the crisis and post-crisis periods, there were more instances of significant shock and volatility spillovers between commodity and stock markets compared to the pre-crisis period.

Among the articles on spillover effects between various markets, the spillover effect of the energy market is also the focus of the current research content. Barbaglia et al. (2020) adopted a VAR model to explore volatility spillovers among numerous energy, agricultural, and biofuel commodities. Their empirical analysis highlighted the presence of volatility spillovers between energy and biofuel, as well as between energy and agricultural commodities.

In addition, Lovcha and Perez-Laborda (2020) examined spillover effects between oil and natural gas volatility, utilizing the Diebold and Yilmaz (2012) index and complementing it with the frequency connectedness measure proposed by Baruník and Křehlík (2018). Their analysis considered the possibility of changes in spillover effects over time and across different frequency bands. The results indicated that the volatility spillover effect exhibited significant temporal variability, with the natural gas market mainly serving as a net transmitter of volatility spillover across most samples.

Exploring spillover effects between crude oil and ten major agricultural commodity markets, Dahl et al. (2020) utilized the volatility spillover index introduced by Diebold and Yilmaz (2012). Their results indicated that prior to 2006, there was limited information transmission between crude oil and agricultural commodities. The spillover between crude oil and agriculture is economically insignificant. However, post-2006, crude oil became a net recipient of information from agricultural commodities. Notably, net volatility spillovers intensified during significant declines in crude oil prices, particularly in 2008 and later in 2014.

The study of the relationship between the oil market and the stock market has been a popular topic in the last two decades. Sarwar et al. (2020) investigated the volatility spillover effects between oil and stock markets, specifically focusing on Karachi, Shanghai, and Bombay, using a bivariate BEKK-GARCH model. Their findings indicated that within the Karachi stock market, the volatility spillover between the oil market and the stock market displayed bidirectional spillovers. In contrast, the Shanghai stock market exhibited unidirectional spillovers from the oil market, while the Bombay stock market presented mixed evidence of volatility spillover effects. These findings highlight the complexity and variability of spillover patterns in different financial markets, revealing their connectedness and response to external shocks.

Turning to the intersection of cryptocurrency and financial markets, Qarni et al. (2019) employed a range of methods, including the Diebold and Yilmaz (2012) volatility spillover index, Baruník et al. (2017) spillover asymmetry measure, and Baruník and Křehlík (2018) frequency connectedness approach. Their study focused on assessing the time-varying dynamics of volatility spillover between U.S. Bitcoin and financial markets. Their results suggested a limited degree of integration and contagion between U.S. Bitcoin and financial markets. Moreover, they identified an asymmetric pattern of volatility spillover, with connectedness primarily observed at high frequencies, indicating rapid information processing in these markets.

0.1.3 Volatility spillover effects among different sectors in the stock market

The stock market serves as a crucial indicator reflecting the state of economic development. Analyzing spillover effects between stocks in various sectors provides valuable information about the constantly evolving transmission dynamics of the financial market.

Mohammadi et al. (2016) investigated the correlation dynamics and spillover effects of 10 major sector indices in the Tehran Stock Exchange using the wavelet coherence approach within the continuous wavelet transform framework (Grinsted et al., 2004).[5] Their

[5] Wavelet coherence is a measure of the coherence or correlation between two time series as a function of frequency and time. It is a way to study the relationship between two signals that may be non-stationary or have time-varying frequency content. It involves computing the wavelet transform of both time series and

findings emphasized the time-varying and scale-dependent nature of these co-movements.

Huang and Wang (2018) used the VAR multivariate GARCH model in the BEKK form to investigate spillover effects within four key financial sectors of the Chinese stock market, including commercial banks, security broker-dealers, insurance companies, and other financial institutions.[6] Their study revealed that the banking sector exhibited a higher degree of stability in terms of volatility spillover compared to other sectors.

Wu et al. (2019) studied systemic connectedness and contagion dynamics among sectors in the Chinese stock market, utilizing the spillover index model proposed by Diebold and Yilmaz (2012). Their research highlighted the crucial role of the Industrial sector as the most influential and central sector in the Chinese stock market. Furthermore, they observed a time-varying nature in the volatility spillover structure, with occasional shifts in central sectors.

Choi et al. (2021) applied the spillover index methodology introduced by Diebold and Yilmaz (2012) to assess dynamic volatility spillovers and identify connectedness networks among 11 sector indices within the Australian Securities Exchange (ASX). Their study revealed that the 2007 financial crises intensified the degree of volatility connectedness across sectors, aligning with the contagion hypothesis. Furthermore, the financial sector acted as the primary transmitter of volatility connectedness among the 11 ASX sectors.

Chirilă (2022) examined the volatility connectedness between different economic sectors in the Polish stock market before and during the COVID-19 pandemic, employing the

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then calculating the cross-wavelet spectrum, which is a measure of the coherence between the two series at each frequency and time point. Wavelet analysis is a tool for analyzing a single time series, while wavelet coherence is a tool for analyzing the coherence between two time series. Both techniques use wavelet functions and decomposition to provide a detailed analysis of the signal, but they have different goals and methods.

[6]It is a multivariate time-series econometric model that combines VAR, Multivariate GARCH, and BEKK models. The VAR model captures the linear interdependence among the variables, and the Multivariate GARCH model captures the time-varying volatility and conditional correlation structure of the variables. The BEKK model specifically estimates the covariance matrix of the residuals of the VAR-Multivariate GARCH model, which ensures the covariance matrix is positive semi-definite and therefore has useful statistical properties. The VAR-Multivariate GARCH-BEKK model can be used to estimate the conditional volatility and correlation structure of multiple time series simultaneously, which is useful in risk management, portfolio optimization, and asset pricing. The model is capable of capturing the complex dynamics and interdependence of multiple time series, which are often observed in financial markets.

TVP-VAR-DY method introduced by Antonakakis et al. (2020). The results illustrated that sectoral connectedness exhibited temporal variations, with heightened connectedness during the pandemic period. Notably, the banking sector exerted the most substantial influence on volatility spillover.

Additionally, there is literature that explores the volatility spillover effects among various entities within a particular sector of the stock market. Baruník and Křehlík (2018) (BK) introduced a innovative framework for measuring spillover index by incorporating variance-based spectral analysis to assess changes in spillover effects at different frequency bands. They explored the connectedness of 11 major financial firms representing the financial sector of the U.S. economy. Their findings revealed that periods characterized by high-frequency connectedness coincided with market phases marked by rapid and stable information processing. During such periods, a shock to one entity in the system mainly impacted the short term. Conversely, lower-frequency connectedness indicated persistent shocks transmitted over more extended periods, often resulting from changes in investor expectations that influenced the market over the long term. These expectations were then transmitted to surrounding entities.

0.2 Study of return spillover effects

In addition to volatility spillover, return spillover has also been a central focus of research among some scholars. This literature review examines three key aspects of return spillover effects: spillovers among stock markets, spillovers among different financial markets, and spillovers among different sectors within stock markets.

0.2.1 Return spillover effects among stock markets

The analysis of return spillover effects among stock markets has gained extensive attention, due to the globalization of financial markets and the surge in cross-border capital flows.

Yang et al. (2006) conducted a comprehensive investigation into the long-term price relationships and dynamic price transmissions between the United States, Germany, and four major Eastern European emerging stock markets (Russia, Poland, Hungary, and the Czech Republic). Their study investigated the consequences of the 1998 Russian financial crisis. To analyze the effects of the crisis on long-run equity market relationships, the study employed the persistence profile technique introduced by Pesaran and Shin (1996).[7] Additionally, they utilized the generalized VAR framework developed by Koop et al. (1996); Pesaran and Shin (1998) to estimate short-term dynamic causal linkages across the stock markets.[8] The findings indicated that both the long-run co-movements of stock prices and the dynamic price transmission were strengthened among these markets following the crisis. Moreover, the influence of Germany on the Eastern European markets became evident only after the crisis, rather than before it.

In addition, Aktan et al. (2009) examined the linkages between the stock markets of the BRICA countries (Brazil, Russia, India, China, and Argentina) and their relationship with the US market. Employing Granger causality tests, their findings highlighted the substantial impact of the US market on all BRICA countries.[9]

In another notable study, Cheung et al. (2010) employed various statistical techniques, including the VAR model, Granger causality test, and Vector Error Correction Model (VECM), to explore return spillover effects during the 2007-2009 Global Financial Crisis.[10] Their analysis focused on the transmission of returns from the US market to other

[7]The persistence profile technique, developed by Pesaran and Shin (1996), is a statistical approach used to assess the long-run relationship between variables in a time series context. It is particularly useful for examining the presence and strength of cointegration, which implies a stable long-run equilibrium relationship between variables.

[8]The generalized VAR framework, developed by Koop et al. (1996); Pesaran and Shin (1998), is a statistical modelling approach used to analyze the dynamic interactions among multiple time series variables. It extends the traditional VAR model by incorporating additional features that account for complex relationships, non-linearity, and structural breaks in the data.

[9]The Granger causality test is a method for evaluating if a time series can be used to predict another through statistical hypothesis testing. It does not imply that the relationship between the two is causal or that one causes the other.

[10]Vector Error Correction Model is an extension of VAR model. It is used to capture both the short-run (VAR component) and long-run relationships (error correction mechanism models) among a set of variables, while allowing for the possibility of cointegration, which means that the variables move together in the long-run despite exhibiting independent behavior in the short-run.

global financial markets, spanning the UK, Hong Kong, Japan, Australia, and China. Their results illustrated a significant return spillover effect from the US market to these markets. Furthermore, the study indicated that the linkage between the US market and other global markets, both in terms of short-term causal relationships and long-term cointegrating equilibrium, became stronger during the crisis. These results align with the contagion theory, suggesting that the interdependence among international stock markets intensifies during times of crisis.

Nguyen and Le (2021) studied return spillover effects from both the US and Japanese stock markets to the Vietnamese stock market. They applied Granger causality tests to assess these relationships while employing the spectral approach introduced by Breitung and Candelon (2006) to analyze them in the frequency domain.[11] The findings emphasized a significant return spillover from the US market to the Vietnamese stock market across all frequencies, while spillover from the Japanese market to the Vietnamese market primarily appeared at higher frequencies. These outcomes suggest that the impact of return spillover varies across distinct frequency bands.

0.2.2 Return spillover effects among different financial markets

Return spillover effects are not limited to stock markets but can also occur between stock markets and other financial markets, such as foreign exchange markets and commodity markets.

Tsagkanos and Siriopoulos (2013) investigated the relationship between stock prices and exchange rates in the European Union (EU) and the United States (USA). The study examined the long-run relationship using the structural non-parametric cointegrating regression method.[12] The findings revealed a long-run causal relationship from stock prices

[11] The frequency-domain causality method proposed by Breitung and Candelon (2006) is a statistical approach used to analyze causal relationships between time series variables in the frequency domain. It builds upon the concept of spectral analysis, which decomposes time series data into different frequency components.

[12] Structural nonparametric cointegrating regression, developed by Wang and Phillips (2009), is a statistical method used to estimate the long-term relationship between nonstationary time series variables. Unlike traditional cointegration analysis that relies on parametric models, the structural nonparametric

to exchange rates in the EU, while in the USA, the relationship was observed to be short-run.

Wang et al. (2023) investigated the transmission of return spillovers among the Chinese and American stock markets and the international commodity market. This study also explored the key factors influencing these cross-market spillovers, including both actual demand and speculative behavior. In this article, the classic VAR model was enhanced by incorporating factor enhancement techniques, which reduced high-dimensional datasets into a set of underlying common factors. The results indicated a growing inter-market linkage between commodity and stock markets. Speculative behavior had a considerably greater impact on return spillovers compared to actual demand. Furthermore, the impact of speculation in emerging economies on their interaction with commodity markets became more prominent than in advanced economies.

Furthermore, Doblas and Lagaras (2023) examined the short-term return spillover patterns among Bahrain stocks, bitcoin, and other commodity assets, taking into account the dynamic impact of the COVID-19 pandemic by employing the VAR model. The findings revealed a consistent one-way short-term spillover of returns from the Bahrain stock market to the futures gold market, observed both before and during the pandemic. Additionally, the results indicated that the notable positive shock in bitcoin returns, granger-caused by the returns of the Bahrain stock market, was significant only in the pre-pandemic period. Moreover, a significant negative simultaneous short-term effect on crude oil market returns can be statistically attributed to shocks occurring solely during the COVID-19 period in the Bahrain stock market.

approach aims to capture the underlying relationship between variables while accommodating potential non-linearities and heterogeneity in the data. It can be particularly useful when the relationship between variables is complex and cannot be adequately captured by linear or parametric models.

0.2.3 Return spillover effects among different sectors in the stock market

Studies have investigated sectoral return spillovers to gain a deeper understanding of the interdependencies and contagion effects that become apparent during periods of market turbulence or specific events.

Fasanya et al. (2019) studied the return spillover effects of stock prices across various sectors in Nigeria using monthly data. The research employed the spillover approach proposed by Diebold and Yilmaz (2012) and employed rolling sample analysis to capture both the long-term and cyclical movements in the sectoral stock market. The findings pointed to interdependence among sector stocks based on the spillover indices, with the return spillover index revealing an heightened level of integration among the sectoral stocks.

In the study conducted by Majumder (2021), they explored return spillovers among eight Nifty thematic indices in India, incorporating Energy, Infrastructure, MNC, PSE, Services Sector, Aditya Birla Group, Mahindra Group, and Tata Group. They employed the VAR (1) asymmetric BEKK-GARCH model to analyze the spillover effects. The findings illustrated the existence of interlinkages among the Nifty thematic indices. Specifically, significant return spillovers were observed from the services sector, Infrastructure, Aditya Birla Group, and Tata Group to other indices.

0.3 Research gap and contribution

With the ongoing wave of economic globalization, the exploration of stock market volatility and return spillover effects has become a key area in research. Researchers have employed a wide array of models and methodologies to examine these phenomena, which are crucial for risk management, portfolio optimization, and overall market stability.

The study of volatility spillover effects is particularly important for understanding the fundamental macroeconomic risks, especially the business cycle risk. Earlier studies often referred to financial contagion as a sudden surge in volatility spillovers, largely because interdependence was traditionally assessed through correlation. However, it is important to acknowledge that the definition of correlation remains somewhat ambiguous, potentially due to its limited scope in capturing the complexity of interactions in dynamic economic systems. Correlation measures linear relationships, which may not fully represent the non-linear behaviors observed in financial markets and macroeconomic factors. Additionally, it provides a static snapshot, overlooking the dynamics of volatility spillovers. Hence, there is a need for improvement in measuring spillover effects.

Presently, measures of volatility spillovers mainly center around pairwise correlations, such as Kendall's τ values and Spearman p values (Zhang and Cheng, 2020). Numerous statistical techniques have been developed to capture linear relationships, including multiple regression, VAR, and VECM models, to describe short- and long-term spillover effects among multiple variables (Yang et al., 2016; Lukietta and Wibowo, 2020). Due to the specific characteristic of volatility clustering in financial time series data, the AutoRegressive Conditional Heteroskedasticity (ARCH) model has found wide application in modeling financial time series, while the multivariate Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model has been extensively employed in spillover studies.

Since the introduction of wavelet analysis into economic research by Ramsey and Lampart (1998), scholars have increasingly utilized multi-scale decomposition results from wavelet transforms, combined with Granger causality tests to analyze correlations among financial variables. As research in this field continues to expand, Diebold and Yilmaz (2012) method and Baruník and Křehlík (2018) frequency connectedness method have gradually come into the research field in recent years.

Building upon previous research on stock market volatility and return spillover effects, further exploration can be conducted in the following areas:

Firstly, regarding the selection of research models, current literature mainly relies on the different GARCH-based models to study the volatility spillover among various economic variables. In terms of return spillover effects, researchers commonly employ

Granger causality tests and VAR models, primarily focusing on the study of spillover relationships between two assets. However, as the study of spillover effects deepens, there are limitations in the study using only the above-mentioned models. The mentioned models may oversimplify spillover effects, potentially overlooking the dynamics in the data. Assumptions within these models might not always hold in real-world scenarios, introducing potential inaccuracies. Additionally, the models may be limited in capturing spillover effects beyond pairwise relationships or in the presence of complex interactions among multiple economic variables.

Secondly, with regard to the selection of research topics, the existing literature on stock market volatility and return spillover primarily focuses on the impact of specific political and economic events on cross-country stock market or exchange rate spillovers. Comparatively, there is relatively limited research on sectoral connectedness.

In this context, our study is the first to investigate sectoral volatility and return connectedness within the Toronto Stock Exchange (TSX) market. Our analysis consists of four steps.

- Step 1:

  We evaluate the static connectedness between sectors in the TSX by employing the Vector Autoregressions Diebold and Yilmaz (VAR-DY) method.

- Step 2:

  We study time-varying volatility and return connectedness using the time-varying spillover index method. This method treats all assets as components of a financial system and analyzes how the characteristics of volatility and return spillover change across the entire network. In contrast to the conventional VAR-DY method, which relies on rolling windows and has limitations such as sample loss and delayed response to sudden market shifts, we use the Time-Varying Parameter Vector Autoregressions Diebold and Yilmaz (TVP-VAR-DY) method introduced by Antonakakis et al. (2020). This approach, based on a time-varying parameter vector autoregressive (TVP-VAR) model, utilizes the multivariate Kalman filter to estimate time-varying parameters. The TVP-VAR-DY method overcomes the shortcomings of the rolling window approach, making it more suitable for analyzing spillover effects, especially when dealing with small samples and weakly smooth variables. Furthermore, it captures the dynamic nature of connectedness effects and mitigates the negative impact of extreme values on parameter estimation. As a result, our analysis primarily focuses on the TVP-VAR-DY method to assess the time-varying volatility and return connectedness among the 11 economic sectors within the TSX. To facilitate comparison and improve understanding, we compare these results with those obtained through the conventional rolling window VAR-DY method.

- Step 3:

  We employ the Baruník and Křehlík (BK) frequency spillover indices to investigate potential transmission channels of volatility and return spillovers within the TSX market across various frequency bands. This decision is made because the Diebold and Yilmaz (DY) framework calculates the total connectedness of variables without the capability to decompose them into different frequencies. The BK method expands upon the original DY spillover indices by incorporating frequency dimension information. It employs the spectrum representation of variance decomposition to measure connectedness across diverse frequency bands, thus enabling the decomposition of total connectedness into short-term, medium-term, and long-term frequencies. This enables the analysis of the effects of corresponding shocks.

- Step 4:

  We utilize these connectedness metrics to investigate the impact of four uncertainty events—the 2015-2016 stock market sell-off, the 2018 cryptocurrency crash, the 2020 COVID-19 outbreak, and the 2022 Russo-Ukrainian War. We employ a dummy variable linear regression model to examine the impact of these uncertainty events on volatility and return spillovers between stock market sectors. Additionally, we conduct an analysis of the TVP-VAR-DY dynamic net pairwise connectedness networks of volatility and return during each period of uncertainty events.

In summary, by introducing the VAR-DY, TVP-VAR-DY, and BK connectedness index models, our study effectively addresses the limitations associated with traditional analytical methods. It overcomes challenges such as the difficulty of quantifying the dynamics of sectoral volatility and return spillovers within specific frequency bands, which is a common challenge in conventional correlation analysis.

Chapter 1

Methodology

List of acronyms

BK Barunik and Krehlik

DY Diebold and Yilmaz

GFEVD Generalized Forecast Error Variance Decomposition

GVAR Generalized Vector Autoregression

NPDC Net Pairwise directional Connectedness

TCI Total Connectedness Index

TVP-VAR Time-Varying Parameter Vector Autoregression

TVP-VAR-DY Time-Varying Parameter Vector Autoregression Diebold and Yilmaz

VAR Vector Autoregression

VAR-DY Vector Autoregression Diebold and Yilmaz

VMA Vector Moving Average

Regarding the connectedness measurement, we use the Diebold and Yilmaz (hereinafter referred to as VAR-DY) method, time-varying parameter Vector Autoregression

Diebold and Yilmaz (hereinafter referred to as TVP-VAR-DY) method and the Barunik and Krehlik (hereinafter referred to as BK) method.

1.1 VAR-DY approach

In the research area of financial market connectedness, Diebold and Yilmaz (2012) have calculated the total connectedness, directional connectedness (TO and FROM), and net total directional connectedness from the conventional standard vector-autoregressive (VAR) model with H-step-ahead variance decomposition, and obtained the time-varying connectedness index by setting a rolling window.

The vector autoregressive (VAR) model was proposed by Sims (1993). The model treats all variables as endogenous variables that can predict each other, and estimates the dynamic shock relationship between the internal parameters by performing simultaneous regression of the endogenous economic variables with the lags of the remaining endogenous economic variables. A vector autoregressive model (VAR(p)) with N variables can be expressed as:

$$x_t = \sum_{j=1}^{p} \varphi_j x_{t-j} + \varepsilon_t, \tag{1.1}$$

where x_t is an N-dimensional vector that can be expressed as the volatility of N sector indices, $\varphi_j (j = 1, 2, ..., p)$ is the $N \times N$ autoregressive coefficient matrix which contains the coefficients of the linear relationships between each variable at the current time and all N variables at the past time j, p indicates the lag order and is determined by the AIC or BIC criterion, ε_t is an $N \times 1$ vector of error terms, and $\{\varepsilon_t\}_{t \in N}$ is a sequence of independent noises. To ensure the stationarity of the VAR model, it is necessary to assume that the roots of $|\varphi(z)|$ lie outside the unit circle. Here, $|\varphi(z)| = |I_N - \varphi_1 z - \cdots - \varphi_p z^p|$ with I_N as the identity matrix.

Since the VAR model has a large number of estimated parameters in most cases and the relationship between the parameters is complex, it is difficult to provide a reasonable explanation for the parameter estimates of the VAR model. Secondly, moving average expressions for these parameters, such as impulse response equations or variance decomposition, can effectively explain the connectedness structure between variables in the system, so the VAR model is transformed into a vector moving average (VMA) model.

$$x_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j}, \tag{1.2}$$

where $A_j = \varphi_1 A_{j-1} + \varphi_2 A_{j-2} + \cdots + \varphi_p A_{j-p}$, with A_0 being the identity matrix and $A_j = 0$ for $j < 0$.

The variance decomposition method can be used to effectively measure the proportion of the change in the variance of the forecast error of a variable in a VAR model subjected to a volatility shock that is influenced by other variables, i.e., that is, to what extent the change of a variable is caused by its own shock or the shocks from other variables in the system. The forecast error is the difference between the model's predicted values and the actual observed values for a given variable.

We do the following variance decomposition based on the generalized vector autoregressive (GVAR) method (Koop et al., 1996; Pesaran and Shin, 1998).

Since the errors ε are assumed to be serially uncorrelated, the H-step-ahead forecast error's overall covariance matrix conditional at the information in time $t-1$, is:

$$\Omega(H) = A_h \Sigma A_h', \tag{1.3}$$

where Σ is the covariance matrix of the disturbance vector ε, A_h is a $N \times N$ matrix of moving average coefficients, which is the same as in Equation (1.2) but at lag h. and A_h' is the transpose of A_h.

Then we establish the covariance matrix of the forecast error by taking into account both the present and the anticipated future shocks to the j-th equation.

We begin by utilizing the conditional forecast error:

$$\gamma_t^k(H) = \sum_{h=0}^{H-1} A_h \left[\varepsilon_{t+H-h} - E\left(\varepsilon_{t+H-h} \mid \varepsilon_{k,t+H-h}\right)\right], \tag{1.4}$$

where ε_{t+H-h} represents the overall error term at time $t+H-h$ and $\varepsilon_{k,t+H-h}$ represents the error term for a specific variable k at the same time point $t+H-h$.

Assuming normal distribution, we have:

$$\gamma_t^k(H) = \sum_{h=0}^{H-1} A_h \left[\varepsilon_{t+H-h} - \sigma_{kk}^{-1}(\Sigma)_k \varepsilon_{k,t+H-h}\right]. \tag{1.5}$$

Finally, we can get the covariance matrix as follows:

$$\Omega^k(H) = \sum_{h=0}^{H-1} A_h \Sigma A_h' - \sigma_{kk}^{-1} \sum_{h=0}^{H-1} A_h (\Sigma)_k (\Sigma)_k' A_h', \tag{1.6}$$

Then the unscaled H-step ahead forecast error variance of the j-th component with respect to the innovation in the k-th component is:

$$\Delta_{jk}(H) = \Big(\Omega(H) - \Omega^k(H)\Big)_{j,j} = \sigma_{kk}^{-1} \sum_{h=0}^{H-1} \Big((A_h \Sigma)_{j,k}\Big)^2, \tag{1.7}$$

After scaling, the fraction of the H-step forecast error variance of the variable j that can be explained by the variable k is:

$$\begin{aligned} \Phi_{jk}(H) &= \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H-1} \Big((A_h \Sigma)_{j,k}\Big)^2}{\sum_{h=0}^{H-1} (A_h \Sigma A_h{}')_{j,j}}, \\ &= \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H-1} \Big(\theta_j' A_h \Sigma \theta_k\Big)^2}{\sum_{h=0}^{H-1} \Big(\theta_j' A_h \Sigma A_h' \theta_j\Big)} \end{aligned} \tag{1.8}$$

where σ_{kk} is the k-th diagonal element of the covariance matrix Σ and σ_{kk}^{-1} is the reciprocal of this diagonal element. θ_j is a $N \times 1$ vector taking the value 1 for j-th element and zero otherwise. When $j \neq k, \Phi_{jk}(H)$ denotes the share of H-step-ahead forecast error variance in j contributed by the shocks of k. Since the variance shares in the generalized VAR framework do not necessarily add up to 1, we normalize each entry by the row sum as follows to obtain the pairwise directional connectedness:

$$\widetilde{\Phi}_{jk}(H) = \frac{\Phi_{jk}(H)}{\sum_{k=1}^{N} \Phi_{jk}(H)}, \tag{1.9}$$

thus, after the normalization, $\sum_{k=1}^{N} \widetilde{\Phi}_{jk}(H) = 1$ and $\sum_{j=1}^{N} \sum_{k=1}^{N} \widetilde{\Phi}_{jk}(H) = N$.

On this basis, the total connectedness index is constructed to assess the overall connectedness effect and it is simply the average of all pairwise directional connectedness for $j \neq k$, that is, the total connectedness of a certain variable to other variables can be expressed as:

$$\mathrm{TCI}(H) = \frac{\sum_{j=1}^{N}\sum_{k=1,k\neq j}^{N}\widetilde{\Phi}_{jk}(H)}{\sum_{j=1}^{N}\sum_{k=1}^{N}\widetilde{\Phi}_{jk}(H)} \times 100 = \frac{\sum_{j=1}^{N}\sum_{k=1,k\neq j}^{N}\widetilde{\Phi}_{jk,t}(H)}{N} \times 100, \tag{1.10}$$

The total connectedness is simply the sum of total directional connectedness "from other" or "to other" elements averaged by the number of variables in the system.

We calculate the FROM (TO) connectedness to quantify the information connectedness effect of one variable received from (transmitting to) all the other elements in the system.

The directional volatility connectedness received by sector j from all other sectors (FROM) is calculated by

$$\mathrm{FROM}_{j\leftarrow *}(H) = \frac{\sum_{k=1,j\neq k}^{N}\widetilde{\Phi}_{jk}(H)}{N} \times 100, \tag{1.11}$$

The directional volatility connectedness transmitted by sector j to all other sectors (TO) is computed as follows:

$$\mathrm{TO}_{j\rightarrow *}(H) = \frac{\sum_{k=1,k\neq j}^{N}\widetilde{\Phi}_{kj}(H)}{N} \times 100, \tag{1.12}$$

The net total directional connectedness (NET) for sector j can be expressed as the difference in directional TO and FROM connectedness, which measures how sector j is receiving or giving connectedness from/to all the others:

$$\mathrm{NET}_{j}(H) = \mathrm{TO}_{j\rightarrow *}(H) - \mathrm{FROM}_{j\leftarrow *}(H). \tag{1.13}$$

Thus, the net total directional connectedness measures the importance of sector j in the system. The positive net connectedness measure of sector j implies that it has a greater influence in this system than other sectors, and its fluctuations can exert more influence on other sectors, rather than being affected by other sectors in turn (Yoon et al., 2019).

The net connectedness effect of j on k , referred to as the net pairwise directional connectedness index (NPDC), is defined as the directional connectedness between j and

k in the system. This index quantifies the degree of influence between any two individual sectors, j and k, within the system.

$$\mathrm{NPDC}_{jk}(H) = \left(\frac{\widetilde{\Phi}_{kj}(H)}{N} - \frac{\widetilde{\Phi}_{jk}(H)}{N} \right) \times 100, \tag{1.14}$$

A positive NPDC means that the connectedness effect of j on k is stronger than the connectedness effect of k on j, which implies that j dominates the change of k. Conversely, a negative NPDC would indicate that k has a stronger influence on j than j has on k.

We can see from the above theory that it answers the crucial question of "how much of the sector j's future uncertainty is attributable to shocks coming from sector k rather than j at horizon H?" based on the generalized VAR variance decomposition connectedness measurements. It also enables the exploration of varied connectedness for different horizons. It makes sense that expanding the horizon would increase the likelihood of connectedness between each pair of sectors.

To study the dynamic connectedness effect, Diebold and Yilmaz introduced the rolling window method. A window width W is first set with $\Delta T = 1$, i.e., the first rolling window contains observations from period 1 to W, the second rolling window contains observations from period 2 to $W+1$, and so on, such that the last rolling window contains observations from the period $(T-W+1)$ to T. Then the model for each of these rolling windows is separately estimated to get the dynamic connectedness indices.

However, the traditional VAR-DY index calculated based on the rolling window suffers from the selected rolling window size. The rolling window method can lead to information loss because it only uses data within the window for each calculation, ignoring information outside of the window. As the window moves forward, older data points are dropped, which might contain valuable information about long-term trends and connectedness. Additionally, this approach is sensitive to extreme values, leading to potential skews in understanding the connectedness. Lastly, when dealing with high-frequency data, such as daily or hourly observations, the traditional VAR-DY index may not align well with the rapid changes in the data, resulting in an inaccurate representation of the connectedness in more volatile periods.

1.2 TVP-VAR-DY approach

Antonakakis et al. (2020) construct a new DY connectedness index based on the TVP-VAR posterior estimates that can eliminate the drawbacks, related to the TVP-VAR-DY method. TVP-VAR-DY index can effectively capture full-sample information as well as sudden market changes, and effectively solve the sample loss problem caused by rolling windows. It uses the multivariate Kalman filter method to obtain the time-varying parameters of the model to capture the dynamics of connectedness effects. This method overcomes the adverse effect of extreme values on parameter estimation. (Antonakakis et al., 2018; Bouri et al., 2021; Gabauer and Gupta, 2018; Li et al., 2021; Umar et al., 2021)

Based on the VAR model, Primiceri (2005) proposed a time-varying parameter vector autoregressive model, also known as TVP-SV-VAR. Nakajima (2011) optimized the computational procedure for estimating the associated parameters. Compared with the ordinary VAR model, the improvement of this model is to characterize the time-varying relationship between simultaneous variables. The TVP-VAR(p) model can be expressed as follows:

$$Y_t = \varphi_t X_{t-1} + \varepsilon_t, \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0, \Sigma_t), \tag{1.15}$$

$$\mathrm{vec}(\varphi_t) = \mathrm{vec}(\varphi_{t-1}) + \xi_t, \quad \xi_t \mid \Omega_{t-1} \sim N(0, \Xi_t), \tag{1.16}$$

where $Y_t = (y_{1,t}, y_{2,t}, \ldots, y_{n-1,t}, y_{n,t})'$ is an $N \times 1$ vector of observed variables at time t and $X_{t-1} = (Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p})'$ is an $Np \times 1$ vector. The parameter p indicates the lag order and is determined by the AIC or BIC criterion. $\varphi_t = (\varphi_{1t}, \varphi_{2t}, \ldots, \varphi_{pt})$ is an $N \times Np$ autoregressive coefficient matrix at time t, $\varphi_{it}(i = 1, \ldots, p)$ is $N \times N$ dimensional matrix. $\mathrm{vec}(\varphi_t)$ is the vectorized form of φ_t, where the process of vectorization involves transforming φ_t, a matrix, into a column vector. ε_t and ξ_t are the error vectors and they are independent. Ω_{t-1} represents the information set available at time $t-1$, Σ_t and Ξ_t are the covariance matrix of ε_t and ξ_t, respectively.

Then, the dynamic coefficient matrix φ_t and covariance matrix of the error terms Σ_t in the TVP-VAR(p) model are obtained by using the multivariate Kalman filter method (Koop and Korobilis, 2014). The state-space equation is used by the Kalman filtering technique to optimally estimate the system state using observed data of the system that includes the effects of noise and disturbances. The Kalman filter-based dynamic connectedness framework provides the following benefits over the conventional rolling-window dynamic connectedness framework. First, it is more flexible and appropriate when used for small sample data sets. This is because, during parameter estimation, only the error covariance matrix of the prior state needs to be known, and there is no necessity to record all previous states. The Kalman filter operates recursively, facilitating efficient estimation and making it particularly beneficial for handling limited data. In addition, it does not require stationary data, so the Kalman filter-based TVP-VAR model is more appropriate than the rolling-window method for calculating connectedness indices among weak stationary series.

With the information set at time t, we can calculate φ_t and Σ_t as follows:

$$\varphi_t = \varphi_{t|t-1} + K_t \left(Y_t - \varphi_{t|t-1} X_{t-1} \right), \tag{1.17}$$

$$\varepsilon_t = Y_t - \varphi_t X_{t-1}, \tag{1.18}$$

$$\Sigma_t = \kappa_2 \Sigma_{t-1|t-1} + (1-\kappa_2)\, \varepsilon_t' \varepsilon_t, \tag{1.19}$$

where $\mid t-1$ represents with the information set at time $t-1$, κ_1 and κ_2 are the forgetting factor and decay factor, respectively, and are set to be $\kappa_1 = 0.99$, and $\kappa_2 = 0.96$ according to Koop and Korobilis (2014). K_t indicates Kalman gain, which describes how much the parameters φ_t should be altered at every given state. Its value depends on the uncertainty parameter and the error variance, that is, when the uncertainty parameter and the error variance are small, the estimation is accurate, thus the parameters φ_t are identical to their previous states and the Kalman gain is small, and vice versa.

Then φ_t and Σ_t are applied in the process of generalized forecast error variance decomposition (GFEVD) at H-step-ahead. Before doing so, we transform the TVP-VAR model to the vector moving average (VMA) form:

$$Y_t = \varphi_t X_{t-1} + \varepsilon_t = \sum_{j=0}^{\infty} A_{j,t}\varepsilon_{t-j}, \tag{1.20}$$

where $A_{j,t} = \sum_{i=1}^{p} \varphi_{i,t} A_{j-i,t}$ is the response function, $A_{0,t}$ is the identity matrix and $A_{j,t} = 0$ when $j < 0$.

Using the estimated parameters of the TVP-VAR model at time t for forecasting, the corresponding forecast error based on the H steps is $\sum_{h=0}^{H-1}\left(A_{h,t}\varepsilon_{t+H-h}\right)$, and the covariance of the error is $\sum_{h=0}^{H-1}\left(A_{h,t}\Sigma_t A'_{h,t}\right)$. In the process of variance decomposition, the proportion of the H-step forecast error variance of the variable j at time t that can be explained by the variable k is given by

$$\Phi_{jk,t}(H) = \frac{\sigma_{kk,t}^{-1}\sum_{h=0}^{H-1}\left(\theta'_j A_{h,t}\Sigma_t\theta_k\right)^2}{\sum_{h=0}^{H-1}\left(\theta'_j A_{h,t}\Sigma_t A'_{h,t}\theta_j\right)}, \tag{1.21}$$

where θ_j is a $N \times 1$ vector taking the value 1 for j-th element and zero otherwise. When $j \neq k, \Phi_{jk,t}(H)$ denotes the share of H-step-ahead forecast error variance in j contributed by the shocks of k. To make all variables together explain 100% of variable j's forecast error variance, we normalize each entry by the row sum as follows to let the sum of the elements in each row equal to 1 as in

$$\widetilde{\Phi}_{jk,t}(H) = \frac{\Phi_{jk,t}(H)}{\sum_{k=1}^{N}\Phi_{jk,t}(H)}. \tag{1.22}$$

Therefore we get $\sum_{k=1}^{N}\widetilde{\Phi}_{jk,t}(H) = 1$ and $\sum_{j=1}^{N}\sum_{k=1}^{N}\widetilde{\Phi}_{jk,t}(H) = N$.

Based on the above analysis, the total connectedness of a certain variable to other variables, i.e. the total connectedness index at time t, can be expressed as:

$$\mathrm{TCI}_t(H) = \frac{\sum_{j=1}^{N}\sum_{k=1,k\neq j}^{N}\widetilde{\Phi}_{jk,t}(H)}{\sum_{j=1}^{N}\sum_{k=1}^{N}\widetilde{\Phi}_{jk,t}(H)} \times 100 = \frac{\sum_{j=1}^{N}\sum_{k=1,k\neq j}^{N}\widetilde{\Phi}_{jk,t}(H)}{N} \times 100, \tag{1.23}$$

Similarly, the directional connectedness index and the net connectedness index can be calculated based on the formulas in the DY connectedness index framework.

1.3 BK approach

Based on the DY connectedness framework, in order to visualize the connectedness between time and frequency dimensions, Baruník and Křehlík (2018) use the spectrum representation of variance decomposition to measure connectedness under different (short-, medium-, and long-term) frequencies. We can calculate the within connectedness, which ignores the outside of the frequency band and only shows how shocks are transmitted within the band.

Since the DY framework calculates the total connectedness of variables, it cannot be decomposed into different frequencies. The BK method allows us to decompose total connectedness values into frequencies and analyze the effects of short-, medium- and long-term shocks. Thus, the sum of all the connectedness values of the different frequencies adds up to the DY approach value (Aybar et al., 2020).

The frequency response function $A\left(e^{-i\omega}\right)$ obtained from the Fourier transformation of the moving average coefficients A_h, with $i=\sqrt{-1}$, can be written as

$$A\left(e^{-i\omega}\right)=\sum_{h=0}^{\infty} e^{-ih\omega} A_h, \tag{1.24}$$

where the term ω represents the frequency of the response function.

Then the generalized causation spectrum over the frequencies $\omega \in (-\pi, \pi)$ can be written as

$$(f(\omega))_{jk}=\frac{\sigma_{kk}^{-1}\left|\theta_j' A\left(e^{-i\omega}\right)\Sigma\theta_k\right|^2}{\theta_j' A\left(e^{-i\omega}\right)\Sigma A'\left(e^{+i\omega}\right)\theta_j}, \tag{1.25}$$

where $(f(\omega))_{jk}$ measures the connectedness of the j-th variable at a given frequency ω owing to the shocks of the k-th variable.

To perform a natural decomposition of the generalized forecast error variance decomposition (GFEVD) at different frequencies, the weight of $(f(\omega))_{jk}$ is assigned by the variance frequency share of the j-th element. This weighting method is defined by

$$W_j(\omega)=\frac{\theta_j' A\left(e^{-i\omega}\right)\Sigma A'\left(e^{+i\omega}\right)\theta_j}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\theta_j' A\left(e^{-i\lambda}\right)\Sigma A'\left(e^{+i\lambda}\right)\theta_j\right)d\lambda}. \tag{1.26}$$

Hence, if we define a frequency band $d = (a, b)$, and $a < b$ and $a, b \in (-\pi, \pi)$. Then the GFEVD corresponding to this specific frequency band d is specified as

$$\Phi_{jk}(d) = \frac{1}{2\pi} \int_d W_j(\omega) \left(f(\omega)\right)_{jk} d\omega. \tag{1.27}$$

Then the standardization form can be expressed as

$$\widetilde{\Phi}_{jk}(d) = \frac{\Phi_{jk}(d)}{\sum_{k=1}^{n} \Phi_{jk}(\infty)}, \tag{1.28}$$

where $\Phi_{jk}(\infty) = \frac{1}{2\pi} \int_{-\pi}^{\pi} W_j(\omega) \left(f(\omega)\right)_{jk} d\omega$.

Using the above equation, we can compute the frequency connectedness on the frequency band d as

$$\mathrm{TCI}(d) = \left(\frac{\sum_{j=1}^{N} \sum_{k=1}^{N} \widetilde{\Phi}_{jk}(d)}{\sum_{j=1}^{N} \sum_{k=1}^{N} \widetilde{\Phi}_{jk}(\infty)} - \frac{\mathrm{Tr}\left\{ \widetilde{\Phi}_{jk}(d) \right\}}{\sum_{j=1}^{N} \sum_{k=1}^{N} \widetilde{\Phi}_{jk}(\infty)} \right) \times 100, \tag{1.29}$$

where $\mathrm{Tr}\{\bullet\}$ is the trace operator.

The frequency connectedness decomposes the original connectedness into distinct parts that in sum give the original overall connectedness measure.

Similarly, we can calculate the directional connectedness measure and the net connectedness measure under the DY connectedness framework. We use the TVP-VAR method as we introduced in section 1.2 to get the dynamic frequency connectedness (Chatziantoniou et al., 2023).

The selection of frequency bands usually depends on the time interval of the original series. In the empirical analysis presented in chapter 3, since we use daily data for modelling, we use one week (1-5 days) as the short term. In addition, since the sample period we selected is long, i.e. 9 years, we use one week to a quarter (5-60 days) as the medium term and more than one quarter (more than 60 days) as the long term (Ouyang et al., 2021).

Chapter 2

Data

List of acronyms

ADF Augmented Dickey-Fuller

ARCH AutoRegressive Conditional Heteroskedasticity

ARCH-LM Lagrange Multiplier test for AutoRegressive Conditional Heteroskedasticity

GARCH Generalized AutoRegressive Conditional Heteroskedasticity

GICS Global Industry Classification Standard

J.B. Jarque-Bera

SD Standard Deviation

TSX Toronto Stock Exchange

This study uses daily closing price data from January 2, 2014 to December 30, 2022 for 11 sector stock indices of the Toronto Stock Exchange (TSX), with a total of 2258 number of days. The 11 sectors according to the Global Industry Classification Standard (GICS) are Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Telecommunications service, Information Technology, Utilities and Real Estate. The data source is S&P Global. Table 2.1 lists representative companies for each sector of the TSX market, sourced from TSX.

Table 2.1: Representative companies for each sector of the TSX market

Sector	Representative companies
Energy	Suncor Energy Inc. (SU),Canadian Natural Resources Limited (CNQ),Cenovus Energy Inc.(CVE)
Materials	Barrick Gold Corporation (ABX),Nutrien Ltd. (NTR),Franco-Nevada Corporation (FNV)
Industrials	Canadian National Railway Company (CNR),Canadian Pacific Railway Limited (CP), Thomson Reuters Corporation (TRI)
Consumer Discretionary	Magna International Inc. (MG),Canadian Tire Corporation, Limited (CTC.A),Dollarama Inc. (DOL)
Consumer Staples	Loblaw Companies Limited (L),Alimentation Couche-Tard Inc. (ATD),Metro Inc. (MRU)
Health Care	Bausch Health Companies Inc. (BHC),Canopy Growth Corporation (WEED),Tilray Brands Inc. (TLRY)
Financials	Royal Bank of Canada (RY),Toronto-Dominion Bank (TD),Bank of Nova Scotia (BNS)
Information Technology	Shopify Inc. (SHOP),Constellation Software Inc. (CSU),Open Text Corporation (OTEX)
Telecommunications Services	BCE Inc. (BCE),Telus Corporation (T),Rogers Communications Inc. (RCI.B)
Utilities	Fortis Inc. (FTS),Emera Incorporated (EMA),Hydro One Limited (H)
Real Estate	Canadian Apartment Properties Real Estate Investment Trust (CAR.UN),RioCan Real Estate Investment Trust (REI.UN),SmartCentres Real Estate Investment Trust (SRU.UN)

We calculate the daily log returns using the daily closing prices of each sector index. Daily volatility data are also estimated based on a GARCH (1, 1) model under skewed t-distribution. The formula is as follows:

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) \times 100\%, \tag{2.1}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 R_{t-1}^2 + \beta_1 \sigma_{t-1}^2, 0 \leq \alpha_1, \beta_1 \leq 1, (\alpha_1 + \beta_1) > 1, \tag{2.2}$$

where P_t is the price on day t, R_t is the return on day t, σ_t^2 is the square of the volatility on day t, α_0 is a constant term, α_1 is the coefficient for the ARCH term R_{t-1}^2, and β_1 is the coefficient for the GARCH term σ_{t-1}^2. The estimates and precision of parameters α_0, α_1, and β_1 are presented in Table 2.2. From the table, we can observe that all the parameters are statistically significant and can be utilized for the analysis.

2.1 Data description for daily volatility series

As seen in Table 2.3, Health Care is the sector with the highest average daily volatility (2.471) in terms of the mean. In terms of standard deviation, Consumer Staples has

Table 2.2: Estimated Parameters and their precision for daily volatility series

	Estimate	Std. Error	t value	Pr(>|t|)		Estimate	Std. Error	t value	Pr(>|t|)
Energy:					Financials:				
α_0	0.0462362	0.0160187	2.886	0.0039**[1]	α_0	0.015843	0.004383	3.615	0.000301***
α_1	0.0768289	0.0120231	6.39	1.66e-10***	α_1	0.150205	0.0222	6.766	1.32e-11***
β_1	0.9152905	0.0119631	76.509	<2e-16***	β_1	0.835053	0.022505	37.105	<2e-16***
Materials:					Information Technology:				
α_0	0.022486	0.008831	2.546	0.0109*	α_0	0.02759	0.0099	2.787	0.005322**
α_1	0.064637	0.010395	6.218	5.03e-10***	α_1	0.08732	0.01523	5.732	9.94e-09***
β_1	0.928644	0.011029	84.201	<2e-16***	β_1	0.90134	0.01696	53.156	<2e-16***
Industrials:					Telecommunications Services:				
α_0	0.03972	0.01044	3.804	0.000142***	α_0	0.04784	0.01047	4.571	4.86e-06***
α_1	0.12437	0.02006	6.201	5.63e-10***	α_1	0.14894	0.02537	5.87	4.37e-09***
β_1	0.83471	0.02575	32.415	<2e-16***	β_1	0.78014	0.03195	24.42	<2e-16***
Consumer Discretionary:					Utilities:				
α_0	0.024309	0.007154	3.398	0.000679***	α_0	0.017278	0.003972	4.35	1.36e-05***
α_1	0.098246	0.015292	6.425	1.32e-10***	α_1	0.193197	0.026081	7.408	1.29e-13***
β_1	0.880613	0.018042	48.808	<2e-16***	β_1	0.784444	0.025879	30.313	<2e-16***
Consumer Staples:					Real Estate:				
α_0	0.021123	0.007962	2.653	0.00797**	α_0	0.011074	0.003652	3.032	0.00243**
α_1	0.077913	0.01594	4.888	1.02e-06***	α_1	0.092411	0.016048	5.758	8.49e-09***
β_1	0.894821	0.023031	38.853	<2e-16***	β_1	0.894159	0.017883	50	<2e-16***
Health Care:									
α_0	0.068923	0.029931	2.303	0.0213*					
α_1	0.097726	0.019795	4.937	7.93e-07***					
β_1	0.900613	0.019716	45.68	<2e-16***					

[1] ***, **, * indicate significant at 1%, 5%, and 10% levels, respectively.

the smallest standard deviation of volatility (0.366), followed by Industrials (0.455) and Telecommunications Services (0.478), while Energy has the largest standard deviation of volatility (1.065). In terms of skewness and kurtosis, all sectors have skewness greater than zero, showing a right-skewed distribution, and kurtosis greater than 3 which is for the normal distribution. From the Jarque-Bera values, which test whether the distribution follows the normal distribution, the volatility distributions of all 11 sectors do not follow the assumption of normal distribution, with fat tails and leptokurtic distributions.

We also verified the existence of unit roots for all volatility series. The results of the augmented Dickey–Fuller test (ADF) test are also shown in Table 2.3, indicating that we reject the null hypothesis of the unit root test at the 1% level (Dickey and Fuller, 1979). That is, all volatility series have no unit root and can be used in the calculation of the following risk connectedness model.

Table 2.3: Descriptive statistics and unit root test for daily volatility series

	Min	Max	Mean	SD	Median	Skew.	Kurt.	J.B.[1]	ADF[2]
Energy	0.945	10.886	2.025	1.065	1.8	4.319	25.942	70442***	-5.5837***
Materials	0.802	5.613	1.58	0.568	1.463	2.151	9.142	9620.3***	-4.7224***
Industrials	0.538	6.388	0.945	0.455	0.833	5.974	50.544	254143***	-7.0212***
Consumer Discretionary	0.553	7.314	1.032	0.623	0.889	6.129	48.233	233340***	-5.9851***
Consumer Staples	0.52	4.694	0.865	0.366	0.798	6.294	51.877	268488***	-6.7675***
Health Care	1.094	7.382	2.471	0.954	2.299	1.318	2.879	1436.5***	-5.8539***
Financials	0.367	8.626	0.846	0.69	0.691	6.465	54.484	295429***	-6.524***
Information Technology	0.674	5.386	1.399	0.595	1.206	2.25	7.622	7383.9***	-5.1198***
Telecommunications Services	0.499	7.084	0.787	0.478	0.678	7.949	80.468	633843***	-7.7275***
Utilities	0.323	9.205	0.767	0.715	0.58	6.55	56.356	315397***	-6.6171***
Real Estate	0.42	7.768	0.847	0.66	0.683	5.924	44.898	203149***	-5.8369***

[1] J.B. is the statistic of the Jarque-Bera test. The null hypothesis is that the sample follows a normal distribution with skewness of 0 and kurtosis of 3. *** indicates significance at the 1% level.
[2] ADF is the statistic of the Augmented Dickey-Fuller test, which considers the null hypothesis of having unit root, i.e. the time series is nonstationary.

Figure 2.1 plots the daily time series of volatility for the 11 sector indices. We observe significant volatility fluctuations during the sample period that were brought on by financial and economic events. These events have impacted either or both the direction or intensity of the dependency across the economic sectors of the equity market.

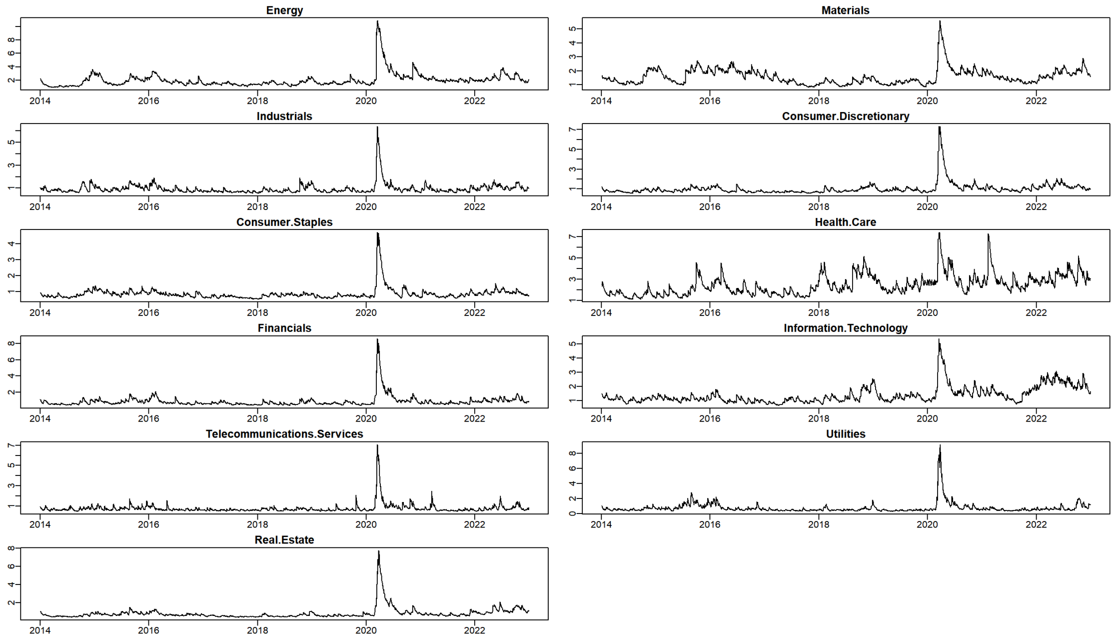


Figure 2.1: Daily volatility series, 1/2014-12/2022.

2.2 Data description for daily log return series

As seen in Table 2.4, Information Technology is the sector with the highest average daily return (0.06) in terms of mean, while Energy (-0.005) and Health Care (-0.067) are the only two assets with negative mean daily returns. In terms of standard deviation, Health Care has the largest standard deviation (2.537), which also indicates the largest range of volatility. Consumer Staples (0.958) and Telecommunications Services (0.966) have the smallest range of volatility. In terms of skewness and kurtosis and Jarque-Bera values, all sectors have skewness less than zero, showing a left-skewed distribution, and kurtosis greater than 3. The return distributions of all 11 sectors do not follow the assumption of normal distribution.

The ADF unit root test is performed on the returns of the 11 sectors. The results in Table 2.4 show that all return series also have no unit root and can be modelled as time series.

Based on the ARCH-LM test (Engle, 1982), we clearly rejected the null hypothesis that there is no ARCH effect. It can be concluded that ARCH effects exist in all 11 sectors, and therefore the following analysis of connectedness indexes based on the skewed t-distribution of GARCH (1,1) volatility is valid.

Table 2.4: Descriptive statistics and unit root test for daily log return series

	Min	Max	Mean	SD	Median	Skew.	Kurt.	J.B.[1]	ADF[2]	ARCH-LM[3]
Energy	-31.782	15.465	-0.005	2.273	0.013	-1.414	24.77	58567***	-12.114***	418.4***
Materials	-10.925	11.757	0.016	1.662	0.021	-0.148	4.001	1518.2***	-11.957***	480.83***
Industrials	-12.054	9.151	0.037	1.069	0.074	-1.095	17.275	28575***	-13.169***	752.14***
Consumer Discretionary	-16.179	12.716	0.028	1.231	0.047	-1.302	31.641	94973***	-11.771***	843***
Consumer Staples	-11.315	9.984	0.045	0.958	0.019	-0.624	20.455	39575***	-14.195***	974.1***
Health Care	-19.062	11.477	-0.067	2.537	-0.059	-0.29	4.022	1557.9***	-12.458***	205.84***
Financials	-13.717	13.93	0.019	1.096	0.079	-0.66	43.102	175205***	-12.984***	1060.6***
Information Technology	-12.225	9.43	0.06	1.515	0.099	-0.322	4.805	2216.6***	-12.18***	453.78***
Telecommunications Services	-13.607	10.35	0.02	0.966	0.064	-1.486	39.189	145536***	-13.905***	962.89***
Utilities	-14.058	11.219	0.016	1.067	0.04	-1.472	46.308	202862***	-13.999***	1087.6***
Real Estate	-15.69	9.508	0.011	1.096	0.064	-3.183	54.031	278876***	-12.336***	838.77***

[1] J.B. is the statistic of the Jarque-Bera test. The null hypothesis is that the sample follows a normal distribution with skewness of 0 and kurtosis of 3. *** indicates significance at the 1% level.
[2] ADF is the statistic of the Augmented Dickey-Fuller test, which considers the null hypothesis of having unit root, i.e. the time series is nonstationary.
[3] ARCH-LM is the statistic of the ARCH-LM test, which has as a null hypothesis that the time series displays no ARCH effects.

Figure 2.2 shows the evolution of the log-returns of the 11 sector indices during the analyzed time periods. The different evolution of these economic sectors can be seen, which means that it is possible to diversify the portfolio by purchasing stocks in different sectors with various fields of activity.

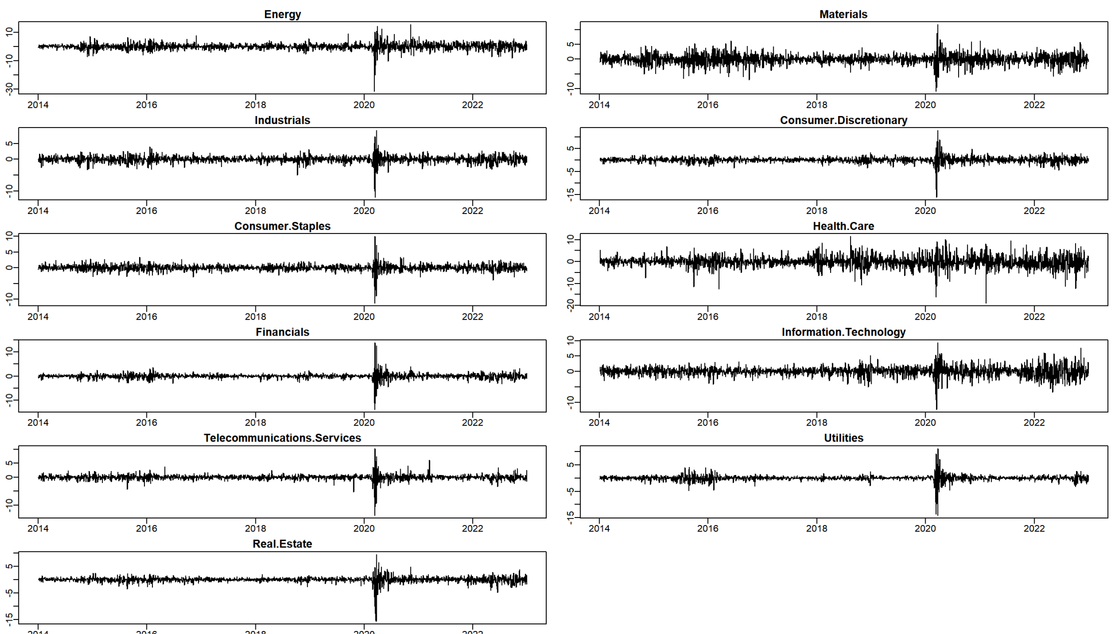


Figure 2.2: Daily log return series, 1/2014-12/2022.

Chapter 3

Empirical Results

List of acronyms

BIC Bayesian Information Criterion

BK Barunik and Krehlik

DY Diebold and Yilmaz

NPDC Net Pairwise directional Connectedness

TCI Total Connectedness Index

TSX Toronto Stock Exchange

TVP-VAR-DY Time-Varying Parameter Vector Autoregression Diebold and Yilmaz

VAR Vector Autoregression

VAR-DY Vector Autoregression Diebold and Yilmaz

This chapter provides a deep analysis of sectoral volatility and return connectedness within the Toronto Stock Exchange (TSX) market. Our analysis involves four steps.

- Step 1: (Section 3.1)

We assess the static volatility and return connectedness of sectors in the TSX using the VAR-DY method (Diebold and Yilmaz, 2012).

- Step 2: (Section 3.2)

  We study time-varying volatility and return connectedness using the TVP-VAR-DY method, as introduced by (Antonakakis et al., 2020). This method effectively addresses the limitations of the VAR-DY method, which relies on rolling windows. The TVP-VAR-DY method operates without the need for predefined window sizes. This feature prevents the loss of sample information and delayed response to abrupt market changes. Consequently, we utilize the TVP-VAR-DY method to examine volatility spillovers among the 11 economic sectors of the TSX market from a time-varying perspective. To facilitate comparison and improve understanding, we compare these results with those obtained through the traditional rolling window VAR-DY method.

- Step 3: (Section 3.3)

  We use the BK method, developed by (Baruník and Křehlík, 2018), to explore the potential transmission channels of volatility and return spillovers within the TSX market across different frequency bands. This decision is made because the DY framework, which computes the total volatility and return connectedness of variables, does not allow for decomposition into distinct frequency components.

- Step 4: (Section 3.4)

  We use these connectedness measures to analyze four significant events—the 2015-2016 stock market sell-off, 2018 cryptocurrency crash, 2020 COVID-19 outbreak, and 2022 Russo-Ukrainian War—and employed a dummy variable linear regression model to examine the impact of these uncertainty events on volatility and return spillover between stock market sectors. Additionally, we analyzed the TVP-VAR-DY dynamic net pairwise connectedness networks of volatility and return during each period of uncertainty events.

3.1 Static connectedness

We start with the static results. This section uses the VAR-DY connectedness index framework developed in Diebold and Yilmaz (2012) as introduced in section 1.1 to calculate the static connectedness indices for the 11 sector indices in the TSX market.

We use the generalized variance decomposition of the 100-step-ahead volatility forecast error based on the vector autoregression of order 1 (VAR(1)), which is determined by the Bayesian information criterion (BIC) to produce the most efficient and parsimonious model.

Table 3.1 and 3.2 are the decomposition tables of the static volatility and return connectedness index of the TSX sector markets, based on the full sample data of VAR-DY approach, including total, directional, net and pairwise connectedness. The diagonal elements of the table represent their own market connectedness, while the off-diagonal elements of the table measure the pairwise connectedness. The entry (j,k) calculated by Equation (1.9) represents the portion of the variable j's contribution to the forecast error variance that is due to the shocks in variable k. The entry (j,j) indicated the sector j's self-explanatory share.

The column "FROM" calculated by Equation (1.11) represents the sum of the connectedness received by the corresponding sectors of each row from all other 10 sectors, i.e., the sum of the j-th row entries except for the entry (j,j), $j \in \{1,2,...,11\}$. The row "TO" calculated by Equation (1.12) represents the sum of the connectedness of each column's sectors to all other 10 sectors, i.e., the sum of the j-th column except for the entry (j,j), $j \in \{1,2,...,11\}$. For example, in Table 3.1 for the energy sector, all volatility spillover from the energy sector to the other 10 sectors is 135.18% and the volatility spillover received by the energy sector from the other 10 sectors is 75.37%. The row sum including the entry (j,j) is equal to 100% according to the normalization of Equation (1.9). However, the column sum including the entry (j,j) is not equal to 100%.

The Total Connectedness Index (TCI) calculated by Equation (1.10) in the bottom right corner of the table represents the average connectedness level, which is equal to the mean of all 11 sectors in the TO row. The row "NET" calculated by Equation (1.13) is defined as "TO" minus "FROM", i.e., it is the difference between the gross volatility shocks transmitted to and those received from all other 10 sectors. For instance, in Table 3.1, the net volatility spillover of the energy sector is 59.8%, which means that the volatility spillover of the energy sector to the other 10 sectors is greater than the volatility spillover received by the energy sector from the other 10 sectors, and it is a net transmitter.

Table 3.1: Static volatility connectedness table for 11 sector indices by VAR-DY approach

	Energy(1)	Materials(2)	Industrials(3)	Cons.Disc(4)	Cons.Staples(5)	Health.Care(6)	Financials(7)	Info.Tech(8)	Tele.Services(9)	Utilities(10)	Real.Estate(11)	FROM
Energy(1)	24.63	4.58	14.3	2.83	5.02	1.78	16.4	7.3	9.99	9.91	3.27	75.37
Materials(2)	14.21	21.34	16.23	1.35	4.55	1.44	12.76	4.92	8.5	11.78	2.91	78.66
Industrials(3)	13.78	2.53	22.36	3.63	6.54	1.64	17.33	6.76	9.59	12.69	3.15	77.64
Cons.Disc(4)	14.48	1.87	15.36	6.83	6.82	2.33	17.77	9.13	10.76	10.96	3.69	93.17
Cons.Staples(5)	15.25	3.23	14.32	2.62	13.39	1.24	16.02	5.65	12.38	12.97	2.93	86.61
Health.Care(6)	11.27	1.27	11.19	3.2	0.86	41.4	7.89	15.17	1.55	4.29	1.91	58.6
Financials(7)	15.63	3	15.2	3.4	6.47	1.61	21.2	5.92	10.91	12.6	4.06	78.8
Info.Tech(8)	11.39	1.32	15.17	5.26	4.05	3.31	12.12	32.49	6.55	5.82	2.53	67.51
Tele.Services(9)	12.82	2.43	13.07	3.15	7.34	1.47	16	4.32	21.89	13.79	3.71	78.11
Utilities(10)	11.98	3.33	14.57	2.58	6.84	1.41	17.33	3.53	12.4	20.17	5.87	79.83
Real.Estate(11)	14.37	2.78	14.66	3.59	6.71	2	17.63	7.13	11.92	12.22	6.99	93.01
TO	135.18	26.34	144.06	31.62	55.21	18.21	151.25	69.81	94.55	107.04	34.04	867.32
NET	59.8	-52.31	66.43	-61.55	-31.4	-40.39	72.45	2.3	16.45	27.21	-58.97	TCI
Conclusion	net transmitter	net recipient	net transmitter	net recipient	net recipient	net recipient	net transmitter	net transmitter	net transmitter	net transmitter	net recipient	78.85

Table 3.2: Static return connectedness table for 11 sector indices by VAR-DY approach

	Energy(1)	Materials(2)	Industrials(3)	Cons.Disc(4)	Cons.Staples(5)	Health.Care(6)	Financials(7)	Info.Tech(8)	Tele.Services(9)	Utilities(10)	Real.Estate(11)	FROM
Energy(1)	37.12	3.66	10.01	8.66	2.6	2.99	13.82	2.34	5.58	6.7	6.51	62.88
Materials(2)	6.27	63.49	4.87	3.25	1.86	2	3.15	2.91	2.85	5.6	3.74	36.51
Industrials(3)	6.49	1.73	23.96	11.8	7.17	2.99	13.65	7.28	8.18	8.5	8.25	76.04
Cons.Disc(4)	5.52	1.2	11.76	23.71	6.81	4.32	13.4	7.42	7.76	7.59	10.51	76.29
Cons.Staples(5)	2.36	0.93	9.12	8.81	31.96	1.84	9.74	5.51	11.41	10.22	8.1	68.04
Health.Care(6)	3.84	1.54	6.05	8.83	2.78	48.41	6.31	8.22	3.63	3.73	6.64	51.59
Financials(7)	8.19	1.02	12.15	12.12	6.82	2.86	22.13	4.47	9.78	9.98	10.49	77.87
Info.Tech(8)	2.58	1.64	11.29	11.24	6.64	6.09	7.93	35.71	4.92	5.09	6.87	64.29
Tele.Services(9)	4.23	1.05	8.74	8.39	10	2.02	11.95	3.18	28.31	12.17	9.96	71.69
Utilities(10)	4.71	2.27	8.73	7.95	8.42	2.03	11.48	3.39	11.59	26.43	13	73.57
Real.Estate(11)	4.5	1.55	8.64	11.36	6.43	3.5	12.07	4.75	9.11	12.6	25.49	74.51
TO	48.7	16.6	91.37	92.41	59.54	30.64	103.5	49.47	74.8	82.19	84.08	733.3
NET	-14.18	-19.91	15.32	16.12	-8.5	-20.95	25.62	-14.82	3.11	8.61	9.56	TCI
Conclusion	net recipient	net recipient	net transmitter	net transmitter	net recipient	net recipient	net transmitter	net recipient	net transmitter	net transmitter	net transmitter	66.66

Volatility spillover and return spillover are related but distinct concepts. Both can be used to measure the connectedness or integration of financial markets, but they capture different aspects of the transmission mechanism. Volatility spillover captures the transmission of uncertainty or risk, while return spillover captures the transmission of price movements or returns.

Volatility spillover refers to the transmission of changes in volatility from one financial asset or market to another. Volatility measures the degree of fluctuation in the price of an asset or market over time. If there is volatility spillover between two assets or markets, it means that a shock in one market affects the volatility of the other market. Return spillover, on the other hand, refers to the transmission of changes in returns from one asset or market to another. Returns measure the relative change in the price of an asset or market over a given period of time. If there is return spillover between two assets or markets, it means that a shock in one market affects the returns of the other market.

As can be seen from Table 3.1, from the perspective of the full sample, the total volatility connectedness index reaches 78.85%, indicating that the overall correlation among the 11 sectors is high, which supports the contagion effect. In comparison, the total return connectedness index in Table 3.2 is 66.66%, lower than the total volatility connectedness index of 78.85%.

The higher total volatility connectedness index indicates that there is a stronger spillover effect of volatility shocks among the 11 sectors in the TSX market, which implies that the volatility of one sector has a greater impact on the volatility of other sectors. On the other hand, the lower total return connectedness index suggests that there is a relatively weaker spillover effect of returns among the sectors, meaning that the return of one sector does not necessarily have a significant impact on the return of other sectors. Overall, the higher total volatility connectedness index and lower total return connectedness index suggest that volatility shocks are more contagious and transmit more easily among the sectors, whereas returns are less contagious and transmit less easily.

Compared to return shocks, volatility shocks are more contagious and easily transmitted due to the broader and more interconnected nature of the factors driving volatility. Volatility shocks are typically driven by market-wide events or news that affect all sectors of the economy. For example, a major economic announcement, such as a change in interest rates or a shift in government policy, can lead to a sudden increase in volatility across all sectors, as volatility is a measure of uncertainty or risk in the market. When there is a sudden increase in volatility, investors become more uncertain about the future prospects of the market and may start to sell off their holdings. This can cause a chain reaction that spreads across different sectors and industries as investors try to mitigate their exposure to risk. In addition, volatility spillovers can be amplified by investor behaviour, such as herding or panic selling, which can lead to increased volatility in other sectors. This can create a chain reaction, where increased volatility in one sector can lead to increased volatility in other sectors.

On the other hand, returns are less contagious and transmit less easily because they are more idiosyncratic to individual stocks or sectors. For example, a company-specific news event, such as a positive earnings report or a new product launch, may have a significant impact on the returns of that particular company or sector, but it may not necessarily affect other sectors or the broader market as a whole. Moreover, return transmission is often related to fundamental factors such as economic growth, interest rates, and corporate earnings, which may not be as heavily influenced by financial market shocks.

From the perspective of volatility connectedness, the Health Care sector has the weakest links with other sectors and limited information transmission, with its own explanatory share accounting for 41.4%. On the other hand, regarding return connectedness, the Materials sector has the weakest connections with other sectors, with its explanatory share accounting for 63.49%. This indicates that regarding the return series, there is not much connection between the Materials sector and other sector markets, resulting in poor information transmission in the market. As for the volatility series, the relationship between the Health Care sector and other sector markets is not close, and the information transmission in the market is poor. Additionally, the Information Technology sector also has high own explanatory shares, exceeding 30%, in both volatility and return connectedness, while Energy and Consumer Staples have high own explanatory shares, exceeding 30%, but only in return connectedness, indicating weaker connections with other sectors compared to the remaining sectors.

The difference in the sectoral own explanatory share rankings between volatility and return connectedness can be attributed to the different types of information that these measures capture. Volatility connectedness measures the extent to which volatility shocks in one sector affect the volatility of other sectors. In other words, it captures the contagion of volatility shocks. In this case, the Health Care sector has the weakest links with other sectors because it is less likely to transmit volatility shocks to other sectors or be affected by volatility shocks from other sectors. This may be due to the unique characteristics of the Health Care sector, such as its defensive nature and stable demand for its products and services, which make it less susceptible to external shocks and less likely to transmit shocks to other sectors.

On the other hand, return connectedness measures the degree to which the returns of one sector are affected by the returns of other sectors. It captures the comovement of returns among different sectors. In this case, the Materials sector has the weakest connections with other sectors because its returns are less correlated with the returns of other sectors. This may be due to the idiosyncratic factors that affect the Materials sector, such as commodity prices and supply chain disruptions, which do not have a strong influence on the returns of other sectors.

The Financials sector emerges as the largest transmitter for both volatility (151.25%) and return (103.5%) connectedness from the perspective of directional connectedness effect of TO. This indicates that the Financials sector has a significant impact on other sectors in terms of both volatility and return connectedness. Moreover, the Financials sector is also the largest recipient in terms of the directional return connectedness effect of FROM, with an 77.87% FROM return connectedness effect. However, the Consumer Discretionary (93.17%) and Real Estate (93.01%) sectors are the largest recipients of the FROM directional volatility connectedness effect, which indicates that the Consumer Discretionary and Real Estate sectors are more susceptible to the volatility spillover effects from other sectors.

The Consumer Discretionary sector includes companies that sell non-essential goods and services, such as entertainment and luxury goods. These types of companies tend to be more sensitive to changes in consumer sentiment and spending habits, which can be influenced by macroeconomic factors and shocks in other sectors. As a result, when there are large volatility shocks in other sectors, such as a sudden drop in stock prices or an economic recession, the Consumer Discretionary sector may experience higher levels of volatility spillover.

The Real Estate sector includes companies involved in the development, ownership, and management of properties, including residential, commercial, and industrial real estate. The performance of this sector is closely tied to interest rates and macroeconomic conditions, as changes in interest rates can affect borrowing costs and demand for real estate. As a result, when there are large volatility shocks in other sectors, such as changes in monetary policy or economic uncertainty, the Real Estate sector may experience higher levels of volatility spillover.

According to the NET connectedness (i.e. To - From), although the Financials sector is the largest net transmitter in both volatility and return connectedness, implying that the Financials sector plays a dominant role in the level of both volatility and return connectedness across the TSX sectors. Moreover, its net return connectedness value is only 25.62%, which is far lower than the net volatility connectedness value of 72.45%. This indicates that the dominant role of the Financials sector is more evident in volatility connectedness. These findings are consistent with those in Choi et al. (2021)'s study on connectedness among sectors in the Australian stock market. It can be said that in these two developed countries, Canada and Australia, the Financials sector is indeed the largest net transmitter in the volatility spillover among stock market sectors.

The Financials sector is often considered the backbone of the economy and plays a critical role in the smooth functioning of financial markets. As a result, any shocks or disruptions in the Financials sector can easily spill over into other sectors and have significant impacts on the overall economy.

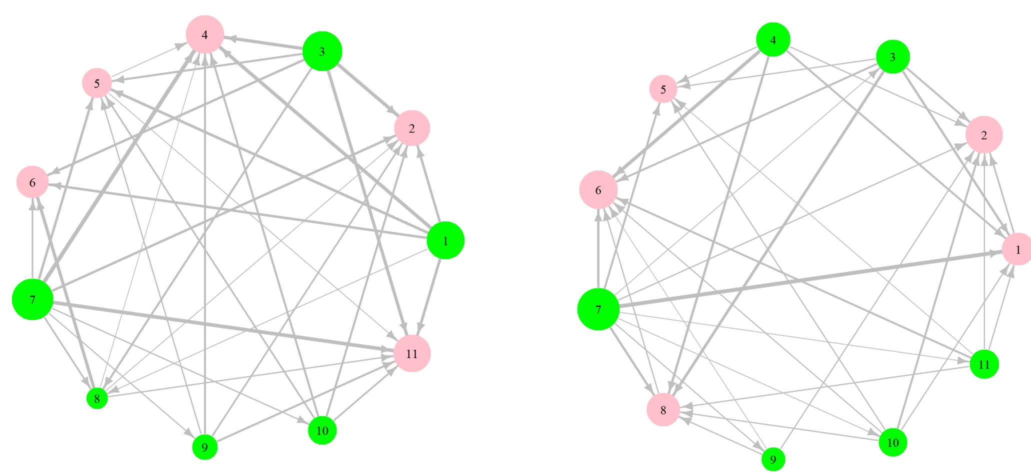
Regarding volatility connectedness, the Financials sector tends to have a higher level of connectedness with other sectors, particularly during times of market stress. During periods of market stress, the connectedness among financial institutions through various financial instruments, such as loans, securities, and derivatives, become more pronounced. Such periods are typically accompanied by high uncertainty, panic behaviour among market participants, and rapid changes in liquidity. Therefore, any shocks or disruptions in the Financials sector, such as credit contractions or sharp declines in asset values, can quickly spread to other sectors, leading to higher volatility connectedness.

On the other hand, return connectedness measures the extent to which shocks in one sector affect the returns of another sector. In this context, the net return connectedness value of the Financials sector may not be higher than its net volatility connectedness value, as volatility shocks are more contagious and easily transmitted, as mentioned earlier. The transmission of returns may not be as pronounced as that of volatility.

Therefore, in terms of shock transmission, the Financials sector's dominant role is more evident in the volatility spillover effects than in the return spillover effects, which explains why its net volatility connectedness value is higher than its net return connectedness value.

Figure 3.1 visualizes the net pairwise volatility and return connectedness networks for the 11 sectors of the TSX market. The sectors and the net pairwise directional connectedness (NPDC) between sectors are denoted as nodes and edges, respectively. The positive or negative of NET in Table 3.1 and 3.2 determines the colour of the nodes. If the NET value is positive, the node is green, representing the net transmitter of volatility connectedness. If the NET value is negative, the node is pink, representing a net recipient of volatility connectedness. The magnitude of the absolute value of NET determines the relative size of the nodes. For the net transmitters, the larger the node, the greater the influence of the node on other nodes in the network. For the net recipients, the larger the node, the stronger the spillover from the other 10 sectors received by this node. For instance, the Financials sector has the largest positive NET value in both volatility and return connectedness, making node 7 the largest green node in both Figures 3.1a and 3.1b. However, the NET return connectedness value in Table 3.2 is only 25.62%, which is significantly lower than the NET volatility connectedness value of 72.45% in Table 3.1. As a result, the relative size difference between node 7 and other nodes is more significant in Figure 3.1a, while the size difference between the Financials sector and other nodes is relatively small in Figure 3.1b.

The transmission direction and strength of the net pairwise directional connectedness are indicated by the directed edges and their thicknesses. The direction of the edge connecting sector j to sector k depends on the sign of the NPDC, and the thickness of the edge is determined by the magnitude of the absolute value of NPDC. According to Equation (1.14), the NPDC between sector j and sector k is equal to the difference between entry (k, j) and entry (j, k) in Table 3.1. A positive NPDC means that the connectedness effect of j to k is stronger than that of k to j, that is, the direction of the edge is from j to k. For example, for the thickest edge directed from 7 (Financials) to 4 (Consumer Discretionary) in Figure 3.1a, the difference between the two corresponding entries (4, 7) (17.77%) and (7, 4) (3.4%) in Table 3.1 is given by 17.77% - 3.4% = +14.37%, so the direction of the edge is from 7 (Financials) to 4 (Consumer Discretionary), and it is the thickest edge in Figure 3.1a.



(a) Static volatility connectedness network (b) Static return connectedness network

Figure 3.1: Static net pairwise connectedness network of VAR-DY approach for return and volatility.
Energy (1), Materials (2), Industrials (3), Consumer Discretionary (4), Consumer Staples (5), Health Care (6), Financials (7), Information Technology (8), Telecommunications Services (9), Utilities (10), and Real Estate (11).

As can be seen in Figure 3.1a, Consumer Discretionary and Real Estate are net recipients, while Energy and Information Technology are net transmitters in volatility connectedness. This indicates that Consumer Discretionary and Real Estate sectors are more susceptible to volatility spillover effects from other sectors, while Energy and Information Technology sectors are more likely to transmit volatility spillovers to other sectors. The difference between volatility and return networks may be due to differences in the types of shocks or events that affect volatility and return spillovers. For example, a shock or event that affects the broader market may cause volatility spillovers to certain sectors, even if their returns are not directly impacted. In contrast, a shock or event that affects a particular sector may cause return spillovers to other sectors that are more directly impacted by the shock. That is, when a specific sector encounters a negative event or shock, the impact is not limited to that sector alone but can also spread to other sectors closely related to it, affecting their returns as well. For example, a contraction in the credit market of the banking industry not only affects the Financials sector but also impacts sectors like Real Estate, Industrials, and Consumer Discretionary that rely on bank loans.

As the largest node, the Financials sector is the most significant net transmitter for both volatility and return connectedness, suggesting that it is the central sector market among the 11 TSX sector indices. In particular, it has the strongest net pairwise volatility connectedness to Consumer Discretionary and the strongest net pairwise return connectedness to the Energy sector.

Financials and Consumer Discretionary sectors may be closely related in terms of their business operations and the way they are affected by changes in economic conditions. For example, in a strong economy, people may have more disposable income, which they can use to invest or spend on discretionary items, which can benefit both the Financials and Consumer Discretionary sectors. Thus, changes in volatility in one sector may have an impact on the other, leading to a high pairwise volatility connectedness between these sectors. On the other hand, Financials and Energy sectors may be linked in terms of the financing needs of the Energy sector. Energy companies require a lot of capital for exploration, production, and infrastructure development, and they often rely on the Financials sector for funding. As a result, this may lead to a high pairwise return connectedness between these sectors.

However, the largest net recipient changes from Health Care in return connectedness as shown in Figure 3.1b to Consumer Discretionary in volatility connectedness in Figure 3.1a.

In terms of return connectedness, the Health Care sector, as the largest net recipient, primarily receives return spillover from other sectors rather than spill over into them. This might be because sectors like Information Technology often drive innovations that directly benefit healthcare. For example, advancements in AI and data analytics are quickly integrated into the Health Care sector, improving diagnostics, treatment options, and patient care. Moreover, due to its highly specialized nature, the Health Care sector tends to be more sensitive to sector-specific or company-specific news. This includes breakthroughs in medical technology, announcements of new drugs, or changes in healthcare policies. Such news can directly impact the returns of companies within the Health Care sector but may not directly influence the financial performance of other sectors like Information Technology or Financials. Therefore, the high specialization of the Health Care sector, combined with the drive of technological innovations in other sectors, leads to the trend of the Health Care sector primarily receiving return spillovers rather than transmitting them to other sectors.

In terms of volatility connectedness, however, the large net recipient is typically a sector that is more exposed to market-wide events or news that affect all sectors of the economy. The Consumer Discretionary sector, for example, may be influenced by changes in consumer sentiment or shifts in macroeconomic conditions that affect spending patterns across the entire economy. These types of market-wide events can lead to a higher level of volatility spillover to the Consumer Discretionary sector.

The reason why the largest net recipient differs between return connectedness and volatility connectedness is because the underlying factors that drive the spillover effects can be different.

Krause and Tse (2013) found that for return series, the transmission of information in the Financials, Information Technology, Energy, and Materials sectors can only be unidirectional from the United States to Canada. However, for volatility series, the transmission of information in the Financials and Information Technology sectors is bidirectional, while the Energy and Materials sectors still only transmit information unidirectionally from the United States to Canada. That is, looking at the multinational vertical perspective, the Energy and Materials sectors have weak information transmission capabilities in terms of volatility and return spillovers, while the Financials and Information Technology sectors have strong information transmission capabilities in terms of volatility spillovers but weak capabilities in terms of return spillovers.

Examining the cross-sectional spillover effects between Canadian sectoral ETFs in the TSX market, we found that the Materials sector also has weak information transmission capabilities in terms of both volatility and return spillovers, consistent with Krause and Tse (2013), which is a net recipient in both networks. The Financials sector shows strong information transmission capabilities in the volatility spillover network as a net transmitter, but is also a net transmitter in the return spillover network with strong information transmission capabilities. The Energy and Information Technology sectors are net recipients in the return connectedness network, indicating weak information transmission capabilities, but net transmitters in the volatility connectedness network, suggesting strong information transmission capabilities.

3.2 Dynamic connectedness

The static approach in section 3.1, while helpful for gaining a broad view, may be lacking accuracy if the relationships between variables vary over time, such as during the financial crisis or shifting market regimes. Hence, we further use the rolling window VAR-DY method and the TVP-VAR-DY method as introduced in section 1.1 and 1.2 respectively to estimate the dynamic connectedness of the 11 TSX sector indices. For the VAR-DY approach, based on traditional conventions in the connectedness research literature, and the size of the dataset used in this study (9 years, 2258 data items), a rolling window size of 200 trading days is chosen to ensure a sufficient number of windows to reflect dynamic characteristics.

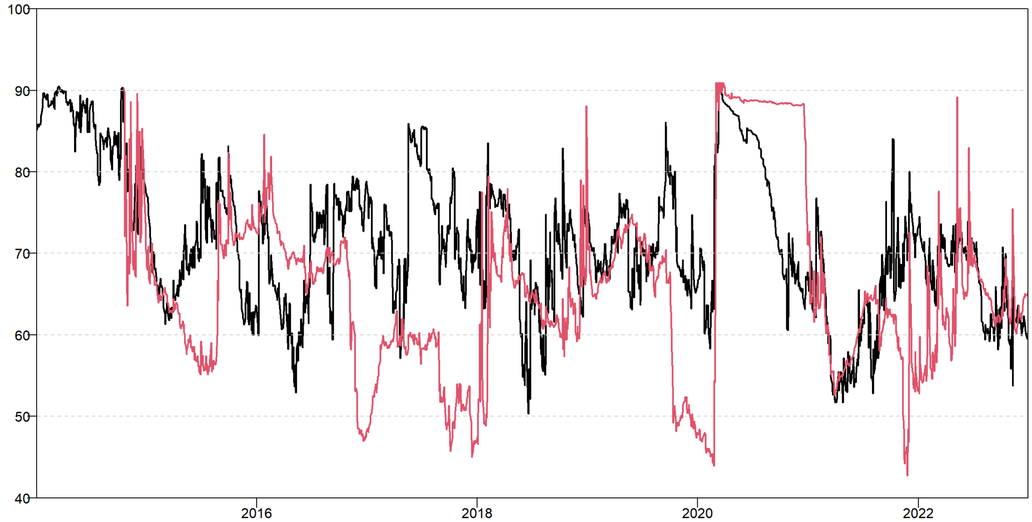
3.2.1 Total connectedness

The dynamic total connectedness indices are shown in Figure 3.2. The black line in Figure 3.2 is the time-varying total connectedness index (TCI) for the TSX market calculated from the TVP-VAR-DY approach. This index reflects the change in the overall connectedness intensity of the TSX market over the full sample period from January 2014 to December 2022. The red line in Figure 3.2 illustrates the time-varying nature of the total connectedness index using a 200-day rolling window VAR-DY approach, reflecting the change in the overall connectedness strength of the TSX market from late 2014 to December 2022.

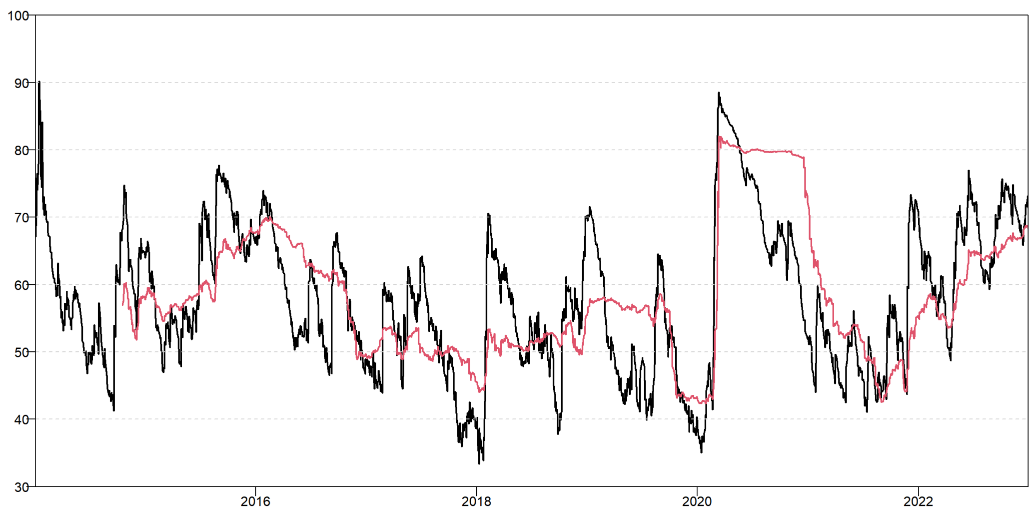
Compared with the construction of the VAR-DY connectedness index method based on the rolling window, the TVP-VAR-DY connectedness index calculation method does not require the rolling window setting, so it can effectively capture the full sample information as well as sudden market changes, effectively solving the problem of sample loss caused by the rolling window. As we expected, it can be seen from Figure 3.2 that the dynamic total connectedness calculated by the rolling window VAR-DY method is less volatile, while the dynamic total connectedness based on TVP-VAR-DY approach is immediately adjusted to events.

For volatility connectedness, overall, the connectedness of the rolling window VAR-DY method is found to be lower on average than the connectedness of the TVP-VAR-DY across the entire sample. Both the peak and trough values of total volatility connectedness calculated using the rolling window VAR-DY method between 2015 and the end of 2019 are slightly lagged behind the dynamic total connectedness based on TVP-VAR-DY. Especially for return connectedness, the peaks are much lower than the TVP-VAR-DY-based dynamic total connectedness, and the troughs are much higher than the TVP-VAR-DY-based dynamic total connectedness. However, the lag is not so clear for return connectedness.

Considering the rapid increase in total connectedness caused by the COVID-19 epidemic in early 2020, the total connectedness calculated based on the rolling window VAR-



(a) Total volatility connectedness index



(b) Total return connectedness index

Figure 3.2: Total volatility and return connectedness index of the rolling window VAR-DY method (red line) and the TVP-VAR-DY method (black line).

DY method remains high for a longer period and continues to decline sharply until early 2021. In contrast, the dynamic total connectedness based on TVP-VAR-DY adjusts down in time with the development of the COVID-19 epidemic, rising in the fall and winter of 2020 with a small peak as the epidemic resurged. However, the total connectedness calculated based on the rolling window VAR-DY method does not exhibit this timely adjustment characteristic and remains high during this period.

The total connectedness calculated using the TVP-VAR-DY method has the following characteristics. From 2014 to 2022, the total connectedness fluctuates sharply, with a maximum of about 90%. Additionally, the largest spike is observed after the beginning of 2020, corresponding to the COVID-19 pandemic.

Figure 3.2 demonstrates that the overall connectedness between the 11 sectoral indices of the TSX market changes over time, increasing dramatically during crises. This phenomenon can be attributed to the tendency for market participants to over-interpret all news related to the market during crisis events. Such over-interpretation is characterized by the excessive analysis and exaggerated significance assigned to news compared to non-crisis times. This amplification in the interpretation and transmission of market-related news during crises contributes to the observed significant increase in connectedness among various sector markets.

Furthermore, the connectedness of return is smoother than the connectedness of volatility in both methods. The difference between the peak and trough values of return connectedness is smaller than that of volatility connectedness in the rolling window VAR-DY method, as the red line in Figure 3.2b is the smoothest of the four lines. Therefore, we can conclude that compared to return series, volatility series are more responsive to crisis events, and the volatility spillover effect is more sensitive. The TVP-VAR-DY method can capture the market's response to crisis events more quickly than the rolling window VAR-DY method.

In summary, we find that the overall connectedness between the 11 sectoral indices of the TSX market changes over time, increasing dramatically during crises. The largest spike in total connectedness is observed after the beginning of 2020, corresponding to the COVID-19 pandemic. Furthermore, the connectedness of return is smoother than the connectedness of volatility in both methods, indicating that compared to return series, volatility series are more responsive to crisis events, and the volatility spillover effect is more sensitive. The TVP-VAR-DY method can capture the market's response to crisis events more quickly than the rolling window VAR-DY method. The TVP-VAR-DY approach is able to capture the full sample information as well as sudden market changes, while the rolling window VAR-DY approach suffers from sample loss due to the rolling window setting. The results show that the dynamic total connectedness calculated by the rolling window VAR-DY method is flatter, while the dynamic total connectedness based on TVP-VAR-DY approach is immediately adjusted to events.

Volatility measures the amount of uncertainty or risk in the market, while returns measure the gains or losses that investors earn on their investments. During crisis events, market participants become more uncertain about the future, and this uncertainty leads to higher levels of volatility. In contrast, the impact of a crisis event on returns can be more idiosyncratic, depending on how individual companies or sectors are affected.

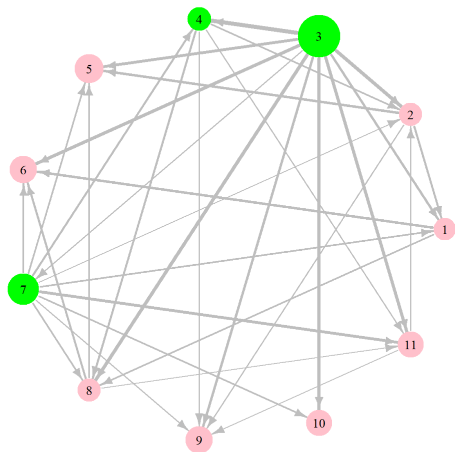
As a result, volatility series are more responsive to crisis events, as they capture the increase in uncertainty and risk in the market. This increased volatility also makes it easier for volatility shocks to spill over to other sectors, leading to a higher level of volatility connectedness. On the other hand, return spillover effects may be more limited, as individual companies or sectors may be affected differently by a crisis event, leading to more idiosyncratic returns.

Therefore, compared to return series, volatility series are more sensitive to crisis events, and the volatility spillover effect is more pronounced.

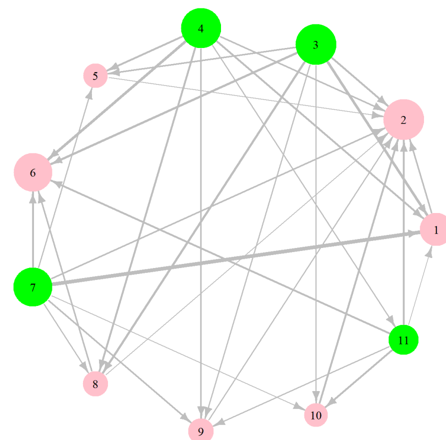
3.2.2 Dynamic net pairwise connectedness network

In this section, we compare the volatility spillover with return spillover in terms of the rolling window VAR-DY and TVP-VAR-DY dynamic net pairwise connectedness. The resulting networks are shown in Figure 3.3, which show the average dynamic net pairwise connectedness over the whole sample period.

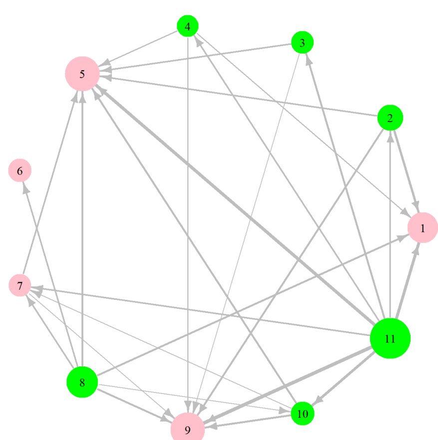
We find that the TVP-VAR-DY dynamic volatility network, which includes all available information and is most sensitive to time-varying changes, provides the best outcome for analyzing cross-sectional volatility and return connectedness of the 11 TSX sector indices. As the networks capture more time-varying information, the results on cross-



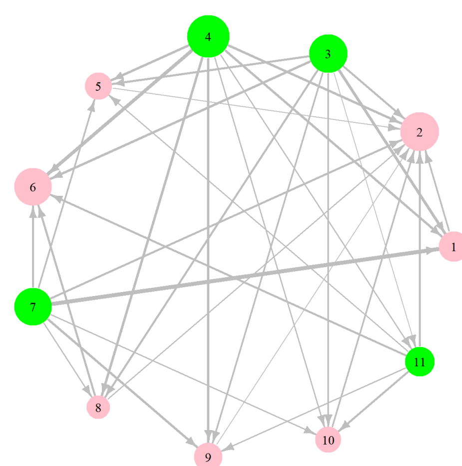
(a) Rolling window VAR-DY dynamic volatility connectedness network



(b) Rolling window VAR-DY dynamic return connectedness network



(c) TVP-VAR-DY dynamic volatility connectedness network



(d) TVP-VAR-DY dynamic return connectedness network

Figure 3.3: Average dynamic net pairwise return and volatility connectedness networks over the whole sample period.
Energy (1), Materials (2), Industrials (3), Consumer Discretionary (4), Consumer Staples (5), Health Care (6), Financials (7), Information Technology (8), Telecommunications Services (9), Utilities (10), and Real Estate (11).

sectional spillovers become more consistent with previous studies (e.g. Krause and Tse (2013)) which look at the multinational vertical perspective.

The identities of net transmitters and recipients in the dynamic rolling window VAR-DY network and TVP-VAR-DY network change in volatility connectedness because these networks capture time-varying information that can affect the direction and magnitude of the transmission of volatility shocks across sectors. This means that the sectors that were net transmitters of volatility shocks at one point in time may become net recipients at another point in time, and vice versa. On the other hand, the identities of net transmitters and recipients remain the same for return connectedness because return spillovers are generally less volatile and much flatter than volatility spillovers.

In the TVP-VAR-DY dynamic volatility network, the Real Estate sector is identified as the largest net transmitter. This means that the Real Estate sector has the strongest influence on the other sectors, indicating that it is the central market for the volatility connectedness of the 11 TSX sector indices. The reason for its central role is its sensitivity to interest rate fluctuations and economic conditions, which can broadly impact other sectors. This sensitivity means that shocks in the Real Estate sector can substantially influence the volatility levels of other sectors, emphasizing its importance in the network. On the other hand, in the TVP-VAR-DY dynamic return network, the Consumer Discretionary sector is identified as the largest net transmitter. This indicates its dominant influence on the returns of other sectors. The Consumer Discretionary sector, consisting of industries that produce non-essential goods and services like entertainment and luxury items, is more sensitive to changes in consumer sentiment and spending habits. As consumers' disposable income increases and their confidence in the economy strengthens, they tend to spend more on discretionary goods and services. This increase in spending not only boosts revenues and profits for companies in this sector but also acts as an indicator of consumer optimism regarding the economic future. This optimism, combined with increased purchasing power, often leads to a rise in demand across various other sectors. Therefore, positive shocks to the Consumer Discretionary sector can spill over to other sectors, establishing it as a key transmitter for return connectedness.

In contrast, in the VAR-DY rolling window dynamic and static networks, the Industrials and Financials sectors, respectively, are identified as the largest net transmitters for both volatility and return connectedness. This suggests that these sectors are more dominant in transmitting information to other sectors than any other sector in the network.

The differences in the identities of net transmitters across the different networks may be due to changes in the underlying relationships between the sectors over time. The TVP-VAR-DY model captures time-varying dynamics and allows for more flexibility in the relationships between sectors, which may explain why the identities of the largest net transmitters change in this model. On the other hand, the VAR-DY rolling window dynamic and static models capture a more stable relationship between sectors over a shorter time period and may explain why the Industrials and Financials sectors are consistently identified as the largest net transmitters.

Regarding return connectedness, the strongest net pairwise connectedness is consistent across the three networks, occurring between the Energy and Financials sectors. This may be due to the fact that the Financials sector is closely related to the oil and gas industry, as it provides financing and other financial services to energy companies. Any shocks or changes in the financial sector may therefore have a significant impact on the energy sector. Additionally, the financial sector may be more sensitive to changes in interest rates, which can affect the energy sector's borrowing costs and investment decisions. These factors may contribute to the observed strong net pairwise return spillover from the Financials to Energy.

However, the strongest net pairwise volatility connectedness varies across networks. The findings also suggest that the Information Technology and Utilities sectors switch from being net transmitters to being net recipients after capturing more time-varying information. Additionally, the Financials sector performs as a net transmitter in cross-sectional return connectedness, contrary to the findings of previous studies from the multinational vertical perspective.

The fact that the strongest net pairwise return connectedness is consistent across the three return networks regardless of the amount of time-varying information captured, occurring between the Energy and Financials sectors, suggests that the transmission of returns between these two sectors is relatively stable over time, regardless of the specific method used to analyze the data. On the other hand, the fact that the strongest net pairwise volatility connectedness varies across the three volatility networks indicates that the transmission of volatility between sectors can be influenced by the specific modelling approach used. This is likely because volatility is naturally more complex and can be affected by a range of factors, including changes in market sentiment, news events, and other variables that are difficult to model accurately. Therefore, it is not surprising that the specific networks used to analyze volatility can impact the results obtained.

In summary, the TVP-VAR-DY dynamic volatility network was found to be the best model for this analysis as it includes all available information and is most sensitive to time-varying changes. As the networks capture more time-varying information, Krause and Tse (2013)'s results on multinational study carry out also in our context of cross-sectional connectedness. In addition, the identities of net transmitters and recipients change in the dynamic rolling window VAR-DY and TVP-VAR-DY networks for volatility connectedness, but remain the same for return connectedness. The Real Estate sector was identified as the largest net transmitter for volatility connectedness in the TVP-VAR-DY dynamic volatility network, while the Consumer Discretionary sector was the largest net transmitter for return connectedness in the TVP-VAR-DY network. In the VAR-DY rolling window dynamic and static networks, the Industrials and Financials sectors, respectively, were identified as the largest net transmitters for both volatility and return connectedness. The strongest net pairwise return connectedness was consistent across the three networks, occurring between the Energy and Financials sectors, while the strongest net pairwise volatility connectedness varied across networks. It concludes that the transmission of returns between Energy and Financials sectors is relatively stable over time.

3.3 Frequency connectedness

It is important to note that DY frameworks studied in Section 3.2 which calculate the total connectedness of variables, cannot be decomposed into different frequencies. Thus, to further investigate the dynamic connectedness, particularly in different frequency bands in the TSX market, we use the BK method, as introduced in Section 1.3 (Baruník and Křehlík, 2018; Chatziantoniou et al., 2023).

In the following analysis, we use one week (1-5 days) as the short term, one week to a quarter (5-60 days) as the medium term and more than one quarter (more than 60 days) as the long term.

3.3.1 Dynamic total connectedness and frequency decomposition

We first focus on the dynamic total connectedness and decomposition in different frequency bands shown in Figure 3.4. The black line in Figure 3.4 represents the dynamic total connectedness index, which is also shown as the black line in Figure 3.2. The red line, green line and blue line in Figure 3.4 represents the frequency decomposition for the short-term (1-5 days), medium-term (5-60 days), and long-term (over 60 days), respectively.

Total connectedness is a useful metric that can show how system-wide risk has evolved during the period under investigation. The black line shows that total connectedness reaches its highest point during financial crises due to the transmission of high levels of uncertainty. It provides an aggregate picture over different economic cycles. However, it does not indicate whether the shocks that lead to a significant increase in connectedness affect the system in the short, medium or long term, which is shown in the frequency decomposition. Given that investors operate on varying investment horizons, they may focus on different components of their consumption and value assets based on expected utility from consumption with different levels of persistence. Consequently, cyclical components will create shocks with heterogeneous responses, leading to different sources of connectedness and varying levels of system-wide risk in the short, medium, and long term

(Baruník and Křehlík, 2018).

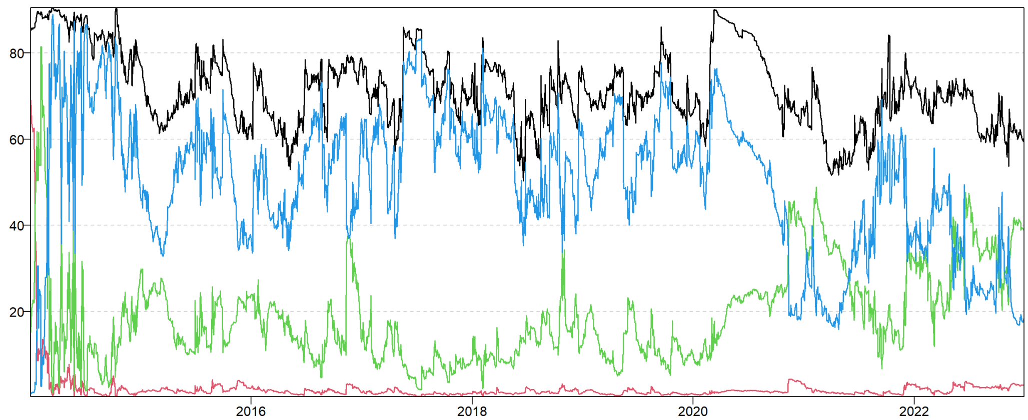
As shown in Figure 3.4a, the volatility spillover effect among different sectors is weakest within 1-5 trading days, indicating that short-term volatility spillovers are not significant. However, the spillover effect increases significantly within 5-60 trading days and beyond 60 trading days. The figure indicates that the volatility spillover effect within the TSX market primarily concentrates on the long term (blue line). It suggests that volatility shocks are being transmitted for longer periods. This behaviour may be attributed to fundamental changes in investors' expectations, which affect system-wide risk in the longer term.

Conversely, in the case of return connectedness, the situation is different. As demonstrated in Figure 3.4b, the return spillover effect among different sectors is weakest beyond 60 trading days, suggesting that long-term return spillovers are not significant. However, the spillover effect increases significantly within 5-60 trading days and within 1-5 trading days. The figure indicates that the return spillover effect within the TSX market mainly concentrates on the short term (red line).

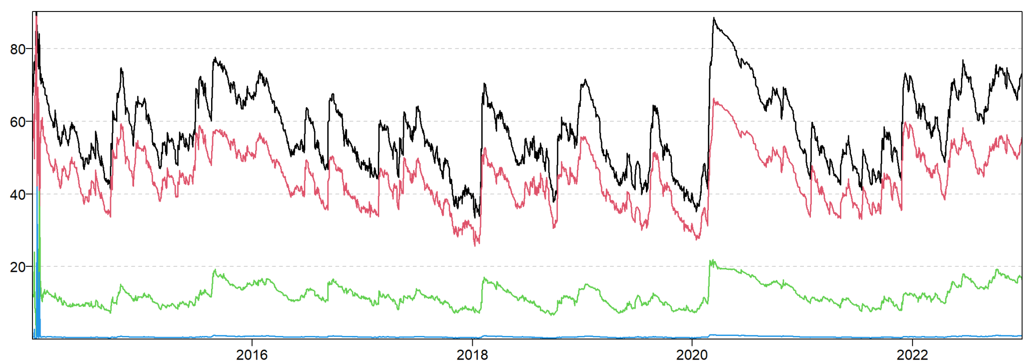
Volatility spillovers tend to occur over a longer time horizon because they are often the result of fundamental changes in the economy, such as changes in government policy, economic indicators, or international events, that take time to play out and have a lasting impact on the market. These changes can lead to alterations in the underlying volatility of individual stocks and sectors, which can then spill over to other sectors over time. These shocks can take time to fully spread through the market. This suggests that volatility contributes significantly to price discovery, as it not only affects the volatility of individual stocks and sectors but may also have a prolonged impact across different areas. It takes time for the effects of these shocks to be fully reflected in market prices and for investors to adjust their expectations accordingly.

On the other hand, return spillovers tend to occur more quickly and in the short term because they are often driven by company-specific news events, such as earnings reports or product launches, that have an immediate impact on the stock price of the company and the returns of the sector. These events can be quickly priced into the market and may not have a lasting impact on the sector or the broader market.

Therefore, the difference in the time horizons of volatility and return spillovers can be attributed to the different underlying factors that drive these phenomena and the time it takes for their effects to be fully reflected in market prices.



(a) Dynamic total volatility connectedness and frequency decomposition



(b) Dynamic total return connectedness and frequency decomposition

Figure 3.4: Dynamic total connectedness and frequency decomposition.
Total (black line), short-term 1-5 days (red line), medium-term 5-60 days (green line), long-term 60 days and more (blue line).

Furthermore, it is worth noting that a particular trend is observable. During a specific period, including the fall and winter of 2020, early 2021, and later 2022, the green line in Figure 3.4a is above the blue line, indicating that the medium-term volatility spillover effect is higher than the long-term volatility spillover effect. One possible reason is that the COVID-19 pandemic had a significant impact on financial markets, and the fall and winter of 2020 and early 2021 saw a resurgence of the pandemic, leading to increased volatility in the medium term.

3.3.2 Dynamic net pairwise connectedness network in different frequency bands

Let us focus on the average dynamic net pairwise connectedness networks in different frequency bands over the whole sample period presented in Figures 3.5 and 3.6.

As seen from Figure 3.5 and as expected, since volatility spillovers mainly occur in the long term, the long-term network in Figure 3.5d is most similar to the total network in Figure 3.5a. Comparing the long-term network and the total network, we notice that except for Consumer Discretionary, which changes from being a net transmitter in the total network to a net recipient in the long-term network, and Health Care, which changes from being a net recipient in the total network to a net transmitter in the long-term network, the identities of all other sectors remain unchanged. Since the nodes of Consumer Discretionary and Health Care sectors are relatively small, it implies that their identities as net transmitters or recipients were already ambiguous. Therefore, we can roughly assume that these two networks are very similar, meaning that the total volatility spillover is primarily driven by the long-term components.

Additionally, the strongest direction of volatility spillovers in both networks is from Real Estate to Consumer Staples. This may be due to the nature of the two sectors. Real Estate is known for its sensitivity to interest rates and economic cycles, while Consumer Staples are more defensive and less cyclical. As a result, as a dominant spillover sector in the TSX market, when Real Estate experiences high volatility due to changes in interest rates or economic uncertainty, it may spill over into the Consumer Staples sector, which may not be well-prepared for such volatility.

Similarly, for the return spillover network in Figure 3.6, since return spillovers mainly occur in the short term, the short-term network in Figure 3.6b is most similar to the total network in Figure 3.6a. Comparing the short-term network and the total network, we notice that the identities of all 11 sectors remain unchanged. Additionally, the strongest direction of return spillovers in both networks is from Financials to Energy. This can be explained by the fact that these two sectors are closely linked in terms of their business activities and economic fundamentals.

Financials and Energy are both important sectors in the Canadian economy, and they are often exposed to similar macroeconomic factors such as interest rates, inflation, and commodity prices. Financial companies provide services such as loans, investments, and insurance to the energy sector, which is heavily dependent on capital for exploration, production, and transportation of oil and gas. In addition, the Canadian financial sector is dominated by banks, which often hold significant energy-related assets and loans on their balance sheets. Therefore, any shocks or changes in the financial sector, such as changes in interest rates or credit conditions, can have significant impacts for the energy sector and may lead to return spillovers from Financials to Energy.

Moreover, as seen in Figure 3.4, we observe that short-term volatility spillovers and long-term return spillovers are very weak, with very small spillover values. Therefore, to highlight the spillover directions of each sector in the short-term volatility spillover and long-term return spillover networks, we set the thickness of the edges to the relative thickness of all edges in each sub-figure in Figure 3.5 and Figure 3.6. For example, in Figure 3.6c and Figure 3.6d, the edges directed from Consumer Discretionary to Financials have similar thicknesses and are the thickest in each sub-figure. However, this should not be interpreted as the spillover magnitudes between these two sectors being identical in the medium-term and long-term networks. As we have learned from Figure 3.4, the spillover intensity in the medium term is notably higher than in the long term. It merely indicates that the strongest return spillovers in both networks are from the Consumer Discretionary sector to the Financials sector. To simplify the figures and better highlight the main spillover directions in each network, we set a threshold to display only those edges in each sub-figure that represent the top 75% of spillover intensities, while omitting the edges that account for the lowest 25% of spillover intensities in each network..

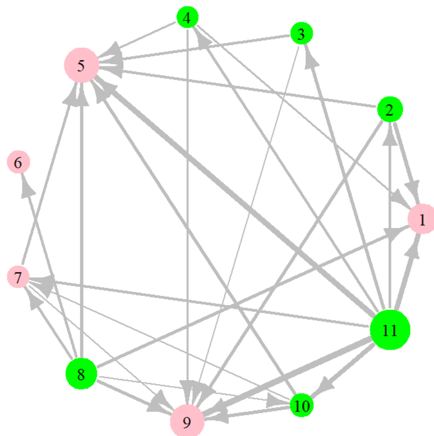
Focusing on the volatility spillover network, since we know that short-term volatility spillovers are very small, as expected, the identities of all sectors in the long-term and total networks are very similar, except for a few sectors, including Consumer Discretionary, Health Care, and Financials, which experience changes. Furthermore, regarding net pairwise spillovers, in addition to the similarity between the long-term and total networks, the short-term and medium-term networks are different from each other.

On the other hand, regarding the return spillover network, the situation is different. Although we know that long-term return spillovers are very small, the identities of all sectors in the short-term, medium-term, long-term, and total networks remain the same. Furthermore, regarding net pairwise spillovers, the medium-term and long-term networks are similar, while the short-term and total networks are similar. This implies that the identities of the return spillovers are relatively stable over time and do not change much across different time horizons.

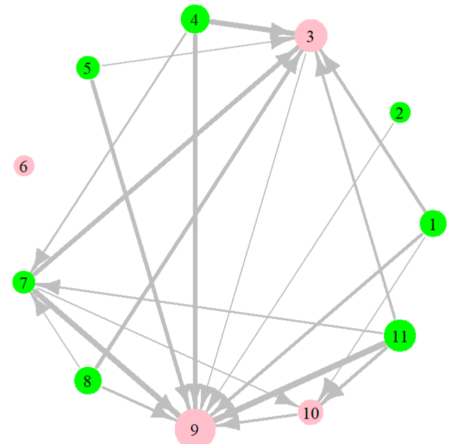
In summary, based on the above analysis, it can be concluded that there are differences in the spillover patterns of volatility and returns across different time horizons in the stock market. In particular, the volatility spillover effect within the TSX market primarily concentrates on the long term, while the return spillover effect within the TSX market mainly concentrates on the short term. Hence, the long-term volatility spillover network is the most similar to the total volatility network, while the short-term return spillover network is the most similar to the total return network. There are also some variations in the identities of the net recipients and transmitters of volatility spillover networks across different sectors and time horizons. However, it is the same for return spillover networks.

To further explore the specific period when the medium-term volatility spillover effect is higher than the long-term volatility spillover effect in Figure 3.4a, we present the average dynamic net pairwise frequency volatility connectedness networks during the resurgence of the COVID-19 pandemic from September 1, 2020 to April 30, 2021, as shown in Figure 3.7.

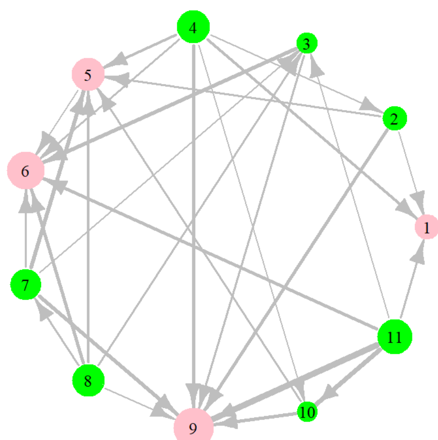
We find that during the resurgence of the COVID-19 pandemic, the Consumer Discretionary sector was the largest net transmitter in the medium-term volatility network, while the Telecommunications Services sector was the largest net transmitter in the long-



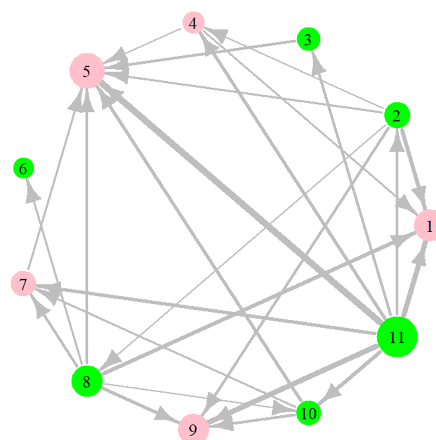
(a) Total



(b) Short-term 1-5 days

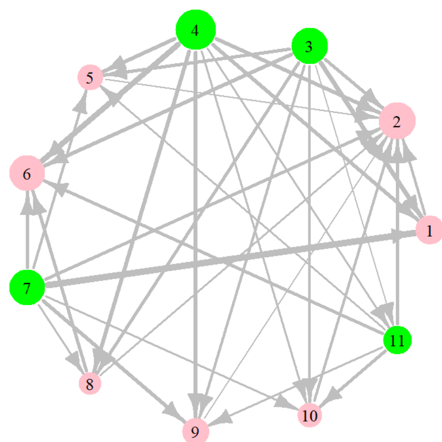


(c) Medium-term 5-60 days

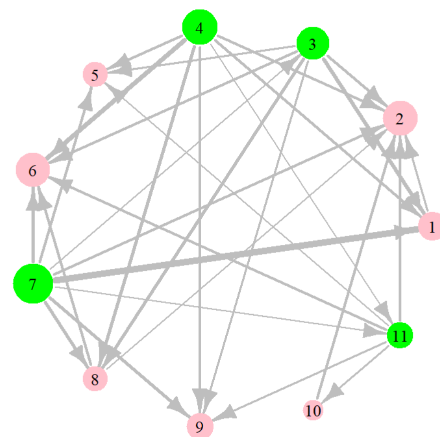


(d) Long-term 60 days and more

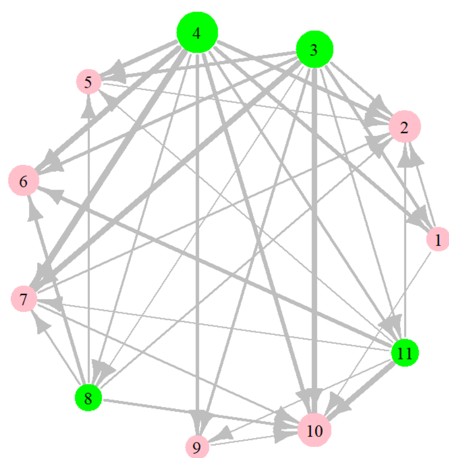
Figure 3.5: Average dynamic net pairwise frequency volatility connectedness networks over the whole sample period.
Energy (1), Materials (2), Industrials (3), Consumer Discretionary (4), Consumer Staples (5), Health Care (6), Financials (7), Information Technology (8), Telecommunications Services (9), Utilities (10), and Real Estate (11).



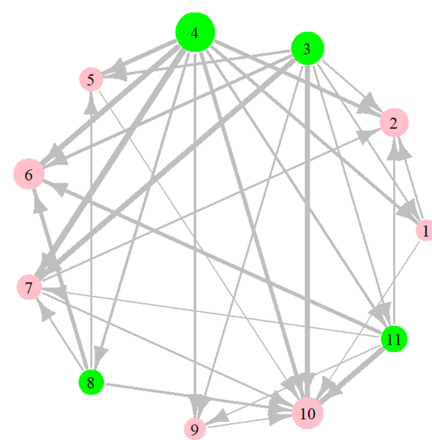
(a) Total



(b) Short-term 1-5 days

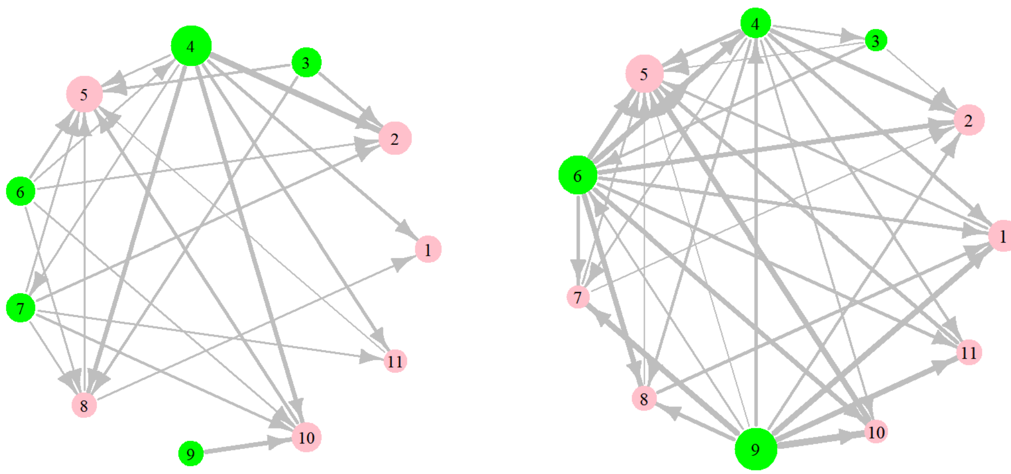


(c) Medium-term 5-60 days



(d) Long-term 60 days and more

Figure 3.6: Average dynamic net pairwise frequency return connectedness networks over the whole sample period.
Energy (1), Materials (2), Industrials (3), Consumer Discretionary (4), Consumer Staples (5), Health Care (6), Financials (7), Information Technology (8), Telecommunications Services (9), Utilities (10), and Real Estate (11).



(a) Medium-term 5-60 days (b) Long-term 60 days and more

Figure 3.7: Average dynamic net pairwise frequency volatility connectedness networks for September 1, 2020 to April 30, 2021.
Energy (1), Materials (2), Industrials (3), Consumer Discretionary (4), Consumer Staples (5), Health Care (6), Financials (7), Information Technology (8), Telecommunications Services (9), Utilities (10), and Real Estate (11).

term volatility network. The medium-term volatility in the Consumer Discretionary sector reflects rapid changes in consumer behavior due to the pandemic, while the long-term volatility in the Telecommunications Services sector indicates a growing dependence on digital communication. During the resurgence of COVID-19, substantial uncertainty around economic recovery, employment, and income levels likely led to rapid shifts in consumer preferences and actions. The 5-60 day medium-term window captures these quick and significant shifts in consumer behavior, reflecting the influence of these changes on the Consumer Discretionary sector's volatility. However, the increased demand for telecommunications services due to remote work and online activities may not result in immediate dramatic effects but is expected to affect the Telecommunications Services sector's volatility in the long run. The long-term network captures these extended impacts of the pandemic, where the importance and reliance on telecommunications services gradually become more evident. Furthermore, the main difference between the two figures is the role of the Financials sector, which acts as a net transmitter in the medium-term volatility network and a net recipient in the long-term volatility network.

We can infer that the Financials sector plays a strong role. As it is a net transmitter in the medium-term network, as a result, the overall medium-term volatility spillover effect is higher than the long-term volatility spillover effect during this period, indicating that the total spillover effect of volatility is mainly concentrated in the medium-term.

3.4 Impact of uncertainty events

Building on the research findings related to the spillover indices from Sections 3.2 and 3.3, this section aims to analyze the impact of four uncertainty events, the 2015-2016 stock market sell-off, the 2018 cryptocurrency crash, the 2020 COVID-19 outbreak, and the 2022 Russo-Ukrainian War, on the spillover contagion across various sectors in the TSX market. A linear regression model incorporating dummy variables for these events will be employed to assess whether these shocks have a significant linear impact on the spillover contagion among different TSX sectors. In addition, to further analyze the impact of various uncertainty events, we also pay attention to the TVP-VAR-DY average dynamic net pairwise connectedness networks of volatility and return during each period in Figure 3.8, 3.9, 3.10 and 3.11. To avoid the dummy variable trap, four dummy variables will be used. The specific model is as follows:

$$y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \beta_3 x_{3,t} + \beta_4 x_{4,t} + \varepsilon_t \tag{3.1}$$

where y_t represents the net spillover index at time t computed in Sections 3.2 and 3.3, which is calculated by Equation (1.13) as "TO" minus "FROM". This index best reflects the spillover status of the sectors. $x_{1,t}, ..., x_{4,t}$ are the 4 dummy variables representing each uncertainty event. That is, $x_{1,t}$ represents the dummy variable for the 2015-2016 stock market sell-off, $x_{2,t}$ for the 2018 cryptocurrency crash, $x_{3,t}$ for the 2020 COVID-19 outbreak, and $x_{4,t}$ for the 2022 Russo-Ukrainian War. A value of 1 is assigned to the dummy variable during the event period, and 0 otherwise. The coefficient β_0 denote the intercept. The coefficients $\beta_1, ..., \beta_4$ measure the effect of each dummy variable after taking into account the effects of all the other dummy variables in the model. Thus, the coefficients measure the marginal effects of the dummy variables. Moreover, ε_t represents the error term.

The events and their respective time periods are presented in Table 3.3. For the 2015-2016 stock market sell-off, June 12, 2015, is considered the starting point, as the collapse of the Chinese stock market triggered a global stock market plunge, which eventually ended on June 30, 2016. For the 2018 cryptocurrency crash, September 20, 2018, marks the beginning, when a decline in Bitcoin prices led to a stock market downturn, ending on December 24, 2018. In the case of the 2020 COVID-19 outbreak, February 20, 2020, is the starting point when the pandemic began to spread globally. Given the multiple waves and ambiguity in defining the time limit, our research focuses on the initial phase of the outbreak, when the spillover index volatility peaked, and ends on April 7, 2020, when the first major wave of the outbreak concluded. For the 2022 Russo-Ukrainian War, February 24, 2022, is the starting point when Russia invaded Ukraine. As the conflict is ongoing, our analysis primarily focuses on the first period of the Russian invasion in 2022, ending on April 7, 2022.

Table 3.3: Events and corresponding time period table

Events	Time period
2015-2016 stock market sell-off	June 12, 2015 to June 30, 2016
2018 Cryptocurrency crash	September 20, 2018 to December 24, 2018
2020 COVID-19 outbreak	February 20, 2020 to April 7, 2020
2022 Russo-Ukrainian War	February 24, 2022 to April 7, 2022

Using the total and frequency-decomposed short-term, medium-term, and long-term net spillover indices of the 11 sectors as dependent variables, we perform the above-mentioned dummy variable regression on the volatility and return series. The results of the linear regression models are presented in Tables 3.4, 3.5, 3.6 and 3.7. In the sections 3.4.1, 3.4.2, 3.4.3 and 3.4.4, we discuss the impact of each uncertainty event separately.

3.4.1 The 2015-2016 stock market sell-off

The 2015-2016 stock market sell-off had a broad impact on the Canadian stock market, with many sectors experiencing declines in their share prices. This sell-off was triggered by a combination of various factors, including a slowdown in global economic growth, deceleration in China's economic growth, sharp decline in oil prices, expectations of the Federal Reserve's interest rate hike, and rising geopolitical tensions.

Since the sell-off was primarily driven by a decline in oil prices, the energy sector, a vital component of the Canadian economy, experienced significant turmoil. Energy companies witnessed a sharp decline in their stock prices during this period. The regression results show that the 2015-2016 stock market sell-off significantly increased the volatility spillover capabilities of the Energy sector, and this effect was observed across all frequency bands. However, in terms of return spillovers, this phenomenon was more pronounced in the short-to-medium term. Additionally, as shown in Figure 3.8, the Energy sector indeed played a net transmitter role during this period.

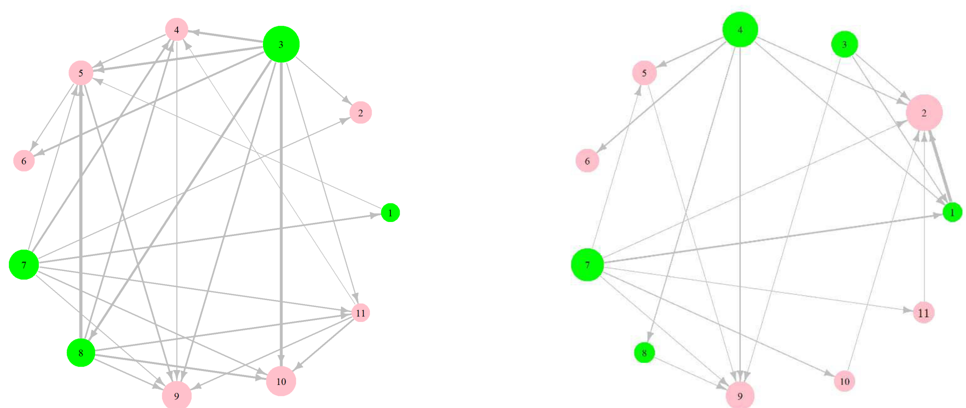
Moreover, the Energy sector is highly interconnected with other sectors, such as the Industrials sector, which may have contributed to the increased volatility spillovers observed in these sectors during the sell-off. The regression results show that the 2015-2016 stock market sell-off significantly increased the volatility spillover capabilities of the Industrials sector, and this effect was observed across all frequency bands. In terms of return spillovers, this phenomenon was more pronounced in the short term. As presented in Figure 3.8, the Industrials sector played a net transmitter role during this period and was the largest net transmitter in the volatility spillover network.

The Industrials sector is heavily exposed to global economic conditions. The sell-off was driven by concerns about global economic growth, which had a significant impact on the Industrials sector. Many companies within the Industrials sector experienced various degrees of decline in their share prices during this time. This was due to a slowdown in global economic growth and market uncertainty, causing investor concerns about the profit outlook for industrial enterprises. Additionally, as global economic growth slowed down, particularly in China, the demand for industrial products weakened. This likely led to a decline in revenue for industrial enterprises, further affecting their profitability and stock performance. Furthermore, during 2015-2016, the expectations of the Federal Reserve's interest rate hike impacted global monetary policies and exchange rates. For industrial enterprises, fluctuations in exchange rates could affect export revenue and raw material costs, thereby influencing corporate profitability. As a result, the sector became more susceptible to volatility and return spillovers during this period.

As expected, the Financials sector was also impacted due to the overall market sell-off, with many banks and other financial institutions experiencing declines in their share prices. During the sell-off, banks may have been more susceptible to volatility and return spillovers due to their exposure to market risks and the potential impact of interest rate changes on their profitability. The regression results show that the sell-off significantly increased the volatility and return spillover capabilities of the Financials sector across all frequency bands. In Figure 3.8, the Financials sector indeed played a net transmitter role during this period.

Interestingly, the sell-off strengthened both the volatility and return spillover capabilities of the Information Technology sector. As seen in Figure 3.8, the Information Technology sector played a net transmitter role during this period. This may be due to the fact that prior to the sell-off, valuations of some information technology companies may have been relatively high. Consequently, during the sell-off, investors may have sold these stocks to reduce risk exposure. Additionally, during the stock market sell-off, investor risk aversion typically increases, leading them to shift funds towards investments considered relatively safer. Since information technology companies are often considered to have higher risk characteristics, they may be more significantly impacted during a market sell-off, potentially resulting in increased volatility and return spillovers. Moreover, the 2015-2016 stock market sell-off was partly driven by a slowdown in global economic growth. This environment may have led businesses to be more cautious about technology spending, thereby affecting the profitability and stock performance of information technology companies.

Notably, the sell-off strengthened return spillovers for the Consumer Discretionary sector, while the effect on volatility spillovers was not significant. In the return network shown in Figure 3.8b, the Consumer Discretionary sector was the largest net transmitter during this period, while in the volatility network presented in Figure 3.8a, it played a net recipient role. This may be because, in times of increased economic uncertainty, consumers tend to be more cautious when purchasing non-essential items, which can impact the revenue of companies in the Consumer Discretionary sector to some extent. However, the fluctuations in revenue may be relatively small, and therefore, volatility spillovers might not have significantly increased.



(a) volatility network

(b) return network

Figure 3.8: TVP-VAR-DY average dynamic net pairwise return and volatility connectedness networks for the 2015-2016 stock market sell-off.
Energy (1), Materials (2), Industrials (3), Consumer Discretionary (4), Consumer Staples (5), Health Care (6), Financials (7), Information Technology (8), Telecommunications Services (9), Utilities (10), and Real Estate (11).

3.4.2 The 2018 cryptocurrency crash

The 2018 cryptocurrency crash mainly affected Information Technology and Financials sectors, as companies related to cryptocurrencies, blockchain, and digital asset management were affected by the crash. The regression results show that the 2018 cryptocurrency crash significantly increased the volatility and return spillover capabilities of the Financials and Information Technology sectors.

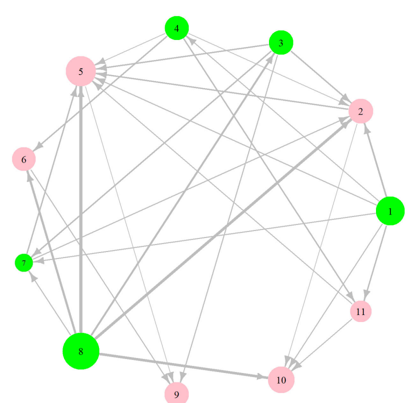
The Information Technology sector, which incorporates companies engaged in cryptocurrency mining and blockchain technology, may have been indirectly affected by the crash. As shown in Figure 3.9, the Information Technology sector indeed played a net transmitter role during this period, particularly in the volatility spillover network, where it was the largest net transmitter.

Additionally, the Financials sector may have been impacted by the volatility in the cryptocurrency markets, as some financial institutions have invested in cryptocurrencies or provided cryptocurrency-related services to clients. In Figure 3.9, we observe that the Financials sector also played a net transmitter role during this period. Notably, in the volatility spillover network, there is an edge indicating spillovers from the Information Technology sector to the Financials sector.

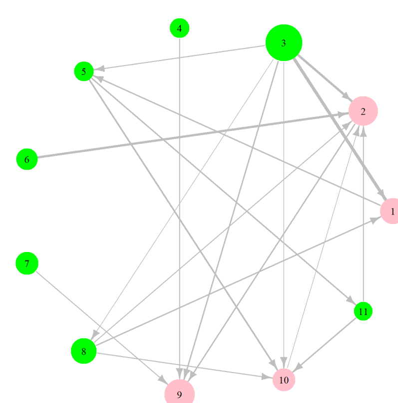
In addition to these two expected sectors impacted by the 2018 cryptocurrency crash, the spillover effects were also intensified in some other sectors, such as the Industrials and Consumer Discretionary sectors. As seen in Figure 3.9, the Industrials and Consumer Discretionary sectors indeed acted as net transmitters during this period. This phenomenon might be attributed to the 2018 cryptocurrency crash, which likely led to increased volatility and return spillovers in these sectors due to a combination of factors, including market sentiment, indirect exposure, concerns about the global economic outlook, and the connectedness of financial markets.

The 2018 cryptocurrency crash had a significant impact on overall market sentiment. As cryptocurrency prices plunged, investors became more risk-averse, potentially selling off stocks in other sectors, including Industrials and Consumer Discretionary. This sell-off contributed to increased volatility and return spillovers in these sectors. Moreover, some companies in the Industrials and Consumer Discretionary sectors may have had indirect exposure to cryptocurrencies or blockchain technology through their operations, investments, or partnerships. The crash in cryptocurrency prices could have affected these companies' financial performance or stock prices, leading to increased volatility and return spillovers in the sectors. Furthermore, the cryptocurrency crash raised concerns about the global economic outlook, particularly regarding financial stability and the potential for system-wide risks. These concerns may have contributed to increased volatility and return spillovers in the sectors. Additionally, financial markets are highly interconnected, and shocks in one market or sector can spill over to others. The 2018 cryptocurrency crash may have triggered a chain reaction, resulting in heightened volatility and return spillovers across multiple sectors.

Cryptocurrency, to a certain extent, is considered a domain for the wealthy, mainly attracting affluent individuals and companies as investors. The downturn in the cryptocurrency market in 2018 might have impacted the wealth of these heavily invested individuals and companies. Since the affluent demographic is a key consumer base for the Consumer Discretionary sector, this sector might have faced repercussions during the period of the cryptocurrency crash. This is reflected in the significant increase in the volatility and return spillover regression results observed during the 2018 cryptocurrency crash period.



(a) volatility network



(b) return network

Figure 3.9: TVP-VAR-DY average dynamic net pairwise return and volatility connectedness networks for the 2018 Cryptocurrency crash.
Energy (1), Materials (2), Industrials (3), Consumer Discretionary (4), Consumer Staples (5), Health Care (6), Financials (7), Information Technology (8), Telecommunications Services (9), Utilities (10), and Real Estate (11).

3.4.3 The 2020 COVID-19 outbreak

The 2020 COVID-19 outbreak had a significant impact on the Canadian stock market, leading to a widespread sell-off across multiple sectors.

However, some sectors closely tied to economic activity, such as the Financials sector, were more affected than others. Financial institutions faced a series of challenges due to increased credit risk, lower interest rates, and heightened economic uncertainty. Stock prices of banks and other financial services companies declined, as investors worried about loan defaults and the overall health of the financial system. The regression results indicate that the 2020 COVID-19 outbreak significantly increased the volatility and return spillover ability of the Financials sector across almost all frequency bands. As illustrated in Figure 3.10, the Financials sector was the largest net transmitter in both volatility and return spillover networks during this period.

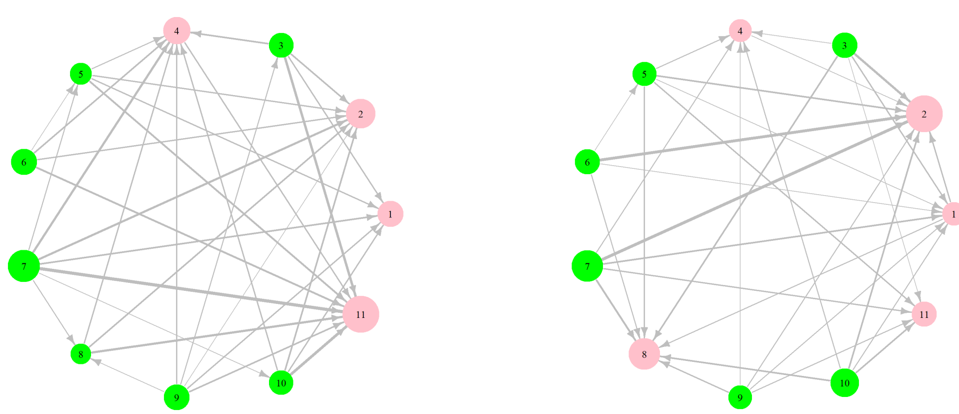
During this time, some sectors such as Consumer Staples, Health Care and Telecommunication Services performed relatively better. Consumer Staples companies performed comparatively well during this period, as demand for essential goods remained stable or even increased. However, supply chain disruptions still posed challenges for some companies. The regression results show that the 2020 COVID-19 outbreak significantly increased the volatility and return spillover ability of the Consumer Staples sector across almost all frequency bands.

The pandemic increased the demand for healthcare services. The Health Care sector, particularly companies involved in pharmaceuticals, medical equipment, and biotechnology, benefited from the increased focus on public health and the development of COVID-19 treatments and vaccines.

Furthermore, the Telecommunication Services sector performed well during the COVID-19 outbreak. With remote work, online education, and increased digital communication becoming the norm, the demand for internet and communication services in the Telecommunication Services sector increased as people shifted to remote work and online entertainment.

The regression results show that the volatility and return spillover effects of these sectors did indeed increase during the COVID-19 outbreak. As seen in Figure 3.10, Financials, Consumer Staples, Health Care, and Telecommunication Services sectors were net transmitters during this period.

Additionally, the regression results indicate that volatility spillover in the Real Estate sector decreased in this period, while return spillover decreased in the short term but increased in the long term. This could be attributed to government interventions, such as interest rate cuts and fiscal stimulus, and real estate being viewed as a reliable and safe investment during times of economic uncertainty. These factors provided market stability and reduced volatility. During the initial stages of the pandemic, the market's response to the Real Estate sector was likely cautious and risk-averse, leading to a decrease in the short-term return spillover for the sector. However, as time progressed, investors might have started to focus more on the long-term value and stability of real estate, especially in a low-interest-rate environment. This shift led to increased long-term investments in real estate, resulting in an increase in long-term return spillover.



(a) volatility network

(b) return network

Figure 3.10: TVP-VAR-DY average dynamic net pairwise return and volatility connectedness networks for the 2020 COVID-19 outbreak.
Energy (1), Materials (2), Industrials (3), Consumer Discretionary (4), Consumer Staples (5), Health Care (6), Financials (7), Information Technology (8), Telecommunications Services (9), Utilities (10), and Real Estate (11).

3.4.4 The 2022 Russo-Ukrainian War

The 2022 Russo-Ukrainian War primarily affected several sectors of the Canadian stock market.

Regression results indicate that the conflict led to increased volatility and spillover effects in the Energy sector. Global energy markets were disrupted due to concerns about supply constraints and heightened geopolitical tensions. This impacted the Canadian energy sector, particularly oil and natural gas companies, as the conflict caused fluctuations in global oil prices. Figure 3.11 demonstrates that the Energy sector was indeed a net transmitter during this period.

The Financials sector was affected by increased market volatility, economic uncertainty, and potential changes in monetary policies in response to the conflict. Banks and other financial institutions experienced fluctuations in their share prices and potential increases in credit risk. As expected, the volatility and return spillovers across almost all frequency bands in the Financials sector were increased. Figure 3.11b shows that the Financials sector was a net transmitter in the return spillover network. However, in the volatility network displayed in Figure 3.11a, the Financials sector was a net recipient. This could be due to the Financials sector receiving more volatility spillovers from other sectors. Financial markets are highly interconnected, and indeed, we observed edge directed from the Energy sector to the Financials sector.

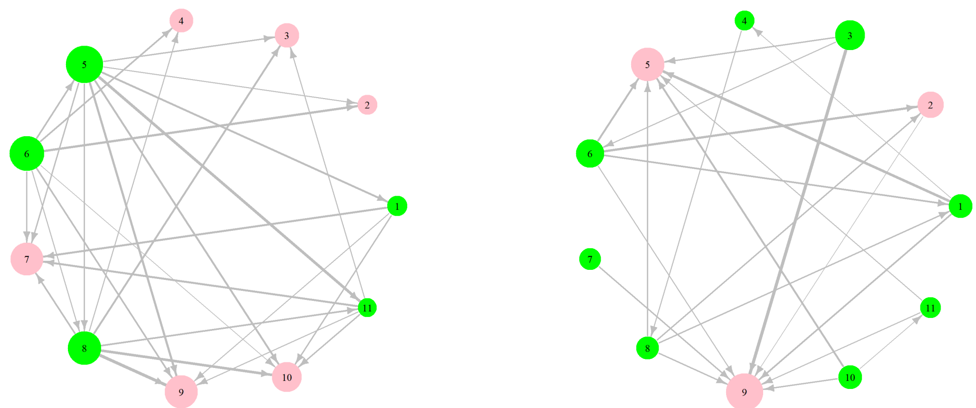
In addition to the sectors mentioned above, some other sectors, such as the Health Care and Information Technology sectors, also experienced increased volatility and return spillovers. This can be attributed to a combination of factors, including market uncertainty, supply chain disruptions, currency fluctuations, interconnectedness of financial markets, changes in market sentiment, and the impact on demand.

The Russia-Ukraine conflict created significant uncertainty in global financial markets, affecting various sectors, including Health Care and Information Technology. In times of heightened geopolitical risks, investors may become more risk-averse and sell off stocks in these sectors, leading to increased volatility and return spillovers. Furthermore, the conflict could have caused disruptions in global supply chains, impacting the production and distribution of products and services in the Health Care and Information Technology sectors. These disruptions might have affected the financial performance and stock prices of companies in these sectors, contributing to increased volatility and return spillovers. Additionally, as geopolitical events, such as the Russia-Ukraine war, can lead to fluctuations in currency values, both the Health Care and Information Technology sectors, which have significant international exposure, could have been affected by currency fluctuations, resulting in increased volatility and return spillovers.

Moreover, financial markets are highly interconnected, and shocks in one market or sector can spill over to others. The Russia-Ukraine conflict might have triggered a chain reaction, causing heightened volatility and return spillovers across multiple sectors, including Health Care and Information Technology. Furthermore, the conflict might have led to a shift in market sentiment, affecting the Health Care and Information Technology sectors. Investors may have reassessed their risk tolerance and investment strategies, causing increased volatility and return spillovers in these sectors. Finally, the conflict might have affected the global economy, leading to changes in demand for products and services in the Health Care and Information Technology sectors. These changes in demand could have impacted the financial performance and stock prices of companies in these sectors, leading to increased volatility and return spillovers.

In conclusion, the analysis of various market events, including the 2015-2016 stock market sell-off, the 2018 cryptocurrency crash, the 2020 COVID-19 outbreak, and the 2022 Russo-Ukrainian War, demonstrates the varying impact of these events on different sectors of the Canadian stock market. Key sectors such as Energy, Financials, and Industrials were significantly affected by these events, experiencing increased volatility and return spillovers. The interconnectedness of financial markets, changes in market sentiment, and shifts in global economic conditions contributed to the transmission of shocks across sectors.

The analysis also highlights the potential influence of market events on other sectors, such as Information Technology and Health Care, which experienced increased volatility



(a) volatility network (b) return network

Figure 3.11: TVP-VAR-DY average dynamic net pairwise return and volatility connectedness networks for the 2022 Russo-Ukrainian War.
Energy (1), Materials (2), Industrials (3), Consumer Discretionary (4), Consumer Staples (5), Health Care (6), Financials (7), Information Technology (8), Telecommunications Services (9), Utilities (10), and Real Estate (11).

and return spillovers during these periods. Factors such as market uncertainty, supply chain disruptions, currency fluctuations, changes in demand, and investors' reassessment of risk tolerance and investment strategies played a role in the spillover effects observed in these sectors.

Overall, the findings emphasize the importance of understanding the interconnected nature of financial markets and the potential for spillover effects across sectors in response to market events. This knowledge can help investors, policymakers, and market participants better assess risks and make informed decisions during times of market stress or uncertainty.

Table 3.4: Dummy variable regression table for volatility series for total net spillover indices

	2015-2016 stock market sell-off	2018 Cryptocurrency crash	2020 COVID-19 outbreak	2022 Russo-Ukrainian War
Energy(1)	+[1]***[2]	+ ***	+	+ ***
Materials(2)	- ***	- ***	- ***	- **
Industrials(3)	+ ***	+ ***	+ ***	- **
Cons.Disc(4)	-	+ ***	-	- ***
Cons.Staples(5)	+	- ***	+ ***	+ ***
Health.Care(6)	- **	- ***	+ ***	+ ***
Financials(7)	+ ***	+ *	+ ***	+ ***
Info.Tech(8)	+ ***	+ ***	-	+ ***
Tele.Services(9)	- ***	-	+ ***	- ***
Utilities(10)	- ***	- ***	+ ***	- ***
Real.Estate(11)	- ***	- ***	- ***	+ **

[1] "+" indicates that the event increases the net spillover effect on the corresponding sector, while "-" indicates that the event reduces the net spillover effect on the corresponding sector.
[2] ***, **, * indicate significant at 1%, 5%, and 10% levels, respectively.

Table 3.5: Dummy variable regression table for volatility series with frequency decomposition

	2015-2016 stock market sell-off	2018 Cryptocurrency crash	2020 COVID-19 outbreak	2022 Russo-Ukrainian War
Short-term 1-5 days:				
Energy(1)	+[1]***[2]	+ ***	- ***	- ***
Materials(2)	-	+ ***	+	- ***
Industrials(3)	+ ***	+ ***	+ ***	- ***
Cons.Disc(4)	- *	-	- ***	+ ***
Cons.Staples(5)	- ***	- **	-	- ***
Health.Care(6)	+ ***	+	-	+ ***
Financials(7)	+ ***	- **	+	+ ***
Info.Tech(8)	+ ***	+ ***	-	- ***
Tele.Services(9)	+ ***	- ***	+ *	+ ***
Utilities(10)	- ***	- ***	+ ***	- ***
Real.Estate(11)	- ***	- ***	- **	+
Medium-term 5-60 days:				
Energy(1)	+ ***	+ ***	- **	-
Materials(2)	- ***	- ***	- ***	- ***
Industrials(3)	+ ***	+ ***	+ **	+ **
Cons.Disc(4)	-	+ ***	- ***	- ***
Cons.Staples(5)	- ***	- ***	+ **	+ ***
Health.Care(6)	+	- ***	+ ***	+ ***
Financials(7)	+ ***	+ ***	+ ***	+ ***
Info.Tech(8)	+ ***	+ ***	-	+ ***
Tele.Services(9)	- ***	- ***	+ ***	- ***
Utilities(10)	- ***	- ***	+ ***	- ***
Real.Estate(11)	-	- ***	- ***	+ *
Long-term 60 days and more:				
Energy(1)	+ ***	+ ***	+	+ **
Materials(2)	- ***	- ***	- **	-
Industrials(3)	+ ***	+	+ ***	- ***
Cons.Disc(4)	+	+ ***	+	-
Cons.Staples(5)	+ ***	+	+ ***	+ ***
Health.Care(6)	- ***	- ***	+ ***	+
Financials(7)	+ ***	+ ***	+ **	+ *
Info.Tech(8)	+ *	+	-	+ *
Tele.Services(9)	+	+ ***	+ ***	-
Utilities(10)	- ***	- *	+ ***	- ***
Real.Estate(11)	- ***	- ***	- ***	+ **

[1] "+" indicates that the event increases the net spillover effect on the corresponding sector, while "-" indicates that the event reduces the net spillover effect on the corresponding sector.
[2] ***, **, * indicate significant at 1%, 5%, and 10% levels, respectively.

Table 3.6: Dummy variable regression table for return series for total net spillover indices

	2015-2016 stock market sell-off	2018 Cryptocurrency crash	2020 COVID-19 outbreak	2022 Russo-Ukrainian War
Energy(1)	+[1]***[2]	- ***	-	+ ***
Materials(2)	- ***	- ***	- ***	- ***
Industrials(3)	+ ***	+ ***	+ ***	+ ***
Cons.Disc(4)	+ ***	+ ***	- ***	- ***
Cons.Staples(5)	- **	+ ***	+ ***	- ***
Health.Care(6)	+ ***	+ ***	+ ***	+ ***
Financials(7)	+ ***	+ ***	+ ***	+ ***
Info.Tech(8)	+ ***	+ ***	- ***	+ ***
Tele.Services(9)	- ***	- ***	+ ***	- ***
Utilities(10)	+	- **	+ ***	+ ***
Real.Estate(11)	- ***	- ***	- ***	+

[1] "+" indicates that the event increases the net spillover effect on the corresponding sector, while "-" indicates that the event reduces the net spillover effect on the corresponding sector.
[2] ***, **, * indicate significant at 1%, 5%, and 10% levels, respectively.

Table 3.7: Dummy variable regression table for return series with frequency decomposition

	2015-2016 stock market sell-off	2018 Cryptocurrency crash	2020 COVID-19 outbreak	2022 Russo-Ukrainian War
Short-term 1-5 days:				
Energy(1)	+[1]***[2]	- *	- ***	+ ***
Materials(2)	- ***	- ***	+ ***	- ***
Industrials(3)	+ ***	+ ***	+ ***	- ***
Cons.Disc(4)	+ ***	+ ***	- ***	- ***
Cons.Staples(5)	+ ***	+ ***	+ ***	+ ***
Health.Care(6)	+	+ ***	+ ***	+ ***
Financials(7)	+ *	+ ***	- **	+ ***
Info.Tech(8)	+ ***	+ ***	- ***	+ ***
Tele.Services(9)	- ***	- ***	+ ***	- **
Utilities(10)	+ ***	- **	+ ***	- ***
Real.Estate(11)	- ***	+ ***	- ***	+
Medium-term 5-60 days:				
Energy(1)	+ ***	- ***	+ ***	+ ***
Materials(2)	- ***	+ ***	- ***	+ **
Industrials(3)	+	- *	+ ***	+ ***
Cons.Disc(4)	-	+ ***	- *	-
Cons.Staples(5)	- ***	+ ***	+ ***	- ***
Health.Care(6)	+ ***	+ ***	+ ***	+ ***
Financials(7)	+ ***	+ ***	+ ***	+ **
Info.Tech(8)	-	+ *	+ ***	+ ***
Tele.Services(9)	- ***	- ***	+ *	- ***
Utilities(10)	- ***	- *	+	+ ***
Real.Estate(11)	+	- ***	- ***	+
Long-term 60 days and more:				
Energy(1)	+	-	+ ***	- **
Materials(2)	- **	+	- ***	+
Industrials(3)	+	-	+ ***	+ ***
Cons.Disc(4)	-	+ ***	+ ***	-
Cons.Staples(5)	-	-	-	- *
Health.Care(6)	+ **	+ ***	+ *	+ ***
Financials(7)	+ ***	+ ***	+ ***	+
Info.Tech(8)	+	+	+ **	+ ***
Tele.Services(9)	- ***	- **	- ***	- ***
Utilities(10)	-	+	+ ***	+ ***
Real.Estate(11)	+	- ***	+ ***	+

[1] "+" indicates that the event increases the net spillover effect on the corresponding sector, while "-" indicates that the event reduces the net spillover effect on the corresponding sector.
[2] ***, **, * indicate significant at 1%, 5%, and 10% levels, respectively.

Conclusion

List of acronyms

BK Barunik and Krehlik

DY Diebold and Yilmaz

TSX Toronto Stock Exchange

TVP-VAR-DY Time-Varying Parameter Vector Autoregression Diebold and Yilmaz

VAR Vector Autoregression

VAR-DY Vector Autoregression Diebold and Yilmaz

In conclusion, this paper provides a comprehensive analysis of sectoral volatility and return connectedness in the Toronto Stock Exchange (TSX) market. The study shows that volatility spillover and return spillover capture different aspects of the transmission mechanism in financial markets. Volatility shocks are found to be more contagious and easily transmitted among sectors, while return shocks exhibit lower contagion and transmit less easily.

We employ the Vector Autoregression Diebold and Yilmaz (VAR-DY) method (Diebold and Yilmaz, 2012) to investigate static connectedness. We find that the Financials sector emerges as the largest net transmitter in both volatility and return connectedness, indicating its dominant role in shaping the overall volatility and return connectedness of the TSX sectors. Given its significance as the backbone of the economy and its critical role in financial market functioning, any shocks or disruptions in the Financials sector can have substantial impacts on other sectors and the broader economy.

While the static approach offers a broad view of connectedness, it may not capture time-varying relationships between variables during changing market conditions. To address this limitation, we employ the rolling window VAR-DY method (Diebold and Yilmaz, 2012) and the Time-Varying Parameter Vector Autoregression Diebold and Yilmaz (TVP-VAR-DY) method (Antonakakis et al., 2020) to estimate dynamic connectedness. The TVP-VAR-DY approach, which does not require a rolling window setting and use the whole sample data, proves effective in capturing sudden market changes and incorporating all available information, thus addressing the sample loss issue associated with the rolling window method.

Comparing the dynamic connectedness measures, we find that the volatility connectedness of the rolling window VAR-DY method is lower on average than that of the TVP-VAR-DY method. However, the rolling window VAR-DY method exhibits lag patterns in peak and trough values for volatility connectedness compared to the TVP-VAR-DY method. The identities of net transmitters and recipients in the average dynamic net pairwise connectedness network change in the rolling window VAR-DY and TVP-VAR-DY networks for volatility connectedness but remain consistent for return connectedness.

Furthermore, we employ the BK method to analyze the transmission channels of volatility spillovers across different frequency bands. The findings reveal that volatility spillover primarily concentrates on the long term, while return spillover is more prominent in the short term. This behaviour suggests that long-term volatility spillovers are influenced by fundamental changes in the economy that take time to play out and have a lasting impact on the market. These changes can lead to changes in investors' expectations, impacting system-wide risk over time. In contrast, short-term return spillovers are driven by company-specific news events that have immediate effects on stock prices and sector returns.

We also investigate the impact of major market events, such as the 2015-2016 stock market sell-off, 2018 cryptocurrency crash, 2020 COVID-19 outbreak, and 2022 Russo-

Ukrainian War, on volatility and return spillover between stock market sectors. These events demonstrate varying effects on different sectors, with Energy, Financials, and Industrials being significantly affected. Factors such as market uncertainty, supply chain disruptions, currency fluctuations, changes in demand, and investors' risk tolerance contribute to the observed spillover effects.

Overall, the analysis highlights the importance of understanding the interconnected nature of financial markets and the potential for spillover effects across sectors during market events. The findings provide valuable information for investors, policymakers, and market participants, enabling them to assess risks more effectively and make prudent decisions in times of market stress or uncertainty.

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Appendix A – Regression results

Table 1: Full dummy variable regression table for volatility series

	Energy(1)	Materials(2)	Industrials(3)	Cons.Disc(4)	Cons.Staples(5)	Health.Care(6)	Financials(7)	Info.Tech(8)	Tele.Services(9)	Utilities(10)	Real.Estate(11)
Total:											
Intercept	-9.989***[1]	19.564***	0.679	1.421*	-19.244***	0.976	-5.007***	9.908***	-22.801***	-3.390***	27.883***
	(1.101)[2]	(1.248)	(1.002)	(0.851)	(1.000)	(1.333)	(0.828)	(1.255)	(0.682)	(0.920)	(1.506)
x_1[3]	11.390***	-29.960***	47.350***	-3.812	2.684	-8.631**	35.566***	16.339***	-6.350***	-26.630***	-27.946***
	(3.117)	(3.534)	(2.837)	(2.411)	(2.831)	(3.775)	(2.345)	(3.554)	(1.932)	(2.605)	(4.264)
x_2	51.185***	-44.491***	23.297***	21.502***	-27.239***	-22.617***	4.937	64.334***	-0.629	-29.704***	-40.576***
	(5.903)	(6.692)	(5.373)	(4.566)	(5.361)	(7.150)	(2.541)	(6.731)	(3.658)	(4.934)	(8.076)
x_3	2.481	-30.328***	15.341***	-10.131	22.613***	16.495***	18.206***	-7.895	29.910***	19.278***	-45.970***
	(8.216)	(9.313)	(4.478)	(6.354)	(7.460)	(5.950)	(6.181)	(9.367)	(5.092)	(6.867)	(11.239)
x_4	14.980***	-23.154**	-18.249**	-17.181***	78.609***	50.399***	39.937***	37.310***	-23.385***	-31.593***	27.800**
	(3.597)	(9.746)	(7.825)	(6.649)	(7.807)	(10.413)	(6.468)	(9.802)	(5.328)	(7.186)	(11.761)
F statistic	21.674***	29.976***	74.760***	16.677***	34.792***	10.011***	70.665***	30.129***	16.512***	37.972***	20.348***
Short-term 1-5 days:											
Intercept	0.798***	-0.036	-1.250***	1.021***	0.518***	-0.145**	0.122**	0.608***	-2.279***	-0.868***	1.512***
	(0.060)	(0.100)	(0.089)	(0.056)	(0.061)	(0.064)	(0.058)	(0.064)	(0.081)	(0.062)	(0.087)
x_1	1.816***	-0.323	0.861***	-0.304*	-1.390***	1.337***	0.860***	0.656***	1.022***	-0.875***	-3.659***
	(0.170)	(0.283)	(0.252)	(0.160)	(0.173)	(0.182)	(0.165)	(0.180)	(0.229)	(0.175)	(0.245)
x_2	3.242***	3.143***	2.760***	-0.105	-0.818**	0.132	-0.713**	3.101***	-4.438***	-1.859***	-4.444***
	(0.322)	(0.537)	(0.478)	(0.303)	(0.328)	(0.346)	(0.312)	(0.341)	(0.434)	(0.331)	(0.464)
x_3	-1.300***	0.152	1.381**	-1.117***	-0.062	-0.303	0.434	-0.199	1.180*	1.451***	-1.618**
	(0.449)	(0.747)	(0.665)	(0.421)	(0.456)	(0.481)	(0.434)	(0.474)	(0.604)	(0.460)	(0.646)
x_4	-1.913***	-2.776***	-3.282***	4.327***	-3.094***	7.092***	1.394***	-2.464***	1.725***	-1.742***	0.733
	(0.469)	(0.782)	(0.696)	(0.441)	(0.477)	(0.503)	(0.454)	(0.496)	(0.632)	(0.482)	(0.676)
F statistic	59.239***	12.454***	17.732***	27.317***	26.393***	61.262***	10.792***	30.252***	35.642***	19.155***	75.923***
Medium-term 5-60 days:											
Intercept	0.083	5.905***	-1.771***	4.662***	-2.096***	-5.523***	2.008***	1.778***	-5.657***	-2.802***	3.413***
	(0.316)	(0.326)	(0.324)	(0.287)	(0.270)	(0.407)	(0.266)	(0.331)	(0.287)	(0.315)	(0.300)
x_1	11.181***	-15.009***	33.389***	-3.757	-13.436***	1.183	19.572***	9.932***	-9.917***	-13.031***	-0.106
	(0.895)	(0.922)	(0.917)	(2.814)	(0.763)	(1.153)	(0.754)	(0.937)	(0.813)	(0.892)	(0.851)
x_2	27.510***	-24.461***	17.712***	11.045***	-32.808***	6.843***	-7.523***	52.486***	-7.727***	-19.971***	-9.421***
	(1.695)	(1.746)	(1.736)	(1.541)	(1.446)	(2.184)	(1.428)	(1.774)	(1.539)	(1.689)	(1.612)
x_3	-5.024**	-12.863***	5.193**	-10.503***	4.274**	11.070***	6.499***	-0.756	10.971***	6.377***	-15.237***
	(2.359)	(2.430)	(2.416)	(2.145)	(2.012)	(3.040)	(1.987)	(2.469)	(2.142)	(2.351)	(2.243)
x_4	-1.338	-15.164***	5.820**	-17.440***	38.551***	31.828***	31.702***	23.021***	-19.419***	-10.294***	3.864*
	(2.468)	(2.543)	(2.529)	(2.245)	(2.105)	(3.181)	(2.080)	(2.583)	(2.241)	(2.460)	(2.347)
F statistic	67.701***	118.749***	346.945***	105.941***	292.232***	31.128***	248.485***	253.629***	66.585***	89.136***	20.186***
Long-term 60 days and more:											
Intercept	-10.870***	13.727***	3.673***	-4.277***	-17.681***	6.678***	-7.164***	7.556***	-14.912***	0.249	23.022***
	(0.916)	(1.098)	(0.829)	(0.708)	(0.886)	(1.152)	(0.735)	(1.130)	(0.603)	(0.757)	(1.375)
x_1	8.393***	-14.662***	13.124***	0.267	17.535***	-11.185***	15.160***	5.724*	2.591	-12.697***	-24.249***
	(2.594)	(3.109)	(2.348)	(2.006)	(2.510)	(3.263)	(2.081)	(3.200)	(1.707)	(2.145)	(3.894)
x_2	20.434***	-23.205***	2.852	10.579***	6.402	-15.941***	13.199***	8.714	11.584***	-7.843*	-26.776***
	(4.913)	(5.888)	(4.447)	(3.798)	(4.754)	(6.180)	(3.942)	(6.059)	(3.232)	(4.062)	(7.374)
x_3	8.806	-17.649**	11.205***	1.504	18.415***	14.306***	11.300**	-6.973	17.806***	11.481***	-29.178***
	(6.838)	(8.194)	(3.189)	(5.286)	(6.616)	(3.601)	(5.486)	(8.433)	(4.498)	(3.653)	(10.262)
x_4	18.228**	-5.243	-20.767***	-4.055	43.172***	11.45	9.608*	16.734*	-5.647	-19.529***	24.734**
	(7.155)	(8.574)	(6.477)	(5.532)	(6.923)	(9.000)	(5.740)	(8.825)	(4.707)	(5.916)	(10.739)
F statistic	8.131***	9.752***	10.880***	2.112*	22.509***	4.898***	17.107***	2.273*	7.752***	11.710***	14.763***

[1] ***, **, * indicate significant at 1%, 5%, and 10% levels, respectively.
[2] The data in parentheses are standard errors.
[3] x_1 represents the 2015-2016 stock market sell-off, x_2 represents the 2018 cryptocurrency crash, x_3 represents the 2020 COVID-19 outbreak and x_4 represents the 2022 Russo-Ukrainian War.

Table 2: Full dummy variable regression table for return series

	Energy(1)	Materials(2)	Industrials(3)	Cons.Disc(4)	Cons.Staples(5)	Health.Care(6)	Financials(7)	Info.Tech(8)	Tele.Services(9)	Utilities(10)	Real.Estate(11)
Total:											
Intercept	-6.307***[1]	-9.963***	12.415***	14.436***	-5.069***	-10.576***	10.895***	-3.494***	-4.496***	-3.540***	5.699***
	(0.255)[2]	(0.224)	(0.244)	(0.230)	(0.280)	(0.273)	(0.248)	(0.247)	(0.183)	(0.242)	(0.265)
x_1[3]	4.899***	-9.688***	3.588***	3.714***	-1.643**	5.019***	4.697***	6.045***	-6.551***	0.684	-3.586***
	(0.723)	(0.635)	(0.691)	(0.651)	(0.794)	(0.773)	(0.704)	(0.699)	(0.518)	(0.685)	(0.749)
x_2	-5.450***	-6.951***	16.049***	12.792***	6.543***	15.172***	4.266***	14.461***	-13.911***	-3.226**	-5.629***
	(1.370)	(1.202)	(1.308)	(1.232)	(1.503)	(1.464)	(1.333)	(1.324)	(0.981)	(1.297)	(1.419)
x_3	-0.373	-15.729***	12.964***	-20.505***	12.986***	19.498***	6.967***	-14.603***	11.946***	17.758***	-14.982***
	(1.907)	(1.673)	(1.821)	(1.715)	(2.091)	(2.038)	(1.855)	(1.842)	(1.365)	(1.805)	(1.975)
x_4	15.856***	-4.928***	9.325***	-11.933***	-23.791***	29.311***	5.089***	11.657***	-32.293***	13.447***	1.564
	(1.995)	(1.751)	(1.906)	(1.794)	(2.189)	(2.132)	(1.941)	(1.928)	(1.429)	(1.889)	(2.067)
F statistic	31.440***	83.275***	53.328***	83.880***	45.918***	98.913***	19.678***	71.769***	228.102***	38.405***	22.383***
Short-term 1-5 days:											
Intercept	-5.357***	-8.346***	8.578***	9.278***	-5.231***	-7.602***	13.497***	-4.295***	-3.551***	-0.425**	3.453***
	(0.199)	(0.187)	(0.193)	(0.199)	(0.204)	(0.206)	(0.212)	(0.215)	(0.163)	(0.186)	(0.220)
x_1	1.725***	-4.691***	3.188***	4.021***	1.603***	0.43	1.142*	6.341***	-3.104***	1.622***	-3.615***
	(0.564)	(0.530)	(0.546)	(0.564)	(0.577)	(0.583)	(0.600)	(0.609)	(0.461)	(0.527)	(0.623)
x_2	-2.017*	-13.129***	17.342***	9.149***	3.964***	5.617***	9.820***	13.358***	-11.626***	-2.247**	7.706***
	(1.068)	(1.003)	(1.035)	(1.069)	(1.093)	(1.104)	(1.136)	(1.154)	(0.874)	(0.998)	(1.179)
x_3	-4.662***	9.730***	15.567***	-20.538***	26.396***	13.396***	-3.437**	-24.702***	11.720***	17.720***	-10.057***
	(1.486)	(1.396)	(1.440)	(1.487)	(1.522)	(1.536)	(1.581)	(1.606)	(1.216)	(1.389)	(1.641)
x_4	9.118***	-7.087***	-4.352***	-11.286***	10.899***	15.731***	6.977***	5.566***	-2.953**	-8.293***	0.368
	(1.555)	(1.461)	(1.507)	(1.556)	(1.592)	(1.608)	(1.655)	(1.680)	(1.272)	(1.454)	(1.717)
F statistic	14.549***	78.241***	114.135***	94.876***	88.786***	47.655***	23.886***	123.995***	80.074***	53.049***	29.492***
Medium-term 5-60 days:											
Intercept	-0.939***	-1.493***	3.647***	4.871***	-0.03	-2.768***	-2.421***	0.790***	-0.888***	-2.913***	2.145***
	(0.119)	(0.109)	(0.115)	(0.081)	(0.112)	(0.119)	(0.093)	(0.107)	(0.098)	(0.099)	(0.109)
x_1	3.017***	-4.740***	0.428	-0.282	-2.868***	4.277***	5.459***	-0.313	-3.234***	-0.906***	0.018
	(0.338)	(0.308)	(0.327)	(0.230)	(0.318)	(0.336)	(0.264)	(0.302)	(0.278)	(0.280)	(0.309)
x_2	-3.414***	5.886***	-1.170*	3.476***	2.910***	8.676***	5.026***	0.945*	-2.157***	-0.980*	-12.246***
	(0.639)	(0.584)	(0.619)	(0.436)	(0.603)	(0.637)	(0.500)	(0.573)	(0.527)	(0.530)	(0.586)
x_3	3.040***	-22.300***	11.205***	-1.105*	11.406***	5.440***	9.287***	9.369***	1.237*	0.629	-5.397***
	(0.890)	(0.812)	(0.861)	(0.607)	(0.839)	(0.886)	(0.696)	(0.797)	(0.734)	(0.737)	(0.815)
x_4	7.334***	2.067**	12.448***	-0.629	-32.125***	12.615***	1.637**	5.024***	-27.640***	20.461***	1.192
	(0.931)	(0.850)	(0.901)	(0.636)	(0.878)	(0.927)	(0.728)	(0.834)	(0.768)	(0.772)	(0.853)
F statistic	45.524***	275.068***	91.558***	16.754***	398.939***	128.854***	163.272***	44.304***	352.470***	182.042***	119.550***
Long-term 60 days and more:											
Intercept	-0.01	-0.124***	0.190***	0.286***	0.192	-0.206***	-0.181***	0.012	-0.057***	-0.201***	0.100***
	(0.034)	(0.040)	(0.020)	(0.006)	(0.172)	(0.045)	(0.022)	(0.039)	(0.010)	(0.023)	(0.021)
x_1	0.157	-0.258**	0.028	-0.026	-0.377	0.313**	0.380***	0.017	-0.213***	-0.033	0.012
	(0.096)	(0.112)	(0.057)	(0.018)	(0.486)	(0.128)	(0.061)	(0.112)	(0.029)	(0.064)	(0.059)
x_2	-0.019	0.292	-0.123	0.167***	-0.331	0.879***	0.528***	0.158	-0.128**	0.001	-1.090***
	(0.182)	(0.213)	(0.108)	(0.033)	(0.921)	(0.243)	(0.116)	(0.212)	(0.055)	(0.121)	(0.111)
x_3	1.249***	-3.160***	1.398***	1.138***	-2.004	0.661*	1.117***	0.730**	-1.012***	0.590***	0.473***
	(0.253)	(0.296)	(0.150)	(0.046)	(1.281)	(0.339)	(0.161)	(0.295)	(0.076)	(0.169)	(0.154)
x_4	-0.596**	0.092	1.229***	-0.019	-2.565*	0.966***	0.251	1.067***	-1.700***	1.279***	0.004
	(0.265)	(0.310)	(0.157)	(0.048)	(1.341)	(0.354)	(0.168)	(0.308)	(0.080)	(0.177)	(0.161)
F statistic	8.049***	30.064***	37.088***	159.996***	1.612	6.841***	25.038***	4.552***	164.906***	16.488***	26.998***

[1] ***, **, * indicate significant at 1%, 5%, and 10% levels, respectively.
[2] The data in parentheses are standard errors.
[3] x_1 represents the 2015-2016 stock market sell-off, x_2 represents the 2018 cryptocurrency crash, x_3 represents the 2020 COVID-19 outbreak and x_4 represents the 2022 Russo-Ukrainian War.