Bull and Bear Market: Asymmetric Volatility Spillover Effects

Project

By

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ABSTRACT

Purpose

To investigate the Asymmetric Volatility Spillover Effects within and across International stock markets.

Study design/methodology/approach

GARCH (Generalized Autoregressive Conditional Heteroscedasticity) Model, Markov-switching model, and Vector Autoregressive Model.

Findings

Volatility spillovers are asymmetric, with the largest impact being auto-influence. Canada has the least impact on other countries, while Japan and the US experience the least cross-influence volatility from abroad. Italy is most impacted by external volatility changes.

In order to realistically and accurately predict volatility, investors' expectations are a significant factor. In contrast to Bensaida (2019), the United States maintains dominance with respect to global market influence.

Originality/value

Existing Literature continues to use either realized volatility or conditional volatility without controlling for expected return of the market. This leads to overestimated volatility as well as biased spillover effects. This research combines GARCH and Markov-switching models to capture conditional volatility and expected return simultaneously. It also contributes to the good and bad volatility literature by showing that using time-varying expected return as threshold to distinguish good and bad is better than using 0.

Practical Implications

Stakeholders in the financial sector (Hedge Funds, Money and Asset managers etc) can leverage findings and insights from this research to inform investment strategies, risk management and the exploitation of spillover opportunities. A reliable and robust data ecosystem, highly qualified analysts and organizational management are required for the implementation and deployment of this model.

Keywords

Expected-Return, Asymmetry, Volatility, Spillover, GARCH, Markov-Switching, Vector Autoregression

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CHAPTER 1: INTRODUCTION

Business Framework

The interdependence of financial markets has been widely investigated both in terms of return and return volatilities (King et al., 1994; Forbes and Rigobon, 2002). During crises, for example, the financial market volatility generally increases sharply and spills over across markets. Diebold and Yilmaz (2012) introduce a simple measure of volatility spillovers across markets by using a generalized vector autoregressive framework. Their methods have been widely applied to many different markets, including stock, energy, foreign exchange, and commodities.

On the other hand, one of the most enduring stylized facts in finance is the negative correlation between stock return and volatility of the return. This negative correlation leads to an asymmetric distribution of stock returns. Bekaert and Wu (2000) and Wu (2001), among others, explain this phenomenon using leverage effects or feedback effects. Other studies (e.g. Chen and Ghysels, 2011; Bekaert et al. 2015) argue that good news and bad news have different impact on stock return volatility, and knowing a volatility reaction to the sign of a shock is relevant to the analysis of market dynamics and the implementation of more effective hedging and trading strategies.

Motivated by this asymmetric relationship between good and bad news and volatility, BenSaida (2019) applies Diebold and Yilmaz's (2012) method to analyze whether the volatility from good news transmitted across financial markets in the same way as volatility from bad news. BenSaida(2019) infers the conditional volatilities from a conditional heteroskedastic model, and he uses the sign of return to determine whether the news is good or bad. In other words, if the return at a period is positive, then the news is good and the inferred conditional volatility at that period will be counted as volatility from good news, and vice versa. Using the directional asymmetric spillovers measure from Diebold and Yilmaz (2012), he finds significant differences in volatility transmission among international stock markets.

Bensaida's (2019) model can be extended in several ways.

1. It assumes a constant zero mean for stock return, this may overlook the time-varying expected return and thus overestimate the volatility.
2. The criterion for good and bad volatility is using 0 as an absolute threshold. However, good and bad news should be evaluated relative to investors' expectations rather than an absolute threshold.

3. It would be interesting to see if the volatility spillover effects are also asymmetric between bull and bear markets.
4. A by-product of this project is the probabilities of each period belonging to the bear market. This can be seen as a bear market index. It would also be interesting to see how bear market index spillovers to other markets.

In this project, we propose a new model to identify bull and bear market along with the good and bad conditional volatility in the stock returns. We consider the following model,

$$r_t = \mu s_t + \epsilon_t \sqrt{h_t}, \varepsilon_t \sim i.i.d(0,1),$$

$$h_t = \alpha s_t + \alpha h_{t-1} + \beta r_{t-1}^2 + \delta 1_{[rt-1<0]} r_{t-1}^2,$$

Where $S_t = 1, 2$ is a two-state Markov-switching regime variable with the transition probabilities $Pr(S_t = j | S_{t-1} = i) = p_{ij}$, where $S_t = 1$ denotes bull market, and $S_t = 2$ for the bear market. We also allow the mean in the conditional heteroskedasticity equation to switch to capture the different nature in volatility in bull and bear markets.

With this model we can assign probabilities of bull and bear markets for each period of data and then calculate the time-varying average return.

Analytics Objectives

- Visualize expected return and conditional volatility in six stock markets.
- Analyze how the volatility of the stock market in one country spills over to other markets.
- Predict and quantify the volatility spillover effects after controlling for expected returns.
- Measure the dynamics of volatility spillover effects during unusual events such as financial crisis, pandemics etc.

CHAPTER 2.1: BACKGROUND AND ANALYTICS OBJECTIVES

Company Background and Macro Environment Analysis

In light of the fact that the potential beneficiaries of our research work in this project includes financial institutions such as hedge funds, mutual investments funds, and related asset managers, we highlight the company background of a particular firm in this sector to implement the assigned task. We provide the company background and macro environmental and industry analysis.

Company: JP Morgan Asset Management Organization

The firm was established as J.P. Morgan & Co., a commercial banking and investment banking firm, by J. Pierpont Morgan in 1871. The firm created its first institutional management division in 1959.

In the 1980s, the firm expanded its investment management business and acquired several asset management firms, including Mitchell Hutchins Asset Management and The First National Bank of Boston's investment management division and till date, acquisitions continue to be one of the firm's growth strategies. Today, J.P. Morgan Asset Management is one of the largest asset management firms in the world, with more than $3 trillion in assets under management. The firm offers a wide range of investment products and services, including traditional and alternative investment strategies, to individual and institutional investors.

Mission and Objectives

J.P. Morgan Asset Management's mission is to provide its clients with investment solutions that help them achieve their financial goals. The firm's objectives are focused on delivering consistent investment performance, innovative products and services, and exceptional client service.

Some of its key objectives includes:

- Investment Performance: J.P. Morgan Asset Management strives to deliver investment performance that meets or exceeds its clients' expectations. The firm invests in a broad range of asset classes and uses a rigorous investment process to identify attractive investment opportunities and manage risk.
- Innovation: J.P. Morgan Asset Management is committed to developing innovative investment solutions that meet the evolving needs of its clients. The firm invests in

cutting-edge technology and research to stay ahead of industry trends and offer its clients access to new investment strategies and products.

- Client Service: J.P. Morgan Asset Management places a high priority on delivering exceptional client service. The firm has a dedicated team of professionals who are available to answer clients' questions and help them make informed investment decisions.
- Responsible Investing: J.P. Morgan Asset Management recognizes the important role that investment management can play in promoting sustainability and addressing social and environmental challenges. The firm incorporates responsible investing principles into its investment processes and offers a range of responsible investing solutions to its clients.

Core Competencies and Value Proposition

JP Morgan Asset Management's core competencies includes:

- Investment Performance: J.P. Morgan Asset Management strives to deliver investment performance that meets or exceeds its clients' expectations. The firm invests in a broad range of asset classes and uses a rigorous investment process to identify attractive investment opportunities and manage risk.
- Investment Expertise: J.P. Morgan Asset Management has a team of experienced investment professionals with deep expertise in a range of asset classes and investment strategies. The firm uses a rigorous investment process to identify attractive investment opportunities and manage risk.
- Global Reach: J.P. Morgan Asset Management has a global presence, with investment professionals and offices located around the world. This allows the firm to offer its clients access to a wide range of investment opportunities and to provide local market insights.
- Innovation: J.P. Morgan Asset Management is committed to developing innovative investment solutions that meet the evolving needs of its clients. The firm invests in cutting-edge technology and research to stay ahead of industry trends and offer its clients access to new investment strategies and products.
- Risk Management: J.P. Morgan Asset Management places a high priority on risk management, and has developed a robust risk management framework to help ensure that its clients' investments are managed in a responsible and sustainable manner.
- Client Service: J.P. Morgan Asset Management is dedicated to delivering exceptional client service. The firm has a team of professionals who are available to answer clients' questions and help them make informed investment decisions.

- Responsible Investing: J.P. Morgan Asset Management recognizes the important role that investment management can play in promoting sustainability and addressing social and environmental challenges. The firm incorporates responsible investing principles into its investment processes and offers a range of responsible investing solutions to its clients.

Description of current marketing programs

J.P. Morgan Asset Management uses a range of marketing practices to promote its products and services and reach its target market. Some of the key marketing practices used by the firm include

- Digital Marketing Programs: J.P. Morgan Asset Management has a strong online presence and uses digital channels, such as its website, social media, and email campaigns, to reach its target audience. The firm also uses online advertising programs to promote its products and services to potential clients.

- Client Outreach Programs: J.P. Morgan Asset Management has a dedicated team of relationship managers who are responsible for building and maintaining relationships with clients. The firm may have specific client outreach programs in place, such as regular client webinars or face-to-face meetings, to promote its products and services and engage with its clients.

- Referral Marketing Programs: J.P. Morgan Asset Management leverages its network of existing clients to generate new business through referral marketing. The firm may have specific referral marketing programs in place to incentivize clients to refer their friends, family, and colleagues to the firm, and to support clients in making the referral.

- Content Marketing Programs: J.P. Morgan Asset Management produces a range of content, such as research reports, investment insights, and thought leadership articles, to educate its target audience about its products and services and build its reputation as a trusted investment advisor. The firm may have specific content marketing programs in place to support the production and distribution of this content.

- Events and Conferences Programs: J.P. Morgan Asset Management participates in a number of industry events and conferences, such as investment conferences, trade shows, and seminars, to promote its products and services and engage with its target audience. The firm may have specific programs in place to support its participation in these events, such as speaker programs or sponsorship programs

Description of current management and human resources practice

J.P. Morgan Asset Management places a high priority on attracting, retaining, and developing talent, and has a range of programs and initiatives in place to support employee development and engagement. The firm has a reputation for providing its employees with a supportive work environment, competitive compensation and benefits, and opportunities for career advancement.

In terms of management practices, J.P. Morgan Asset Management is known for its strong leadership, clear strategic vision, and commitment to delivering results for its clients. The firm has a well-established investment process that is supported by a culture of risk management and accountability. J.P. Morgan Asset Management also places a strong emphasis on ethical behavior and compliance with regulatory requirements.

The firm has a diverse and inclusive culture, and has been recognized for its efforts to promote diversity and equality in the workplace. J.P. Morgan Asset Management provides its employees with training and development opportunities, and encourages a work-life balance.

Overall, J.P. Morgan Asset Management's management and human resources practices are designed to support its employees and contribute to the success of the firm and its clients.

Industry Analysis:

Professionally managed assets under management grew for a third consecutive year reaching an all time high of $123 trillion. By the end of 2021, the largest concentration is in the North American market with $62.9 trillion followed by Europe at $40.5 trillion, Asia Pacific at $17.4 trillion and the rest of the world contributing $2.7 trillion to the total as shown by Deloitte Insights (2022). The recorded compound annual growth rate has shown double digits over the 7 years with Asia Pacific recording the largest growth rate at 14.7%

In 2021, private capital outperformed hedge funds returning 39.7% compared to 10.2% on an absolute return basis for a one-year period. Open-ended funds take the largest share of investments as of end of year 2021 accounting for 57.5% of all investments followed by 30.5% (all others), private capital at 8% and hedge funds at 3.8%.

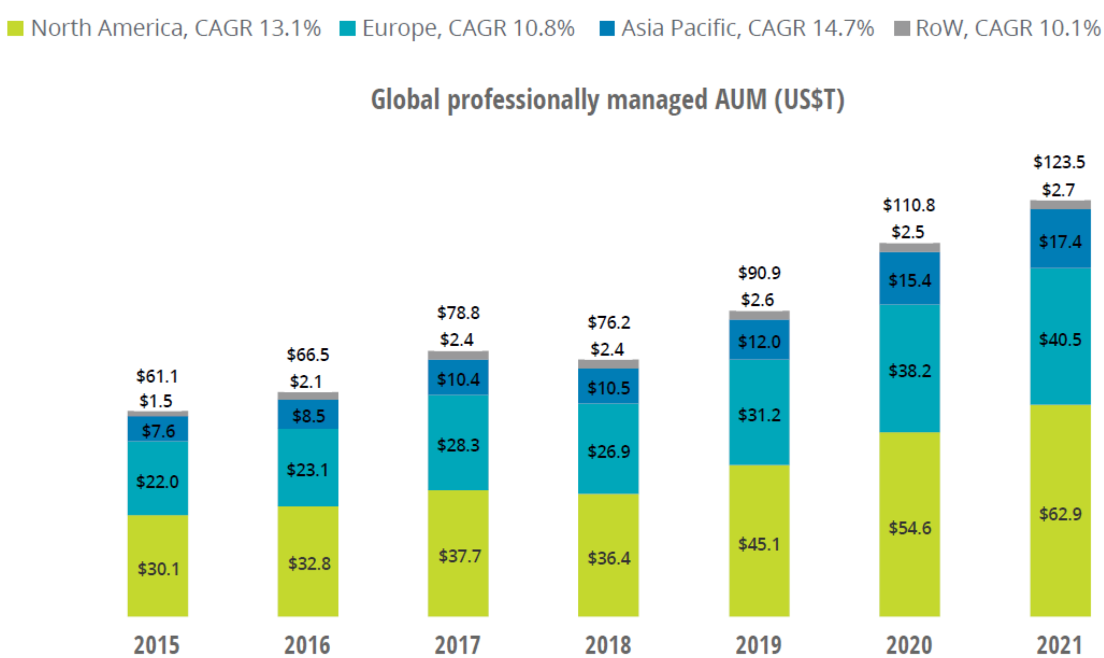
The year 2021 was a difficult one for many active managers, and the outlook for 2022 and beyond is expected to bring even more challenges. According to a survey of global managers, 66% and 59% of respondents are worried that inflation and the geopolitical landscape will have a negative effect on their firms in the next 12 months (Deloitte Insights, 2022). Those with significant concerns about inflation are mainly located in the United States.

These worries appear to be having an impact on US public markets, which entered a bear market in the second quarter of 2022. This means that stock prices have dropped significantly from their peak levels, making it difficult for investors to make money from their investments. The bear market has been caused by a combination of factors, including rising inflation expectations, increasing interest rates, and political uncertainty (JPM-AM, 2022).

Inflation is likely to remain an issue in 2023 as well, as it has been steadily increasing since 2020. This could lead to higher prices for goods and services, which could further reduce investor confidence in the stock market. Additionally, geopolitical tensions could also cause volatility in the markets as countries compete for resources or try to gain an advantage over one another.

Given these challenges, active managers will need to be more strategic than ever when it comes to investing in 2023 and beyond. They will need to carefully consider how different economic and political factors may affect their investments before making any decisions. Additionally, they should also look for opportunities where they can take advantage of any potential upside while minimizing risk exposure.

According to Deloitte Insights (2022), portfolio managers are increasingly turning to advanced technologies such as artificial intelligence, data acquisition and data analytics to gain an edge over traditional index investing. By leveraging these capabilities, portfolio managers can identify and capitalize on opportunities that may not be available through index investing. This allows them to generate superior risk-adjusted returns for their clients. Additionally, these technologies can help portfolio managers better understand the markets and make more informed decisions about their investments. Ultimately, this can lead to higher returns for investors while also reducing the risk associated with investing.



Sources: Investments and Pensions Europe; Investment Company Institute; Deloitte Center for Financial Services analysis.

Fig 1. Global professionally managed AUM

A mutual fund is a professionally managed investment fund that pools money from many investors to purchase securities. The term is typically used in the United States, Canada, and India, while similar structures across the globe include the SICAV in Europe ('investment company with variable capital') and open-ended investment company (OEIC) in the UK.

Mutual funds are often classified by their principal investments: money market funds, bond or fixed income funds, stock or equity funds, or hybrid funds. Funds may also be categorized as index funds, which are passively managed funds that track the performance of an index, such as a stock market index or bond market index, or actively managed funds, which seek to outperform stock market indices but generally charge higher fees. Primary structures of mutual funds are open-end funds, closed-end funds, and unit investment trusts.

Open-end funds are purchased from or sold to the issuer at the net asset value of each share as of the close of the trading day in which the order was placed, as long as the order was placed within a specified period before the close of trading. They can be traded directly with the issuer.

Mutual funds have advantages and disadvantages compared to direct investing in individual securities. The advantages of mutual funds include economies of scale, diversification, liquidity, and professional management.However, these come with mutual fund fees and expenses.

Mutual funds are regulated by governmental bodies and are required to publish information including performance, comparison of performance to benchmarks, fees charged, and securities held. A single mutual fund may have several share classes by which larger investors pay lower fees.

Hedge funds and exchange-traded funds are not mutual funds, and each is targeted at different investors, with hedge funds being exclusively available to high net worth individuals.

Industry size and Industry outlook

At the end of 2020, open-end mutual fund assets worldwide were $63.1 trillion.The countries with the largest mutual fund industries are:

1. United States: $23.9 trillion
2. Australia: $5.3 trillion
3. Ireland: $3.4 trillion
4. Germany: $2.5 trillion
5. Luxembourg: $2.2 trillion
6. France: $2.2 trillion

7. Japan: $2.1 trillion
8. Canada: $1.9 trillion
9. United Kingdom: $1.9 trillion
10. China: $1.4 trillion

At the end of 2019, 23% of household financial assets were invested in mutual funds. Mutual funds accounted for approximately 50% of the assets in individual retirement accounts, 401(k)s and other similar retirement plans.

Luxembourg and Ireland are the primary jurisdictions for the registration of UCITS funds. These funds may be sold throughout the European Union and in other countries that have adopted mutual recognition regimes.

Nine major competitors and their strategies

Competitor analysis is a crucial component of any market research process. By studying your competitors, you can determine what they do well and what they could do better, which can inform your own strategies for differentiating your products and services in the marketplace.

According to J.P. Morgan, the fund seeks current income with liquidity and stability of principal by exclusively investing in high-quality, short-term securities that are issued or guaranteed by the U.S. government or by U.S. government agencies. The fund has a stated expense ratio of .59% as of November 1, 2021. Fund document's state that the 10 year, quarter end average annual return as of December 31, 2021 is .36%. As of the most recent reporting period, the total assets of the fund were $259,896 million.

The following text lists nine companies that are considered competitors in the industry.

1. Vanguard Total Stock Market Index Fund Admiral Shares (VTSAX)
   Total Assets ($ millions): 1,308,922
   Asset Class: Domestic Equities
   Description: According to Vanguard, the fund is designed to provide exposure to the entire U.S. equity market. The fund has a stated expense ratio of .04% as of April 29, 2021. Fund document's state that the 10 year, quarter end average annual return as of December 31, 2021 is 16.29%.

2. Vanguard 500 Index Fund Admiral Shares (VFIAX)
   Total Assets ($ millions): 816,307
   Asset Class: Domestic Equities
   Description: According to Vanguard, the fund is designed to provide diversified exposure to the U.S. equity market through investments in the largest 500 U.S. companies. The

fund has a stated expense ratio of .04% as of April 29, 2021. Fund document's state that the 10 year, quarter end average annual return as of December 31, 2021 is 16.51%.

3. Vanguard Total International Stock Index Fund Admiral Shares (VTIAX)
   Total Assets ($ millions): 407,995
   Asset Class: Global Equities
   Description: According to Vanguard, the fund is designed to provide exposure to equities in both developed and emerging international economies, tracking global stock markets outside the U.S. The fund has a stated expense ratio of .11% as of February 25th, 2022. Fund document's state that the 10 year, quarter end average annual return as of December 31, 2021 is 7.68%.

4. Fidelity® 500 Index Fund (FXAIX)
   Total Assets ($ millions): 399,363
   Asset Class: Domestic Equities
   Description: According to Fidelity, the fund is designed to provide investment results that correspond to the total return of U.S. publicly traded common stocks. The fund has a stated expense ratio of .015% as of April 29, 2021. Fund document's state that the 10 year, quarter end average annual return as of December 31, 2021 is 16.54%.

5. Vanguard Total Bond Market Index Fund Admiral Shares (VBTLX)
   Total Assets ($ millions): 312,467
   Asset Class: U.S. Investment Grade Bonds
   Description: According to Vanguard, the fund is designed to provide broad exposure to U.S. investment-grade bonds by investing in U.S. Treasuries and mortgage-backed securities. The fund has a stated expense ratio of .05% as of April 29, 2021. Fund document's state that the 10 year, quarter end average annual return as of December 31, 2021 is 2.86%.

6. American Funds: The Growth Fund of America ® (CGFAX)
   Total Assets ($ millions): 292,071
   Asset Class: Growth Assets
   Description: According to Capital Group, the fund seeks growth of capital via investments in domestic and international growth stocks, cyclical companies, turnarounds, and asset classes outside of stocks. The fund has a stated expense ratio of .65% as of November 1, 2021. Fund document's state that the 10 year, quarter end average annual return as of December 31, 2021 is 17.42%.

7. Fidelity® Government Money Market Fund (SPAXX)
   Total Assets ($ millions): 256,044

Asset Class: U.S. Government Money Market
Description: According to Fidelity, the fund seeks current income with liquidity and preservation of capital by investing "at least 99.5% of the fund's total assets in cash, U.S. Government securities and/or repurchase agreements that are collateralized fully." The fund has a stated expense ratio of .42% as of June 29, 2021. Fund document's state that the 10 year, quarter end average annual return as of December 31, 2021 is .42%.

8. Vanguard Total Bond Market II Index Fund (VTBNX)
   Total Assets ($ millions): 249,597
   Asset Class: U.S. Investment Grade Bonds
   Description: According to Vanguard, the fund is designed to provide broad exposure to U.S. investment-grade bonds, keeping pace with U.S. bond market returns. The fund has a stated expense ratio of .02% as of April 29, 2021. Fund document's state that the 10 year, quarter end average annual return as of December 31, 2021 is 2.81%.

9. Fidelity® Government Cash Reserves (FDRXX)
   Total Assets ($ millions): 229,915
   Asset Class: U.S. Government Money Market
   Description: According to Fidelity, the fund seeks current income with liquidity and preservation of capital by investing "at least 99.5% of the fund's total assets in cash, U.S. Government securities and/or repurchase agreements that are collateralized fully." The fund has a stated expense ratio of .33% as of January 29, 2021. Fund document's state that the 10 year, quarter end average annual return as of December 31, 2021 is .44%.

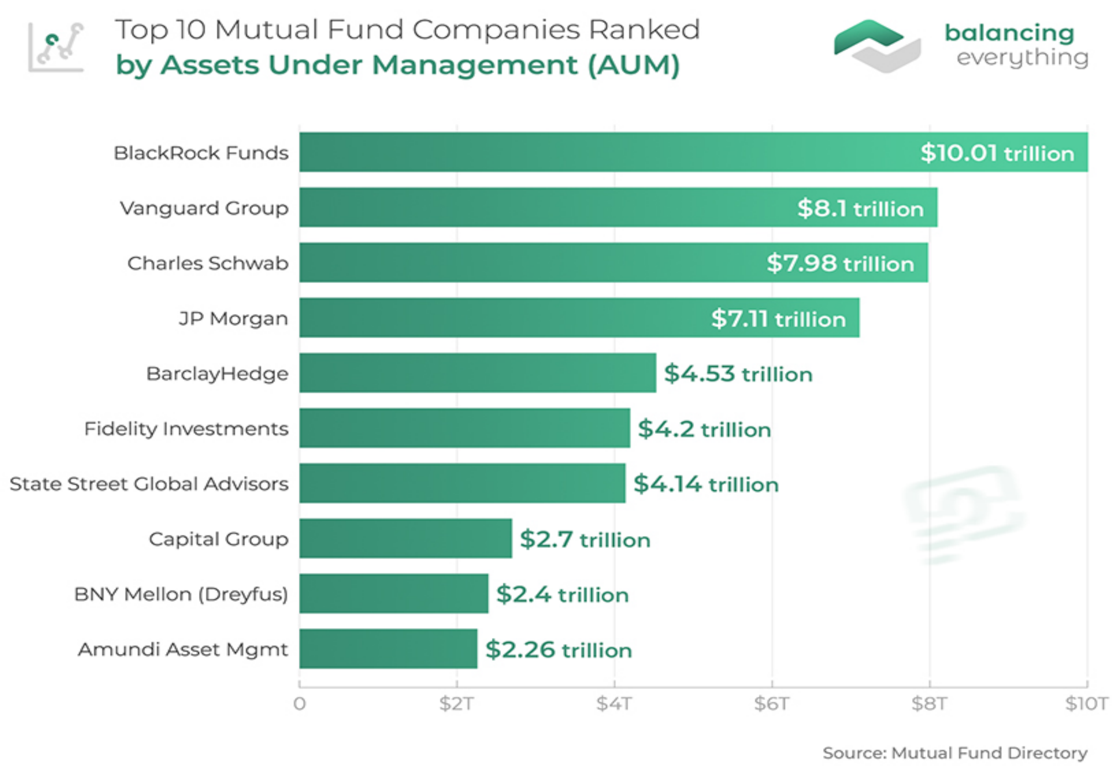


Fig 2. Top 10 mutual fund companies

Customer Analysis

JP Morgan is one of the world's leading financial services institutions, offering a wide range of investment products and services to individual and institutional investors. Founded in 1871, JP Morgan has grown to become a global leader in the financial services industry, with headquarters in New York City, New York.

JP Morgan's investment management division provides traditional and alternative investment strategies to its clients. As of December 2022, JP Morgan had total revenue of $32.3 billion and a net profit margin of 34.12%. The company also had assets under management totaling $7.11 trillion, making it one of the largest asset managers in the world.

JP Morgan's key objectives are to provide superior investment performance, foster innovation, deliver exceptional client service, and promote responsible investing. To achieve these goals, JP Morgan has established a number of initiatives such as its Sustainable Investing Program which focuses on environmental, social and governance (ESG) criteria when selecting investments for its clients. Additionally, JP Morgan has developed an innovative technology platform that allows clients to access their accounts online and manage their investments more efficiently.

In addition to its core business activities, JP Morgan is committed to giving back to the communities it serves through philanthropic efforts such as its JPMorgan Chase Foundation which provides grants for education and economic development initiatives around the world. The company also supports numerous charitable organizations through employee volunteerism programs and corporate donations.

JP Morgan is composed of four major business segments based on their revenue and net income ending Q4 FY 2021: Consumer and community banking; Corporate and investment banking; Asset and wealth management; and Commercial banking. Total revenue reported was approximately $29.2 billion with a net income of $10.4 billion for a net profit margin of 36%. JP Morgan clients within these segments include global financial intermediaries, sovereign wealth funds, central banks, pension funds, endowments and foundations. The following are JP Morgan's customer segments by revenue:

1. Consumer and Community Banking
   Percent of total revenue: 40%
   Percent of total net income: 37%
   Description: The consumer and community banking segment is composed of both consumers and businesses. JP Morgan offers services to consumers and businesses including investment products, deposit, cash management, credit, mortgage and loans. The reported revenue for this segment is $12.3 billion with a net income of $4.2 billion for a net profit margin of 34%.

2. Corporate and Investment Banking
   Percent of total revenue: 37%
   Percent of total net income: 42%
   Description: The corporate and investment bank segment is composed of corporations, investors, financial institutions and governments. Services offered by JP Morgan in this segment include investment banking, prime brokerage, capital raising, market-making, treasury, and securities services. The reported revenue for this segment is $11.5 billion with a net income of $4.8 billion for net profit margin of 42%.

3. Asset and Wealth Management
   Percent of total revenue: 14%
   Percent of total net income: 10%
   Description: JP Morgan offers strategies and solutions across all asset classes in the asset and wealth management segment as well as brokerage, banking, and retirement

services. The reported revenue for this segment is $4.5 billion with a net income of $1.1 billion for a net profit of margin of 24%.

4. Commercial Banking
Percent of total revenue: 8%
Percent of total net income: 11%
Description: The commercial banking segment is composed of small businesses, mid sized corporations, large corporations and local governments. Products and services offered by JP Morgan in this segment include asset management, investment banking, risk management, lending and payments, and a variety of financial solutions. The reported revenue for this segment is $2.6 billion with a net income of $1.3 billion for a net profit of margin of 50%.

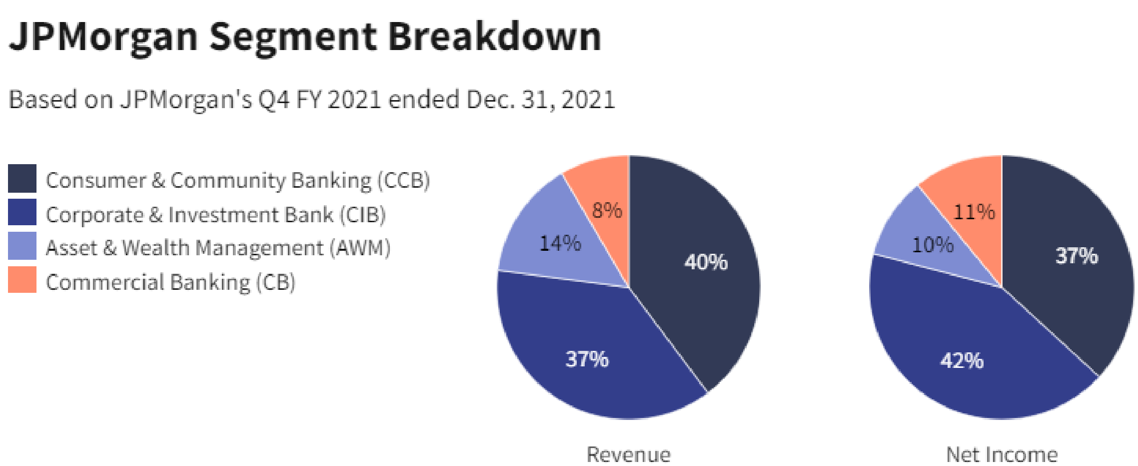


Fig 3. JP Morgan Customer Segment Breakdown Pie Chart

SWOT Analysis

Strengths

JP Morgan has several key strengths, and the following are some of the most significant ones.

- Leading market position: JP Morgan's strong brand name going back two centuries and well-established financial base have helped it build a positive reputation in the market, allowing the company to expand its business into diverse markets.
- Strong Financial position: JP Morgan Chase benefits from robust free cash flows, which give the company the resources it needs to pursue new ventures and expand its operations. With assets worth $3.7 billion, JP Morgan ranks as the fifth largest bank in

the world, and it also holds the distinction of being the largest bank worldwide in terms of market capitalization.

- International presence: With operations spanning over 100 countries and a vast employee base of approximately 250,000 individuals, JP Morgan maintains a significant global presence.
- Corporate social responsibility: In 2019, the company invested a total of $324.5 million in global philanthropic and business projects, with the aim of reaching a total of $1.75 billion by 2023. This commitment to CSR is part of their mission to create positive change in communities around the world.

Weaknesses

- Legal and regulatory problems: JP Morgan has previously dealt with a number of legal and regulatory problems, including fines and settlements relating to a variety of alleged misconduct and violations.
- Risk concentration: JP Morgan Chase has a presence in more than 100 countries, but they are mainly dependent on US activities. This reliance on the US market can be seen as a potential vulnerability, as any economic downturn in this area could have a significant impact on the bank's performance. If the US market were to experience a crisis, it could have serious repercussions for JP Morgan Chase and its operations worldwide.
- Cost-intensive processes: JP Morgan has a large operational expense and operates in more than 100 countries. Also, a sizable portion of the bank's costs are related to the salary it must pay its sizable employees. The fact that JP Morgan employs 250,000 people raises the company's operating expenses.
- Exposure to interest rate risk: JP Morgan is susceptible to interest rate risk because it is a bank, which could have a detrimental effect on the company's financial performance and earnings in a rising rate environment.

Opportunities

- Expansion into new markets: JP Morgan has the chance to grow into new areas and regions both domestically and internationally as a well-known financial firm. Doing so would reduce the company’s reliance on US activities. Currently, 53% of JP Morgan’s overall revenue is produced in the North American market.
- Contribution to sustainability: JP Morgan has the chance to engage in sustainability programs and goods to meet shifting consumer preferences as environmental, social, and governance (ESG) issues grow more significant to investors.

- Development of online banking: JP Morgan may take advantage of the rising trend and invest in its digital capabilities to better serve consumers and get a competitive edge with the growth of digital banking and online financial services. As all companies should, JP Morgan needs to innovate to stay ahead of its increasing competition.

Threats

- Regulations Changes: JP Morgan, like any other financial institution, perceives regulators as a threat due to the growing regulatory demands that keep evolving, causing compliance costs to surge for financial organizations. The government has the power to modify its policies at any time, which may impact the operations of a company. Therefore, it is crucial for companies to remain vigilant about such prospective changes.

- Competitor companies: The traditional banking sector has been disrupted by the growth of financial technology (fintech) businesses, and JP Morgan may experience more competition from these new entrants. JP Morgan must constantly innovate to maintain its position in the market and potentially even claw its way into the fintech sector in order to compete in such a market.

- Cybersecurity risks: As a large financial firm, JP Morgan is a major target for cyberattacks and data breaches that could cause monetary losses, legal repercussions, and reputational harm to the business. In February 2018, JP Morgan Chase encountered a technical difficulty which resulted in a security breach that enabled some customers to view other customers' account information. This caused an uproar among those affected, who took to social media to express their outrage.

- Economic Crisis: The company might have a financial crisis at any moment in the future without its knowledge, so to stay out of problems in those situations it needs to conduct a thorough financial analysis of its business and set aside funds specifically for certain situations.

Summary: SWOT Quadrants

In conclusion, JP Morgan Asset Management is a well-known and recognizable brand with a broad geographic reach and a solid financial foundation. But, the business also has to deal with issues like high operating costs and interest rate sensitivity. To maintain competitiveness and achieve long-term success in the constantly changing financial sector, JP Morgan must continue to capitalize on its strengths while minimizing its flaws.

CHAPTER 2.2: LITERATURE REVIEW, ANALYTICAL OBJECTIVES AND HYPOTHESIS DEVELOPMENT

Investigation of Currently Available Research Framework/Model

- Predictive Directional Measurement of Volatility Spillovers

  Diebold and Yilmaz (2012) introduce a simple measure of volatility spillovers across markets by using a generalized vector autoregressive framework. This framework measures total and directional volatility spillover. The research proposes that significant spillovers from one market to another intensify as a market intensifies, more specifically the US stock market during its financial crisis beginning in 2007.

- Asymmetric Volatility Spillovers Across Major Financial Markets

  BenSaida (2019) applies Diebold and Yilmaz's (2012) method to analyze whether the volatility from good news transmitted across financial markets in the same way as volatility from bad news. He infers the conditional volatilities from a conditional heteroskedastic model, and he uses the sign of return to determine whether the news is good or bad.

- The BEGE Model

  Bakaert, Engstrom, and Ermolov (2015) propose a model that utilizes two gamma distributed shocks that produces a conditional stock distribution with time varying heteroskedasticity, kurtosis, and skewness. This model expands on the asymmetric volatility frameworks using the generalized autoregressive conditional heteroskedasticity (GARCH) model by admitting non-Gaussianities.

- Asymmetric Volatility At Firm and Market Level

  Bekaert, and Wu (2000) present a framework to concurrently measure asymmetric volatility and risk at the firm and market level in order to examine leverage effects and volatility feedback as potential explanations of the asymmetry. This framework incorporates a conditional capital asset pricing model (CAPM) along with the generalized autoregressive conditional heteroskedasticity (GARCH) framework.

- High Frequency Data Volatility Prediction Models

Chen, and Ghysels (2011) introduce parametric models that can be applied to both high and low frequency returns to forecast volatility. This framework is used to predict next day volatility based on intra-daily news and returns as well as the impact on volatility of good versus bad news.

Diebold and Yilmaz (2012) paper titled "Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers' ' is a highly influential paper in the field of financial econometrics. The key findings of their paper are:

1. The authors proposed a new measure of spillover effects in financial markets, called the Spillover Index (SI), which is based on the principle of Granger causality. The SI captures the extent to which shocks in one market spill over to another market and provides a directional measure of spillovers.

2. The authors demonstrated that the SI is a useful tool for predicting financial crises, as it provides early warning signals of spillovers across markets. They showed that the SI can be used to construct a spillover index portfolio that outperforms traditional risk-based portfolios in terms of risk-adjusted returns.

3. The authors found evidence of significant spillover effects among major financial markets, including equity markets, bond markets, and commodity markets. They showed that the extent of spillovers varies over time and is influenced by global economic and financial conditions.

4. The authors also provided empirical evidence that spillover effects are asymmetric, meaning that spillovers from negative shocks are stronger than spillovers from positive shocks. This has important implications for portfolio management and risk-hedging strategies.

Overall, Diebold and Yilmaz's paper provided a novel and innovative approach to measuring and predicting spillover effects in financial markets, and their findings have important implications for both academic research and practical applications in finance.

Ahmed BenSaïda's (2019) paper titled "Good and bad volatility spillovers: An asymmetric connectedness" investigates the spillover effects of volatility shocks between the US equity market and four other major financial markets (Europe, Japan, UK, and Canada) during the period of 1999-2017. The paper's key findings include:

1. The paper finds that spillover effects between the US equity market and the four other markets are asymmetric, meaning that the transmission of negative volatility shocks is stronger and more persistent than the transmission of positive volatility shocks.

2. The paper identifies that there are "good" volatility spillovers, which refer to positive spillovers that contribute to the stability and efficiency of the financial system, and "bad" volatility spillovers, which refer to negative spillovers that increase systemic risk and financial instability.

3. The paper shows that the US equity market has a dominant role in the transmission of both good and bad volatility spillovers to the other markets. The US market is found to be the most connected and influential market with the highest level of spillover connectedness.

4. The paper highlights that the Brexit referendum in 2016 had a significant impact on the spillover effects of volatility between the UK market and the US market, leading to an increase in the transmission of bad volatility spillovers from the UK market to the US market.

Overall, BenSaïda's paper provides insights into the asymmetric nature of volatility spillovers and their impact on financial stability, emphasizing the importance of understanding the direction and nature of spillover effects in financial markets.

The GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model, first proposed by Robert Engel in 1982 and extended by Tim Bollerslev in 1986, is a popular model for modeling and forecasting volatility in financial time series data. The important findings from the research:

1. GARCH models can effectively capture the time-varying volatility patterns that are often observed in financial time series data. These patterns can be important for risk management and asset pricing.

2. GARCH models can help identify periods of high volatility and measure the uncertainty around volatility estimates.

3. The performance of GARCH models can be improved by incorporating additional features, such as leverage effects and asymmetries in the volatility response to positive and negative shocks.

4. GARCH models have been applied in a wide range of financial applications, including volatility forecasting, option pricing, portfolio optimization, and risk management.

5. The development of GARCH models has spurred research into other types of conditional volatility models, such as EGARCH and IGARCH, which incorporate additional features to improve their performance in specific contexts.

Overall, the GARCH model has had a significant impact on the field of financial econometrics and has become an important tool for researchers and practitioners alike in understanding and managing financial risk.

- The development of ARCH models

  ARCH models were first introduced in the early 1980s by Robert Engle. Engle was interested in modeling the volatility of financial time series, and he found that traditional time series models that assumed constant volatility were not able to capture the volatility clustering that is often observed in financial data. The ARCH model is a relatively simple model, but it is very effective in capturing volatility clustering. The ARCH model assumes that the variance of the time series is a linear function of the squared residuals from the previous period. This means that the volatility of the time series is dependent on its own past volatility.

- The estimation of ARCH models

  ARCH models can be estimated using a variety of methods, including maximum likelihood estimation, least squares estimation, and Bayesian estimation. Maximum likelihood estimation is the most common method for estimating ARCH models, but it can be computationally demanding for large datasets. Least squares estimation is a simpler method that is often used for small datasets. Bayesian estimation is a more recent method that is becoming increasingly popular for estimating ARCH models.

- The forecasting performance of ARCH models

  ARCH models have been shown to be effective in forecasting volatility. In a number of studies, ARCH models have been shown to outperform traditional time series models in forecasting volatility. However, ARCH models are not perfect, and they can sometimes make inaccurate forecasts.

- The use of ARCH models in risk management

  ARCH models are often used in risk management applications. For example, ARCH models can be used to calculate Value at Risk (VaR), which is a measure of the potential loss that a financial institution could incur. ARCH models can also be used to set stop-loss orders, which are orders that automatically sell a security if it falls below a certain price.

Regime switching is a common phenomenon in financial markets.

Financial markets are often characterized by periods of high volatility and periods of low volatility. These periods of different volatility are often referred to as regimes. Regime switching is the phenomenon of financial markets switching between these different regimes.

There are several reasons why regime switching might occur in financial markets. These reasons include changes in economic policy, changes in investor sentiment, and changes in market fundamentals.

Regime-switching models can capture the stylized behavior of many financial series.

Stylized facts are statistical properties that are observed in many financial series, but that cannot be explained by traditional financial models. These stylized facts include fat tails, heteroskedasticity, skewness, and time-varying correlations.

Regime-switching models can capture these stylized facts by allowing for different regimes with different statistical properties. For example, a regime-switching model might have a regime with high volatility and fat tails and another regime with low volatility and normal tails.

Regime switching can have a significant impact on the optimal portfolio choice of investors.

The optimal portfolio choice of investors depends on the expected returns, volatilities, and correlations of the assets in the portfolio. Regime switching can affect all these factors.

For example, if the regime-switching model predicts that the market is about to enter a period of high volatility, then an investor might want to reduce their exposure to risky assets. Conversely, if the regime-switching model predicts that the market is about to enter a period of low volatility, then an investor might want to increase their exposure to risky assets.

The Autoregressive Conditional Heteroskedasticity (ARCH) and Changes in Regime, by James D. Hamilton and Raul Susmel, are as follows:

- ARCH Model: The authors introduced the ARCH model to capture the time-varying volatility in financial data. They found that traditional models assuming constant volatility, such as the ordinary least squares (OLS) regression, are inadequate in capturing the volatility clustering and heteroskedasticity observed in financial data.

- Volatility Clustering: The ARCH model demonstrated that volatility tends to cluster together in time, meaning that periods of high volatility are followed by additional periods of high volatility, and periods of low volatility are followed by additional periods of low volatility. This finding suggests that financial markets exhibit time-dependent volatility patterns.

- Conditional Heteroskedasticity: The authors showed that the variance of the error term in a regression model is not constant but depends on past error terms or lagged squared error terms. This conditional heteroskedasticity is captured by the ARCH model, which allows for the estimation of time-varying volatility.
- Changes in Regime: Hamilton and Susmel expanded the ARCH model to incorporate regime changes, where the volatility dynamics shift between different states. They found that financial markets often experience distinct periods characterized by different volatility regimes. These regime shifts can be triggered by external events, changes in market conditions, or shifts in investor sentiment.
- Forecasting Volatility: The ARCH model and its extensions proved to be valuable tools for forecasting volatility in financial time series. By incorporating lagged squared error terms, the ARCH model allows for the estimation of future volatility based on past observations, providing insights for risk management and investment decision-making.

Overall, the research by Hamilton and Susmel on ARCH and changes in regime contributed to a better understanding of the time-varying volatility patterns in financial markets. Their findings highlighted the importance of capturing volatility clustering, conditional heteroskedasticity, and regime shifts in modeling and forecasting financial data, paving the way for further advancements in volatility modeling and risk analysis.

Assessment of the adequateness of the gathered information/data in solving business problems

The insights and information obtained through our model can help identify solutions to current business problems and, perhaps more importantly, prevent future issues. As such, there is a strong correlation between the data gathered and the ability to effectively address business challenges.

Need for additional analysis to address the said business problems?

There are several ways in which Bensaida's (2019) model could be expanded. Firstly, the model assumes a constant zero mean for stock returns, which may not account for time-varying expected returns and result in an overestimation of volatility. Secondly, the use of an absolute threshold of 0 for defining good and bad volatility may not accurately reflect the impact of news on investors' expectations. Instead, a relative evaluation of good and bad news could be more appropriate.

Another interesting avenue for exploration would be to investigate whether the spillover effects of volatility are asymmetric between bull and bear markets. Additionally, the project's by-product of a bear market index could be used to examine how bear market conditions spill over into other markets.

Overall, there are several potential avenues for extending Bensaida's model and gaining further insights into market dynamics.

This project redefines good and bad volatility and assigns probabilities to bull and bear markets using weekly data. We may then study the effects of good and bad volatility on market dynamics and identify bull and bear volatility. With this information, we can gain insights into how volatility in bull and bear markets impacts each other.

Below we outline the proposed analytical objectives

Analytical Objective 1:

Visualize expected return and conditional volatility in six countries' stock markets.

Analytical Objective 2:

Analyze how volatility of stock market in one country spill over to other G7 market

Analytical Objective 3:

Predict and quantify the volatility spillover effects in bull and bear markets.

Analytical Objective 4:

Measure the dynamics of volatility spillover effects during unusual events such as financial crisis, pandemics etc.

CHAPTER 3: PROPOSED ANALYTICAL METHODS

Sampling frame and method

In the context of our research project, the typical sampling frame does not necessarily apply here. What constitutes our sampling frame encompasses the range of sample data that can be used for our model implementation. We outline these below:

Population

Time series data, such as stock market indices, is typically viewed through the lens of stochastic processes. A stochastic process is a mathematical object defined as a collection of random variables. These variables are interrelated and indexable by a set representing time.

This provides a versatile and dynamic way to understand the evolution of random phenomena over time, capturing uncertainty, randomness and temporal changes within a structured model.

Each observation within a time series, such as a specific day's closing price in a stock market index, represents a realization or 'outcome' from the underlying stochastic process. This means that, for that specific point in time, the stochastic process - which might involve variables like previous price movements, macroeconomic conditions, investor sentiment, and so on - has led to a specific outcome. This observation is just one among countless possible outcomes from the stochastic process.

Every realization is a 'sample point' drawn from the population space defined by the stochastic process. In other words, while the observation itself is specific and concrete, it is merely a single instance taken from the countless possible outcomes that could have been generated by the stochastic process at that point in time. The time series data that we have available is therefore a sample drawn from this broader population space. We don't see every possible outcome of the stochastic process, but instead observe a series of realizations that have actually occurred over time.

Specifically, we leverage the publicly available weekly returns of the major stock market indices in our analysis. The data for the United States' S&P 500 and Canada's TSX 60, German DAX40, Paris Stock Exchange, Italian Stock Exchange and the Tokyo stock exchange for the period of 1999-2022.

Data Wrangling and Visualization

Data wrangling is arguably the most important step of this analytics process. The team implemented relevant and applicable data wrangling techniques to understand the global landscape of the data and ensure completeness and accuracy prior to undertaking the core analytical objectives. The team implemented the following:

- checks and removal of duplicate and low variation data
- removal of incorrect and irrelevant data
- checks for outliers
- created summary statistics and applicable visualizations
- Transformation in terms of dimension reduction of the raw G6 index data into return data variables.

Summary Statistics

Table 3.1

	Minimum	Q1	Median	Q3	Maximum	Mean	SD	Skewness
SP500	-0.182	-0.011	0.002	0.014	0.121	0.0011	0.025	-0.568
TSX60	-0.155	-0.009	0.003	0.013	0.143	0.0010	0.024	-0.812
Nikkei	-0.243	-0.016	0.002	0.019	0.171	0.0008	0.030	-0.595
MIB30	-0.233	-0.017	0.003	0.019	0.214	0.0001	0.032	-0.763
DAX40	-0.216	-0.016	0.004	0.018	0.161	0.0011	0.032	-0.514
CAC40	-0.204	-0.013	0.003	0.016	0.160	0.0006	0.029	-0.624

Visualization

We utilize visualization to model stock return time series, identify bull and bear markets using smoothed regime probabilities, visualize the estimated time-varying conditional heteroscedasticity, and visualize the volatility spillover effects between the stock markets of the six countries that we analyze.

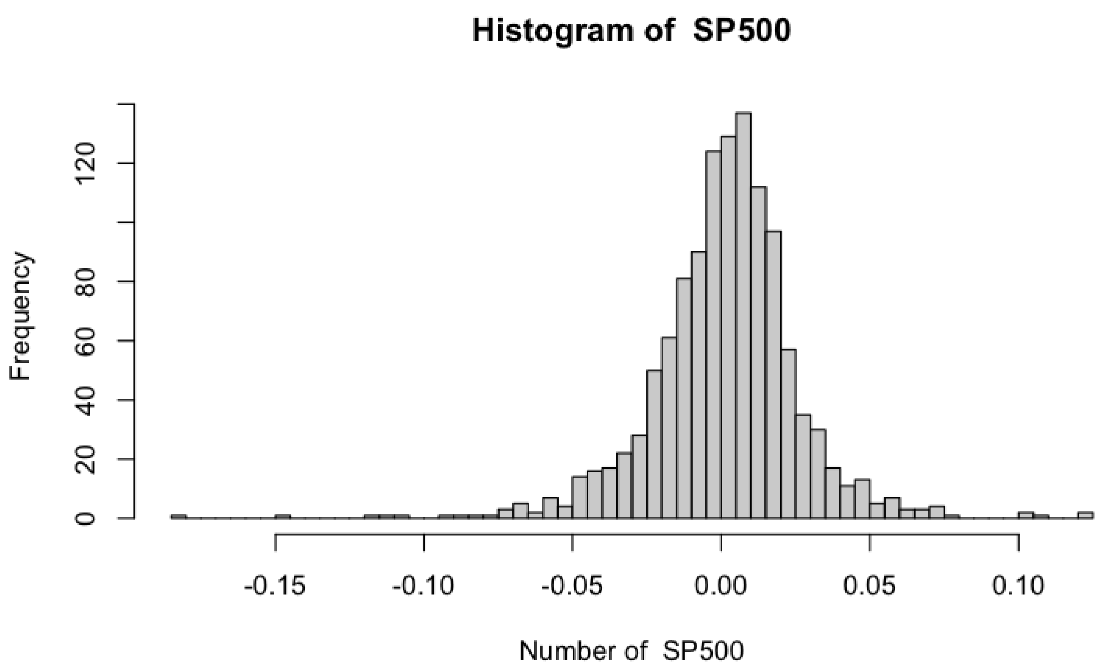


Fig 4. Frequency of SP500

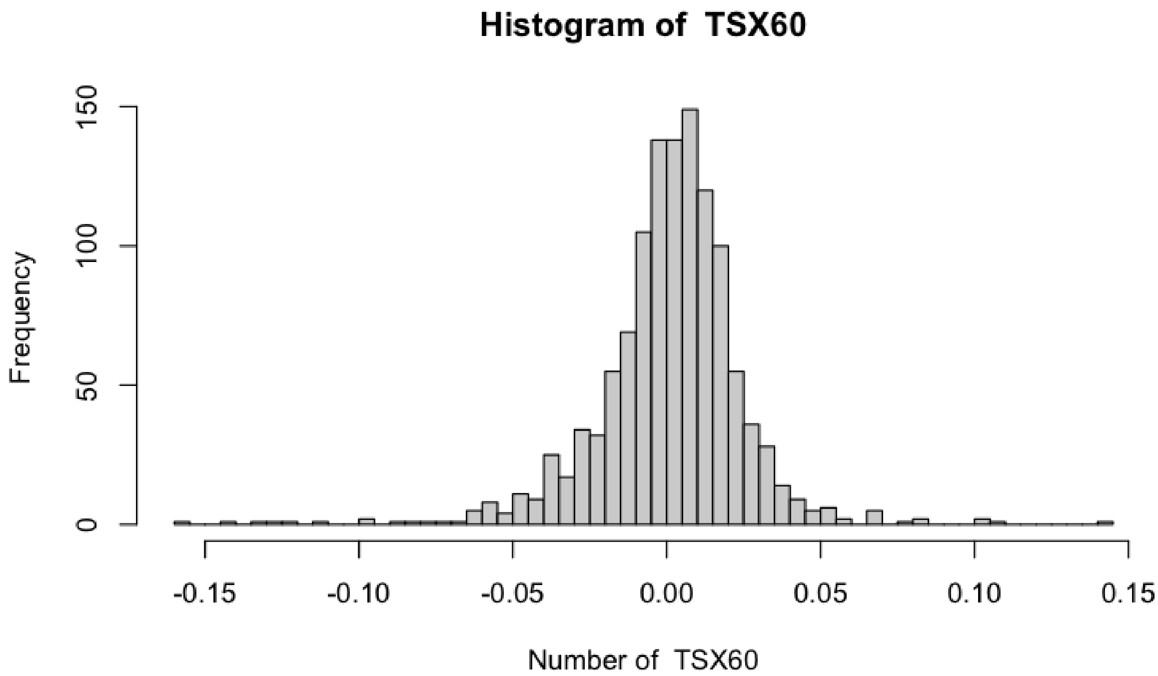


Fig 5. Frequency of TSX60

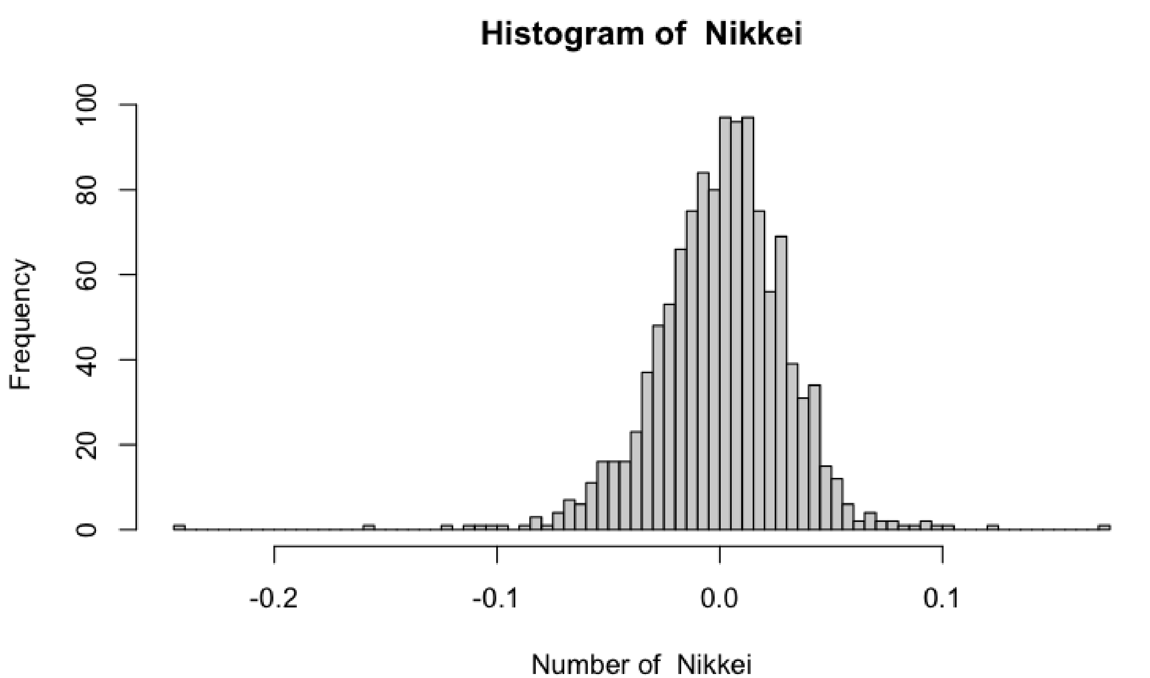


Fig 6. Frequency of Nikkei

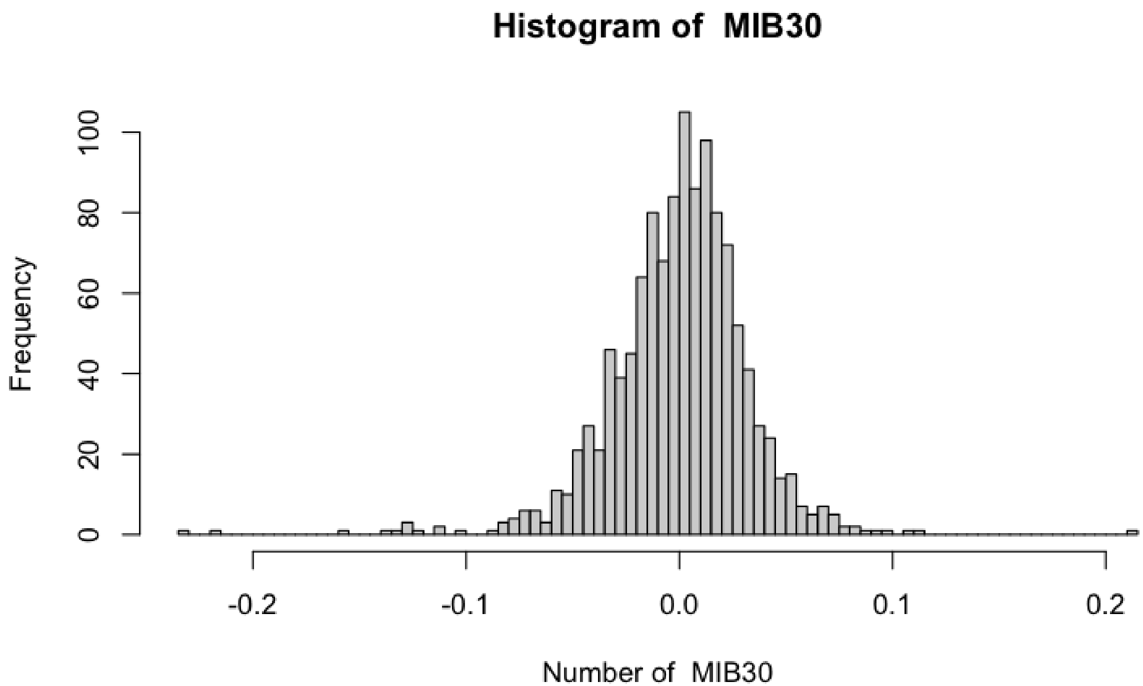


Fig 7. Frequency of MIB30

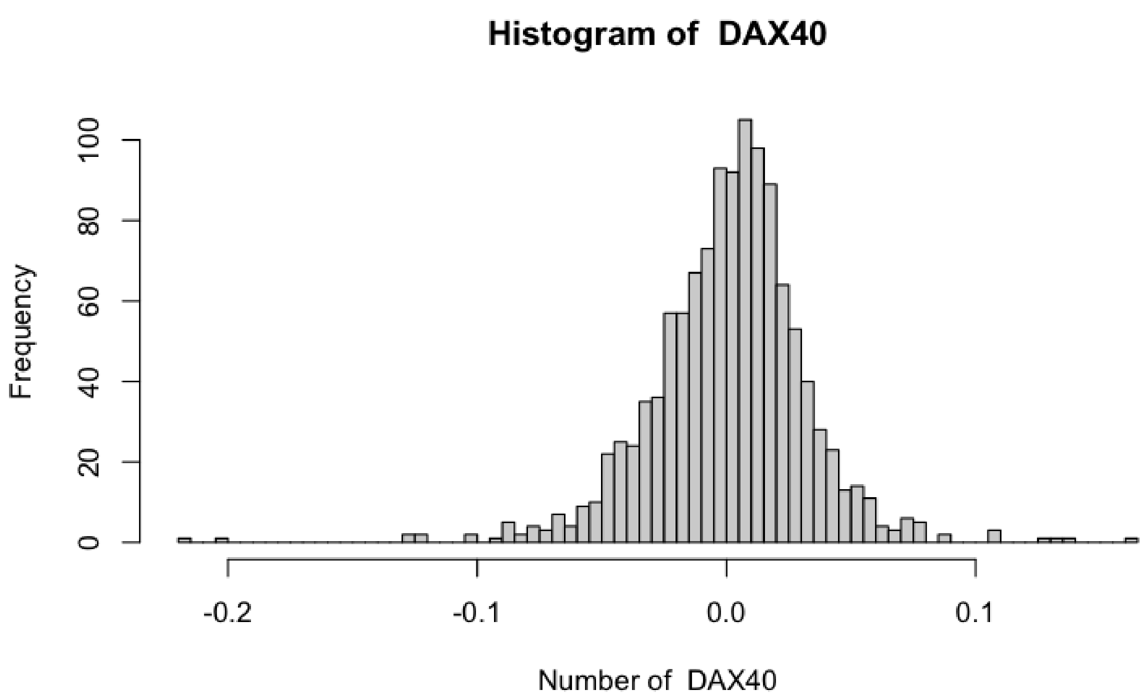


Fig 8. Frequency of DAX40

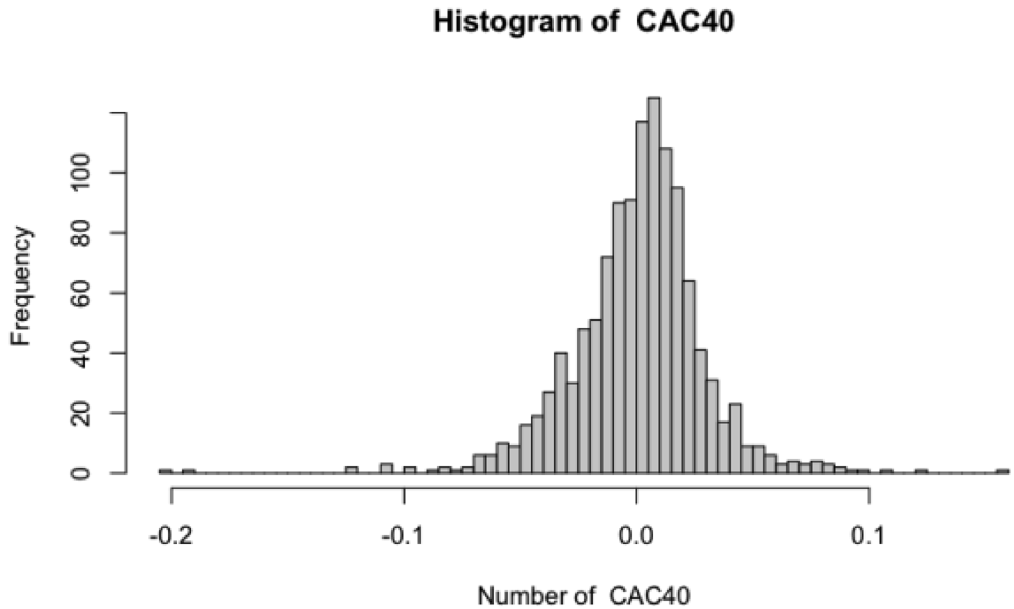


Fig 9. Frequency of CAC40

Programming

In this project, we use R language for our analysis, as it offers a wide range of default packages that can help us achieve our desired results. To achieve our goals, we plan to write and use a likelihood function that will be central to our analysis, and which we will use consistently throughout the project. This function will allow us to estimate the parameters of the statistical model we will be using, and enable us to make predictions and draw conclusions from the data.

Additionally, we plan to utilize the Markov-switching technique in our analysis. This method is a powerful tool that can help us identify structural breaks and changes in trends, which could be critical to our analysis. By using this technique, we hope to gain a deeper understanding of the underlying patterns and dynamics of the weekly return data, and uncover insights that could prove invaluable in our research.

Measures

Price: This variable indicates the closing price of the stock on the given trading day. This is the last price at which the stock was traded for that day. This variable is a continuous numerical variable.

Change: This variable is the growth rate of the given stock. It Indicates the change in the closing price of the stock from the previous trading day. It is calculated as the difference between the current day's closing price and the previous day's closing price. It is also a continuous numerical variable.

Date: This variable indicates the day on which the stock was traded.

Open: This variable indicates the opening price of the stock on the given trading day. This is the price at which the stock began trading for that day.

High: This variable indicates the highest price at which the stock was traded during the day. It is a continuous numerical variable.

Low: This variable indicates the lowest price at which the stock was traded during the day. It is a continuous numerical variable.

Volume: This is the trading volume of the index. This variable represents the total number of shares of the index that were traded during each week. This variable is a discrete numerical variable.

Analytics Methods to Employ

To accomplish our first and second analytical objectives, which are identification of bull and bear markets, and estimation of the conditional heteroscedasticity, we undertake the following methodologies as described below:

We propose a new model to identify bull and bear markets, as well as good and bad conditional volatility in stock returns. This model is based on a two-state Markov-switching regime variable, St=1,2, with transition probabilities Pr(St=j|St-1=i)=pij. St=1 denotes bull market, while St=2 denotes bear market. Additionally, the mean in the conditional heteroskedasticity equation is allowed to switch in order to capture different volatilities in bull and bear markets. With this model, we can assign probabilities of bull and bear markets for each period of data and then calculate the time-varying average return.

$$r_t = \mu s_t + \epsilon_t \sqrt{h_t}, \varepsilon_t \sim i.i.d\ N(0, 1),$$

$$h_t = \alpha s_t + \beta h_{t-1} + \gamma r_{t-1}^2,$$

We incorporated conditional heteroskedasticity in our model by using ARCH (autoregressive conditionally heteroskedastic) models. This type of model was first introduced by Engle (1982), and it accounts for changes in the variance over time by using past values of the variance. The variance at time t is modeled as a linear combination of past squared residuals. This allows us to capture the changing nature of the variance over time, which can be useful for forecasting and other applications.

$$r_t = \sqrt{h_t}\varepsilon_t, \varepsilon_t \sim N(0,1)$$

$$h_t = \alpha + \gamma r_{t-1}^2$$

ARCH models are well-suited for this purpose, as they are able to capture non-linear relationships between the variance and other variables. Furthermore, they can be used to identify outliers or other anomalies in the data that may not be captured by traditional linear models. By incorporating ARCH models into our model, we are able to better capture the changing nature of the variance over time and improve our forecasting accuracy.

Bolerslev (1986) proposed a more comprehensive structure for the variance model, which is known as GARCH (generalized ARCH). This structure is more similar to an ARMA model than an AR model. GARCH models are used to capture the time-varying volatility of financial returns. It is a stochastic process that models the variance of a time series as a function of its own past values and past errors. The GARCH model can be used to forecast future volatility and to measure the risk associated with a given asset. It can also be used to detect outliers in financial data and to identify structural breaks in the data. GARCH models are widely used in finance, economics, and other fields where time-varying volatility is important.

$$r_t = \sqrt{h_t}\varepsilon_t, \varepsilon_t \sim N(0,1)$$

$$h_t = \alpha + \beta h_{t-1} + \gamma r_{t-1}^2$$

To capture leverage effect, Glosten et al. (1993) proposed an extension of GARCH model as,

$$r_t = \sqrt{h_t}\varepsilon_t, \varepsilon_t \sim N(0,1)$$

$$h_t = \alpha + \beta h_{t-1} + \gamma r_{t-1}^2 + \delta 1\left[r_{t-1} < 0\right] r_{t-1}^2$$

CHAPTER 4: MODELING, ANALYSIS AND RESULTS

Model

Recent studies to model and discuss the existence of asymmetry and volatility spillovers in financial markets have largely utilized the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. For instance, Bensaida (2019), Yarovaya et al. (2017), and Diebold and Yilmaz (2012). The GARCH model is a type of autoregressive model that captures the conditional variance of a time series by modeling the variance as a function of past squared residuals, past variances, and a constant term. The model assumes that the variance of the error term at time t depends on the information up to time t-1, and the model can be extended to capture the asymmetric nature of volatility by introducing separate parameters for positive and negative shocks.

In this research we leverage an extension of the GARCH model which incorporates a Markov-Switching component to capture changes in the volatility regime over time. This model is formally known as the Markov-Switching GARCH (MS-GARCH). The model assumes that the time series is governed by an unobserved discrete-state variable that switches between different volatility regimes, and the conditional variance of the time series is modeled as a GARCH process within each regime. In the literature, this model has also been exploited to model volatility of cryptocurrencies and other financial assets Maria Caporale & Zekokh (2019).

The key similarity between the GARCH and MS-GARCH models is that they both aim to model the conditional variance of a time series. However, the key difference between the two models is that the MS-GARCH model explicitly accounts for changes in the volatility regime over time by allowing the volatility process to switch between different states (good and bad volatility periods in the context of our research). This added flexibility allows the MS-GARCH model to capture time-varying volatility patterns more accurately than the GARCH model. This is particularly why MS-GARCH is most suitable for our research.

Model Assumptions

As with any model, we impose two key assumptions in our analysis. The first assumption is that we exploit a MS-GARCH 1-1 model to estimate the conditional volatility. There are MS GARCH 1-1, 1-2, and 2-2 Models. The information criteria (AICC) returned the least score for GARCH 1-1 among our candidate models. In other words, it provides the least Root Mean Square forecast errors. The second assumption is that we also exploit a Vector Autoregression (VAR) model with lag order 1 and a four week (~ roughly one month) outlook volatility forecast errors. We allow only the last period of volatility to affect future volatility. We assume that, conditional on last period volatility, volatility that happened two periods ago has zero effect on future volatility. This again is due to the model selection method.

Modeling Input and Analysis Implementation

The analysis process is multi-step and extensive. Using the R statistical language, the model takes as initial inputs the weekly G6 stock index return data which is generated from transformed weekly Index data. This is followed by a creation of matrices to store the results and a definition of a transformation function to transform our model parameters. This is preparatory for the core analysis and helps to ensure that the parameters estimates are reliable and meaningful.

Next we initiate an optimization algorithm to find the best-fit parameter values that maximize the log-likelihood of the MS-GARCH model. The likelihood function takes the GARCH-M model parameters as input, performs a transformation to ensure that the input parameter values are always reasonable and then uses the parameters to calculate the log-likelihood of the model. The higher the log-likelihood, the better the fit of the model to the data.

Then the estimated model is used to simulate the volatility and returns of the indexes. The simulation involves iterating over time, calculating the probabilities of being in each state (using the likelihood function), updating the conditional variance of each state using the GARCH equation, and drawing a random return from each state's distribution. The resulting volatility and return series are stored in matrices for each of the G6 indexes and used for the next phase of the analysis.

The next phase is the Vector autoregressive part, where we apply a linear regression model to estimate the parameters of a VAR model. The linear model function is used for each of the six variables, with the previous day's values of all seven variables as independent variables.

Using the Vector autoregressive model below:

$$h_t = \Phi_0 + \Phi_1 h_{t-1} + u_t$$

where $h_t = (h_{1,\ t, \dots,}\ h_{6,\ t})$ and $h_{i,\ t}$ denotes the conditional volatility estimated from i^{th} market; Φ_0 is (n x 1) vector, $\left\{\Phi_i\right\} p_{i=1}$ are (n x m) matrices; $u_t = (u_{1,\ t\, \dots,}\ u_{6,\ t})$ are the error terms.

Based on the vector autoregressive model above, we can have the following vector moving average representation,

$$\tilde{h}_t = \omega + \sum_{j=0}^{\infty} A_j \tilde{u}_{t-j}$$

Where A_j are (n x n) matrices that obey the following recursion,

$$A_j = \sum_{i=1}^{p} \Phi_i A_{j-i}$$

with start value being the identity matrix, $A_0 = I_{n,}$ and $A_j = 0$ for $j < 0$; the (n x 1) vector ω is the intercept term of the vector moving average representation and it will not be used in the analysis.

The generalized m-step-ahead forecast error variance decomposition shares are defined as:

$$\theta_{ij}(m) = \frac{\sigma_{jj}^{-1} \sum_{l=0}^{m-1} (e_i' A_l \Sigma e_j)^2}{\sum_{l=0}^{m-1} (e_i' A_l \Sigma A_l' e_i)}$$

where σ_{jj} is the standard deviation of the error term for the j^{th} equation and e_i is a selection column vector with i^{th} element equals to one and zeros elsewhere. As $\sum_{j=1}^{n} \theta_{ij}(m) \neq 1$, we can further normalize it as:

$$\tilde{\theta}_{ij}(m) = \frac{\theta_{ij}(m)}{\sum_{j=1}^{n} \theta_{ij}(m)}$$

The measure above can be understood as the proportion of the m-step ahead forecast error variance of h_i which is accounted for by the innovations in h_j in the VAR. In other words, it measures how the future volatility in stock market i is affected by the news in stock market j, or how the volatilities in stock market j spillover to stock market i. And this can have many applications in hedge funds and asset management companies.

We first estimate the overall directional volatility spillover of each index in percentages, and go on further to decompose the spillover effects into two different states: good and bad volatility both with expected return threshold and zero threshold. Using a logic statement, we define good volatility as when expected return is greater than actual return and bad volatility as when it is less than actual return. Then we juxtapose this with using zero as an absolute threshold, where bad volatility is when return is less than zero and good volatility is when return is greater than zero.

Results

Table 4.1.

Directional spillovers

Index	U.S (S&P 500)	Canada (TSX 60)	Japan (Nikkei 225)	Italy (MIB 30)	Germany (DAX 40)	France (CAC 40)	Contribution from others
U.S	21.8	21.0	9.3	19.7	16.3	11.9	46.7
Canada	8.9	60.2	3.3	11.6	8.0	8.0	66.8
Japan	12.1	12.8	47.7	9.8	8.5	9.1	32.0
Italy	7.4	10.5	4.9	43.7	18.7	14.9	91.4
Germany	9.7	11.0	7.0	27.0	27.8	17.4	69.7
France	8.6	11.4	7.6	23.3	18.3	30.9	61.3
Contribution to others	78.2	39.8	52.3	56.3	72.2	69.1	

Note: This table reports the volatility directional spillovers in %, without separating the good from the bad part. Spillovers are computed using Diebold and Yilmaz's (2012) framework. The results are based on generalized variance decompositions of 4-week ahead volatility forecast errors. The entry on the ith row and jth column is the spillovers from market i to the forecast error variance of market j.

Table 4.1 reports the volatility directional spillovers in percentages. First, we can see that the diagonal cells have the largest value in each column. This represents that each country's volatility is affected by its own shock the most. Second, volatility spillover effects are highly asymmetric. For example, a one standard deviation shock in U.S. volatility can contribute to a 21.0% increase in Canada volatility. However, a one standard deviation shock in Canada volatility can contribute to a 8.9% increase in U.S. volatility. Overall, Japan receives the least volatility from other countries. This is consistent with the general belief that Japan has one of the most stable financial markets. The U.S. also receives a relatively small amount of volatility from other countries. This can be due to its diversification in portfolios. In contrast, Italy receives the largest amount of volatility from other countries. This may be due to its weak economic performance over the last decade. In terms of spillover effects to other countries, the U.S. has a dominant role. This result not only is consistent with the perspective of the investors (Jones, 2021), but also is in sharp contrast with the results in Bensaida (2019), where the U.S. is only the third dominant market in G6 countries. This indicates the importance of controlling investors' expectations in volatility forecasting.

Next, we investigate volatility spillover effects under good and bad volatility. Table 4.2 presents the volatility spillover effects under good and bad volatility using expected return and 0 as threshold. We can see that the 0-threshold estimates constantly overestimate the spillover effects compared to expected return based estimates.

Table 4.2.

Directional asymmetric spillovers

Good	Index	U.S.	Canada	Japan	Italy	Germany	France	Contribution from others
	U.S	26.0 26.6	17.4 18.1	6.8 6.7	23.1 20.9	16.1 15.4	10.6 12.2	45.7 53.3
	Canada	11.8 12.5	53.8 50.8	3.6 5.7	12.6 12.9	8.9 9.7	9.4 8.4	44.1 60.1
	Japan	8.4 7.3	6.0 9.9	53.0 43.8	13.8 14.1	10.1 11.5	8.8 13.5	35.6 38.0
	Italy	8.3 10.6	6.2 9.8	7.0 6.5	47.4 43.0	18.1 16.1	12.9 14.0	99.4 96.8
	Germany	9.5 12.5	6.9 12.0	7.8 8.5	27.6 25.9	32.7 26.4	15.6 14.7	71.1 67.9
	France	7.6 10.3	7.6 10.4	10.5 10.6	22.5 23.1	17.9 15.1	33.9 30.6	57.2 62.8
	Contribution to others	74.0 73.4	46.2 49.2	47.0 56.2	52.5 57.0	67.3 73.6	66.1 69.4	
Bad	U.S	32.4 24.0	27.0 19.5	3.7 7.5	14.3 19.7	16.2 18.4	6.3 10.8	51.5 38.9
	Canada	13.7 8.7	60.1 52.8	0.8 5.2	10.3 13.5	8.5 11.1	6.5 8.7	77.4 76.3
	Japan	9.5 5.6	12.9 16.1	61.6 44.4	6.2 13.1	6.1 10.1	3. 10.6	13.0 31.4
	Italy	8.9 8.2	11.7 13.3	2.7 6.5	51.6 37.8	12.7 18.8	12.4 15.3	66.4 94.6
	Germany	13.0 9.7	12.9 14.3	3.0 5.1	14.7 24.9	46.6 30.0	9.8 16.1	57.1 77.1

France	6.3 6.7	12.9 13.0	2.7 7.1	20.8 23.5	13.6 18.7	43.6 31.2	38.7 61.5
Contribution to others	67.6 76.0	40.0 47.2	38.4 55.6	48.4 62.2	53.4 70.0	56.4 68.8	

Note: This table reports the volatility spillovers in %, separating the good from the bad part. Spillovers are computed using Diebold and Yilmaz's (2012) framework. The results are based on generalized variance decompositions of 4-week ahead volatility forecast errors. The entry on the ith row and jth column is the spillovers from market i to the forecast error variance of market j. The numbers without underline represent the volatility spillover effects that use time-varying expected return as threshold to separate good from bad volatility; the numbers with underline represent the volatility spillover effects that use 0 as threshold to separate good from bad volatility.

Rolling window analysis: Dynamic Spillover effect to other countries

To investigate the dynamics of the spillover effects, we adopt rolling window analysis. The window size we chose is 52 which represents observations in a year.. These figures provide visual representations of the data and help to illustrate the patterns and trends that we have observed in our analysis.

In the following section, we will examine the spillover effects from a particular country to other countries. Specifically, we will begin by analyzing the spillover effects from the United States to other countries. The figure below shows the spillover effects of the US on other countries.

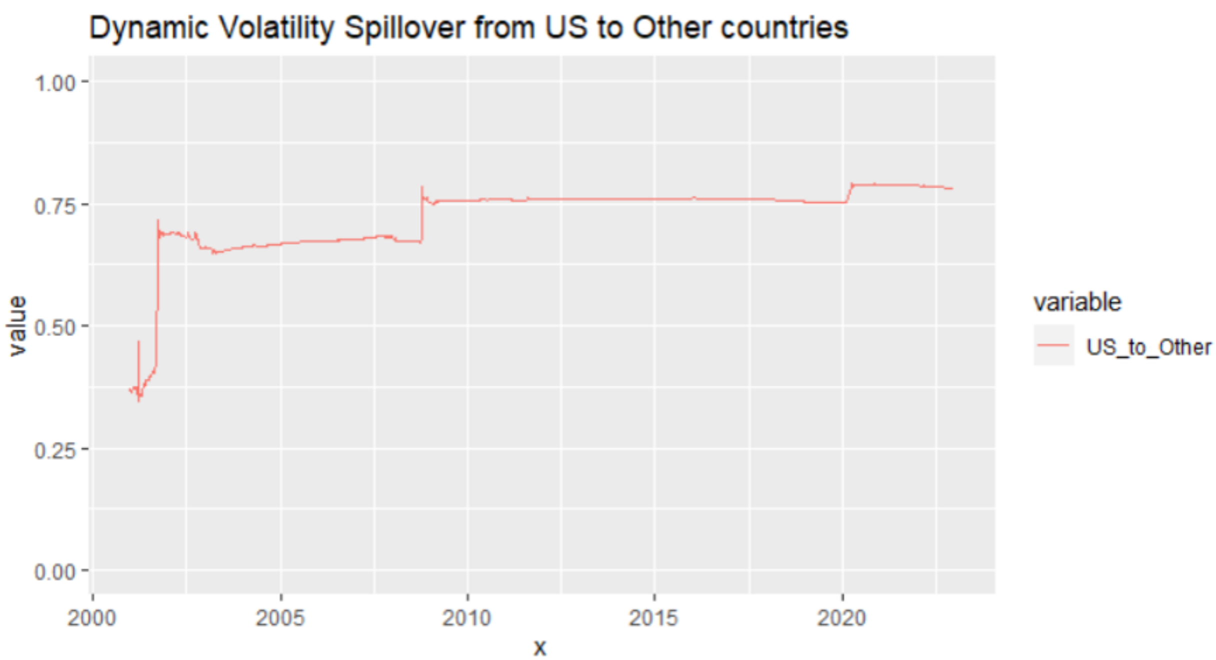


Fig 10. Spillover from US to other countries

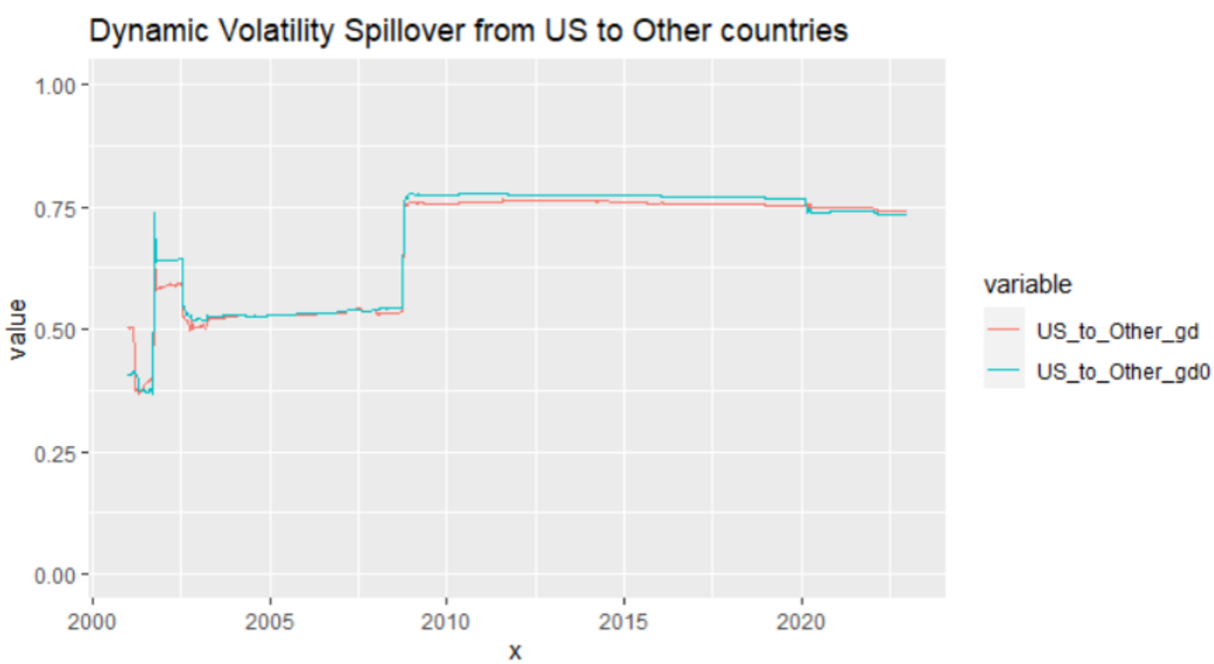


Fig 11. Good volatility spillover from US to other countries

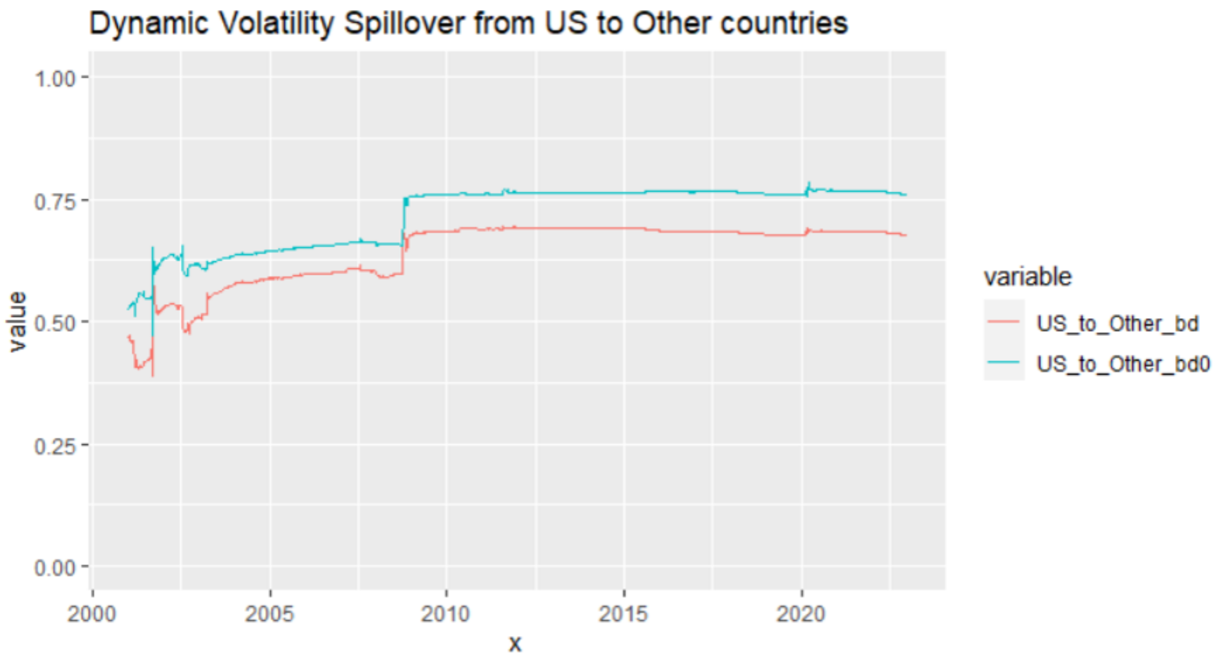


Fig 11. Bad volatility spillover from US to other countries

It is obvious from the data that three important events have led to a significant increase in spillover volatility. The 2000 recession, the 2008 financial crisis and now a wild outbreak in 2020 are among the main events that have occurred. These events have had a major impact on global financial markets, increasing interconnectedness and the transmission of volatility across asset classes.

As a result of the global events, greater integration into international financial markets may give rise to an increased sense of urgency for individuals to explore safer alternatives within the international market. This phenomenon arises when people are confronted with a domestic market characterized by a higher degree of risk. Under these circumstances, people are being encouraged to widen their horizons and make international markets that offer greater perception of security as a result of searching for a safe and reliable investment environment. Individuals wish to reduce potential losses and better manage an uncertain economy through diversification in their investments into geographic areas.

Figures 12-14 present the dynamic spillover effect from Canada to other countries. We can see that the spillover effects from Canada to other countries have a similar pattern to the U.S. spillover effect, but the magnitude is smaller.

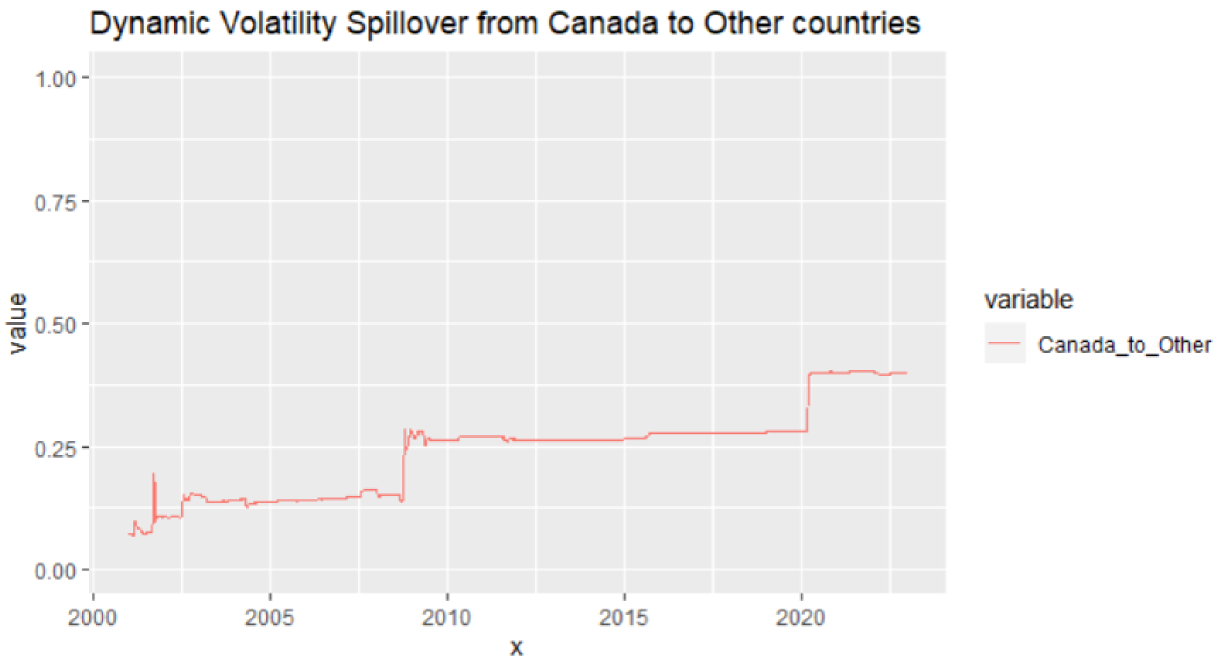


Fig 12. Volatility spillover from Canada to other countries

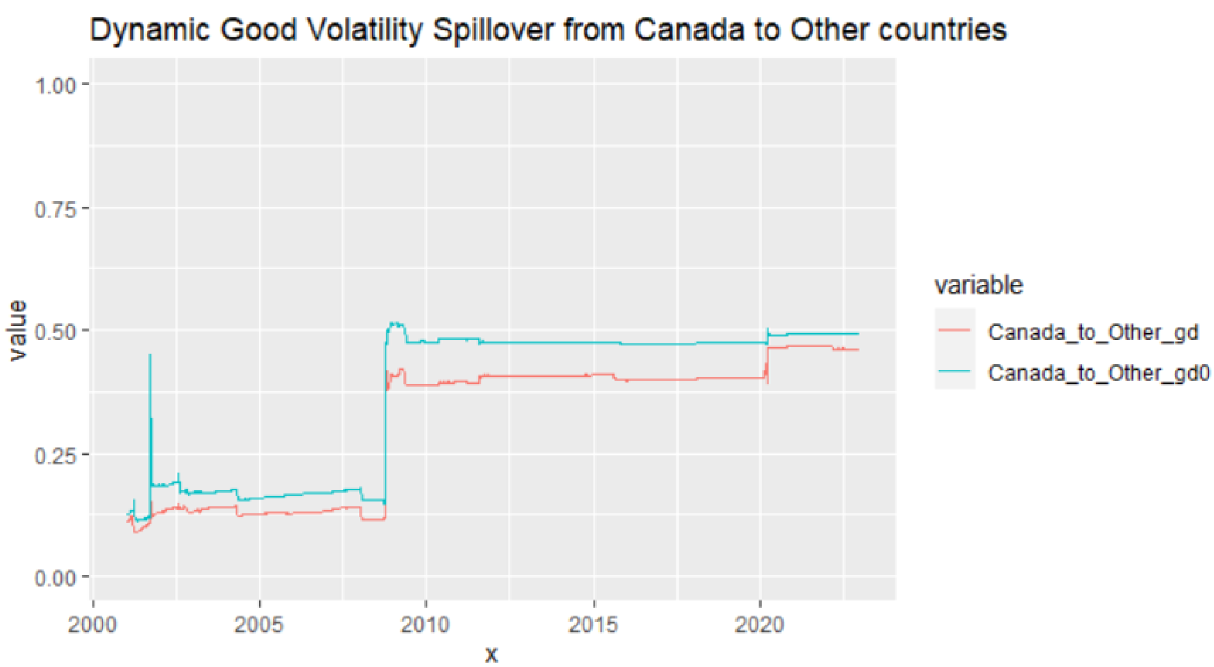


Fig 13. Good volatility spillover from Canada to other countries

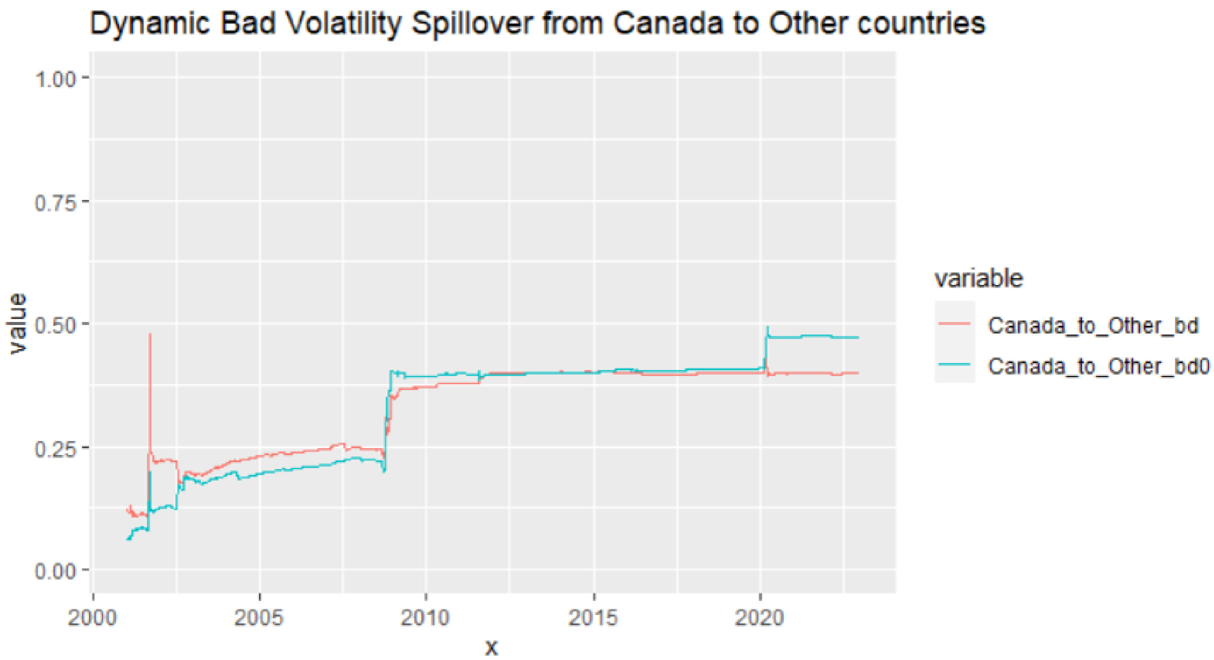


Fig 14. Bad volatility spillover from Canada to other countries

As the impact of Japan's financial markets on the global economy becomes clear, we will now look at figures showing a spillover effect from Japan to other countries. It is interesting to see that Japan’s spillover effects gradually decreased after the financial crisis and had a significant drop during COVID period. This may be due to the success in controlling COVID-19 pandemic in Japan and a more stable financial system.

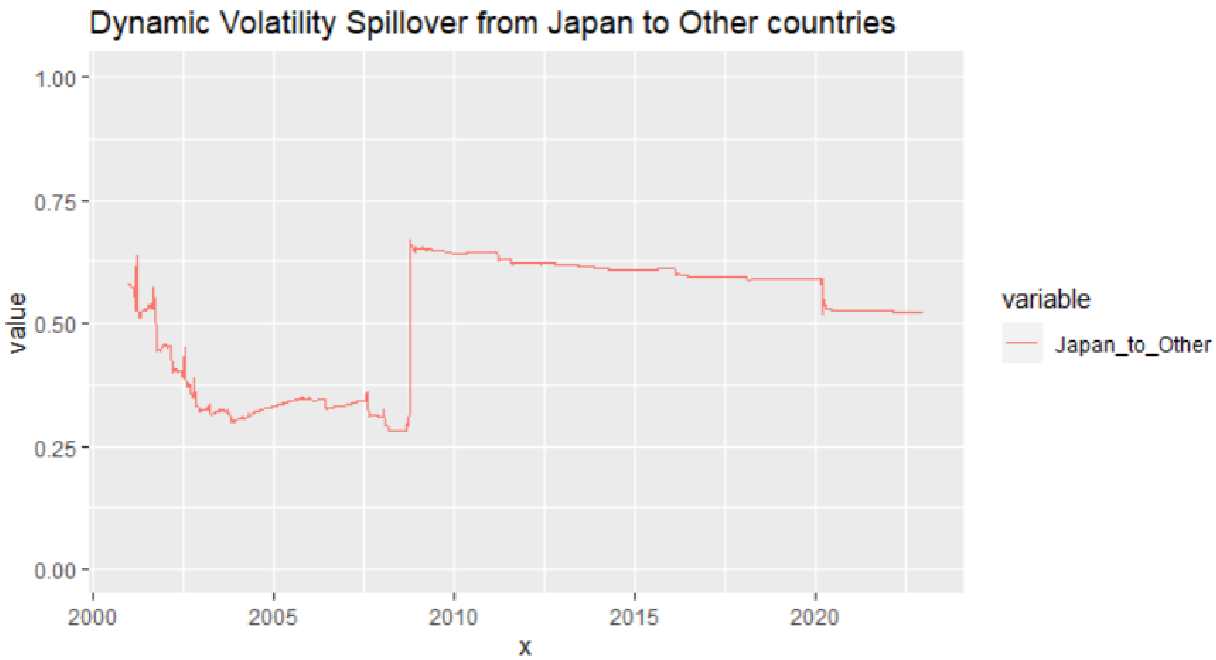


Fig 15. Volatility spillover from Japan to other countries

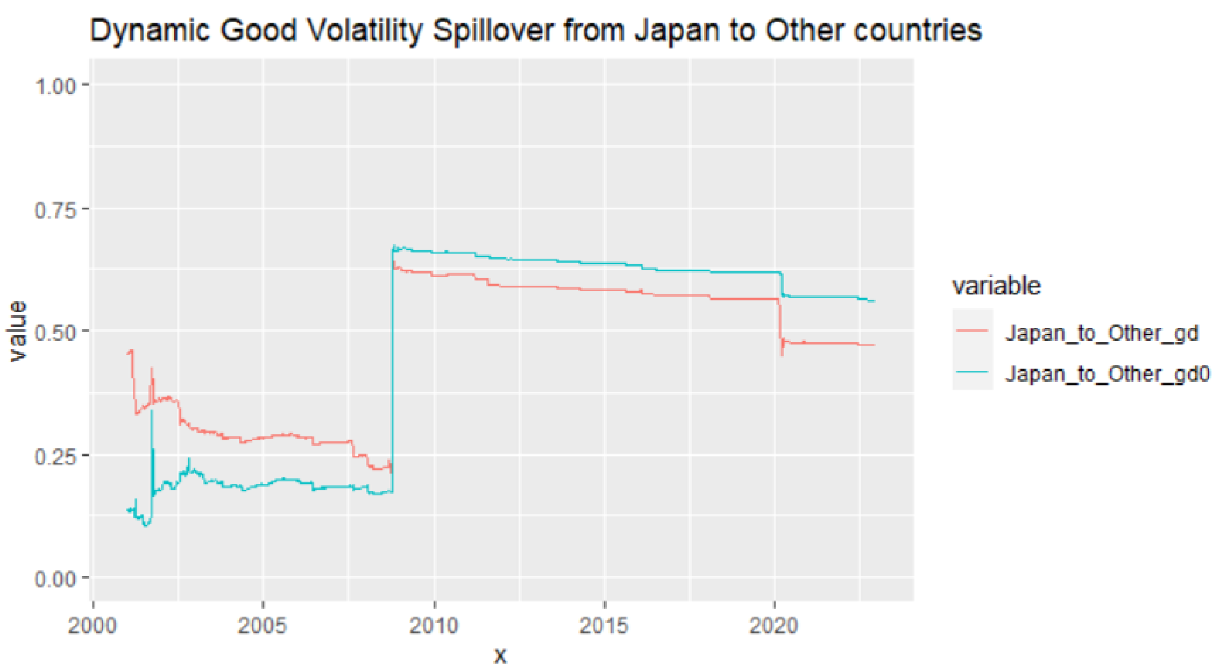


Fig 16. Good volatility spillover from Japan to other countries

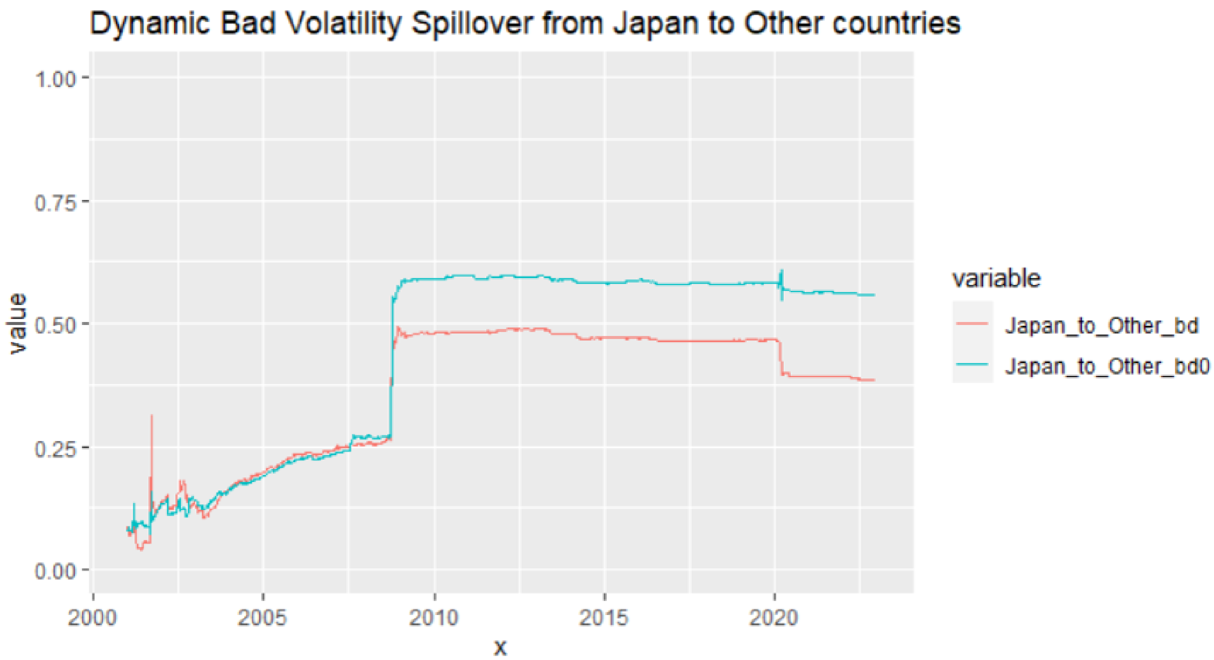


Fig 17. Bad volatility spillover from Japan to other countries

Figures 18-26 present the spillover effects from the 3 European countries to others. The patterns are similar in these three countries. The spillover effects dropped in early 2000, and increased dramatically during the financial crisis, then roughly remained constant during COVID period.

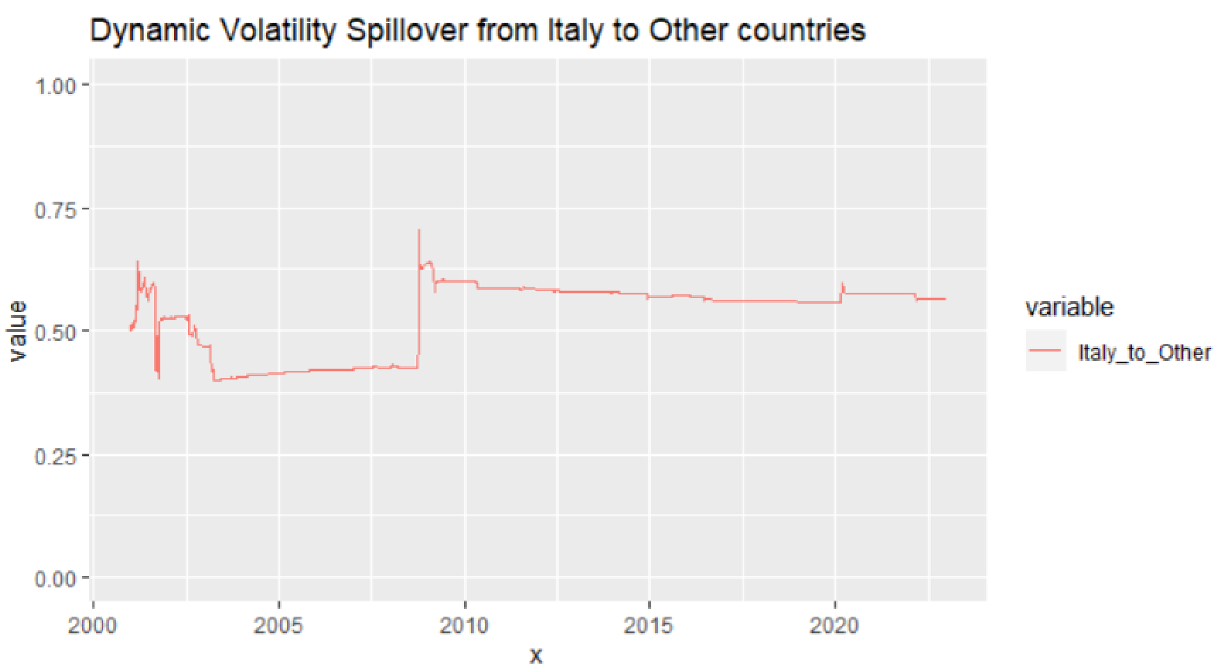


Fig 18. Volatility spillover from Italy to other countries

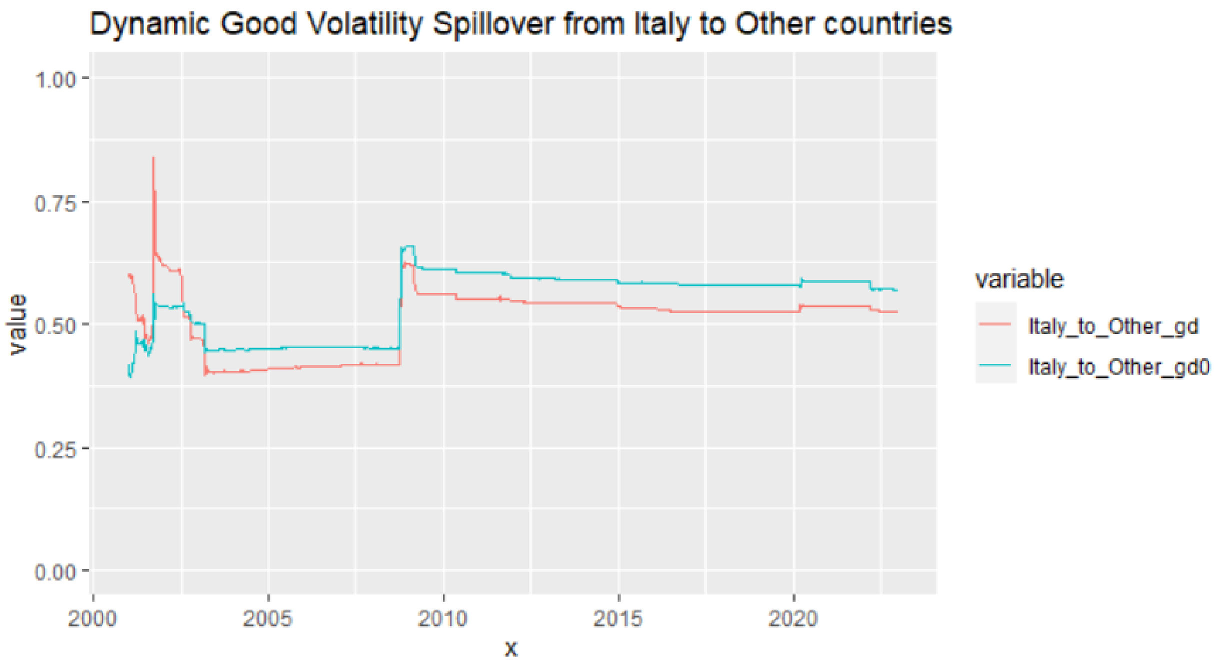


Fig 19. Good volatility spillover from Italy to other countries

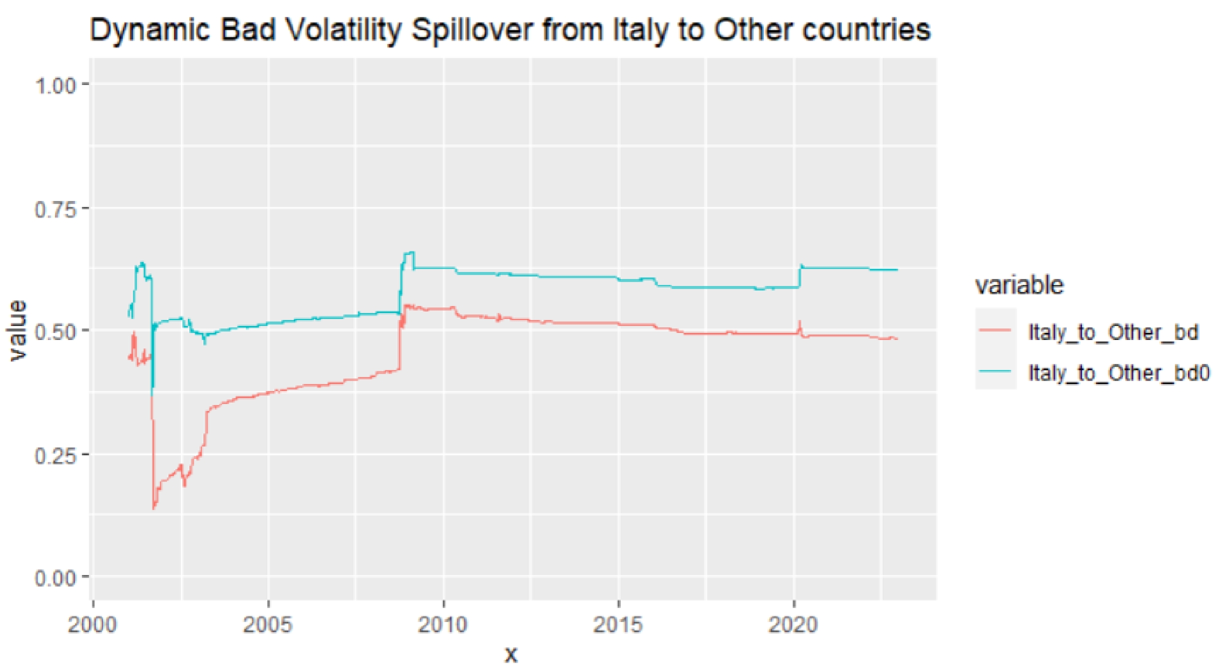


Fig 20. Bad volatility spillover from Italy to other countries

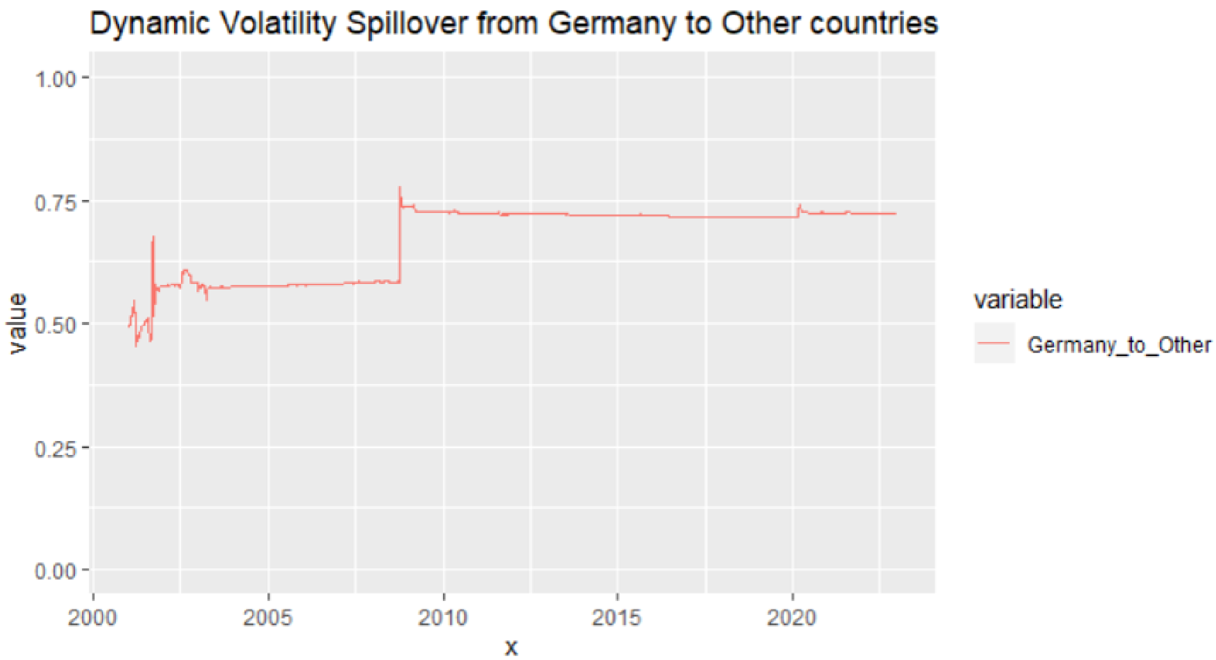


Fig 21. Volatility spillover from Germany to other countries

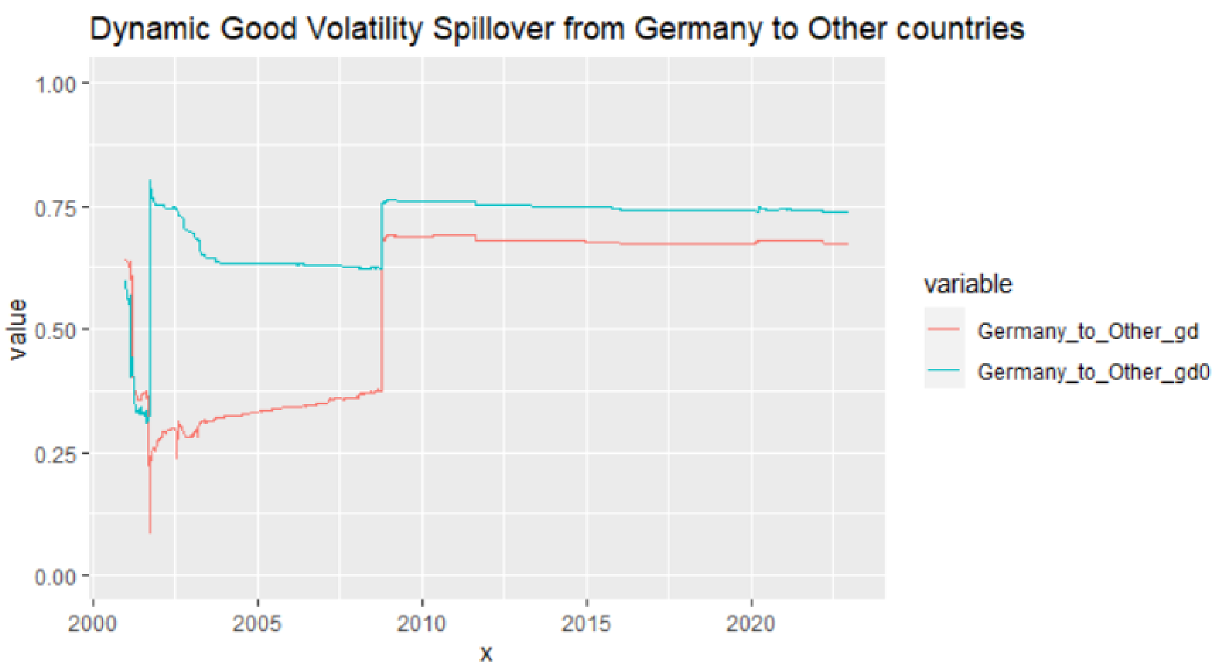


Fig 22. Good volatility spillover from Germany to other countries

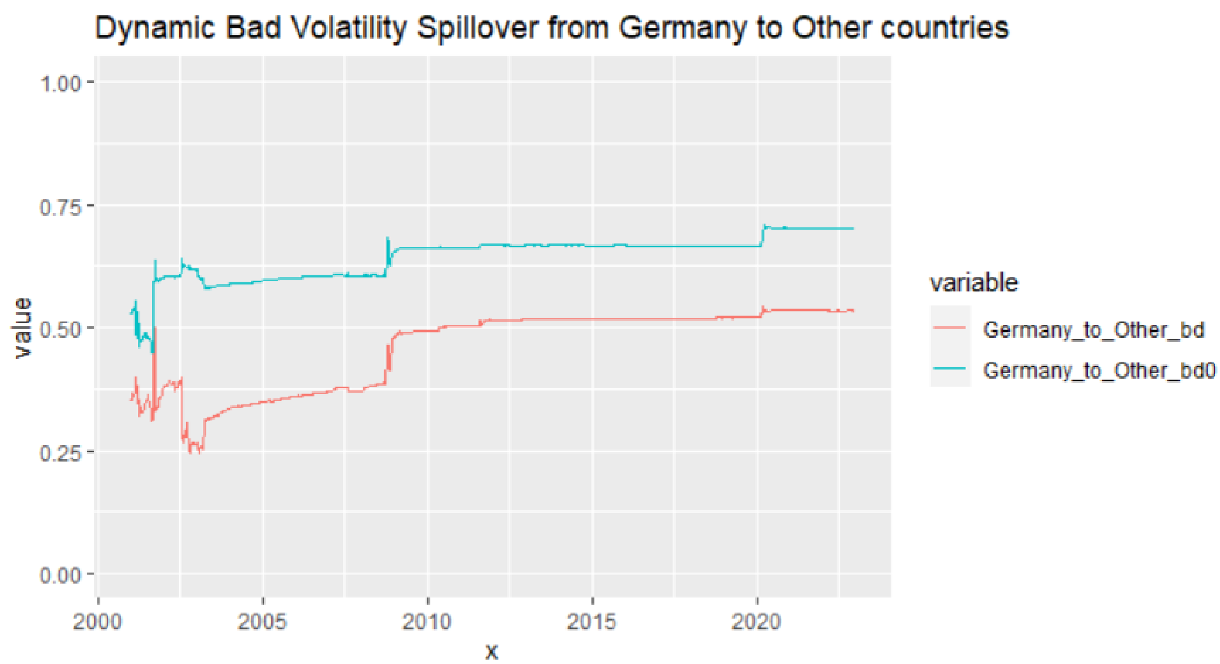


Fig 23. Bad volatility spillover from Germany to other countries

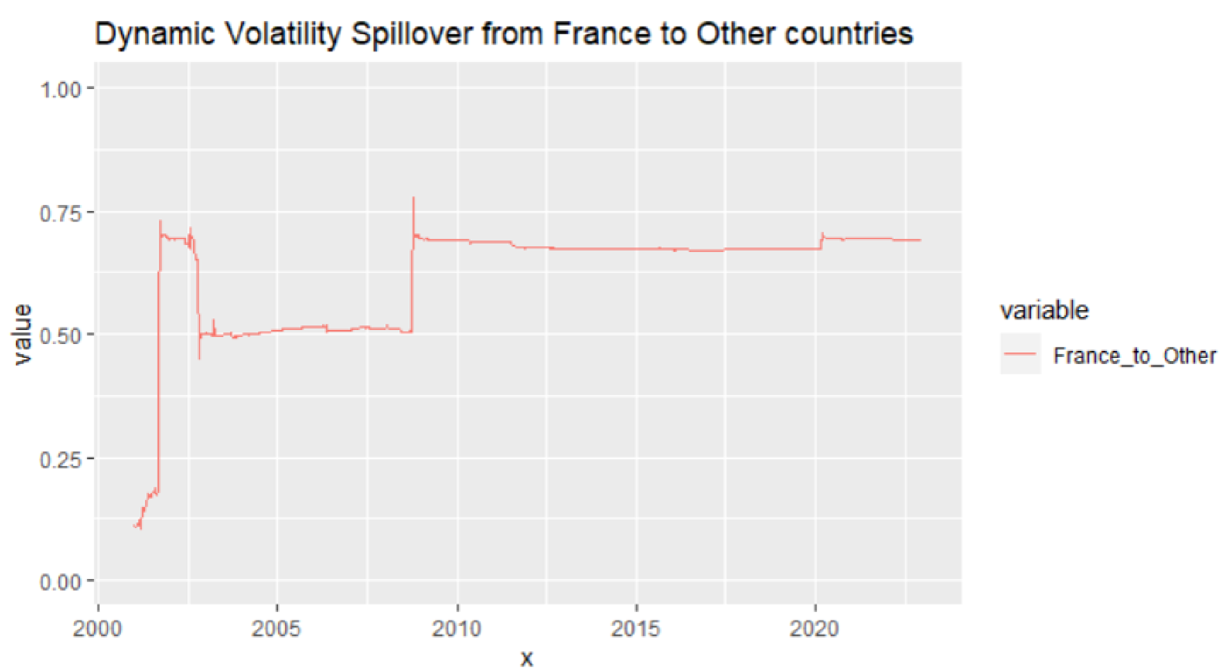


Fig 24. Volatility spillover from France to other countries

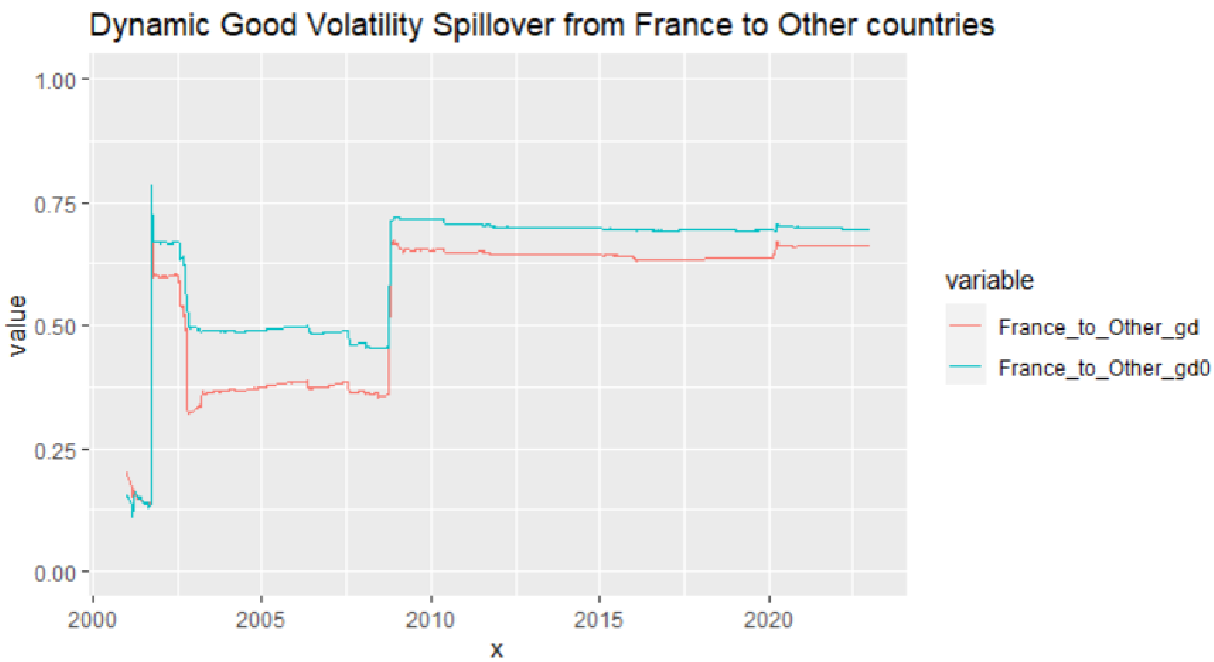


Fig 25. Good volatility spillover from France to other countries

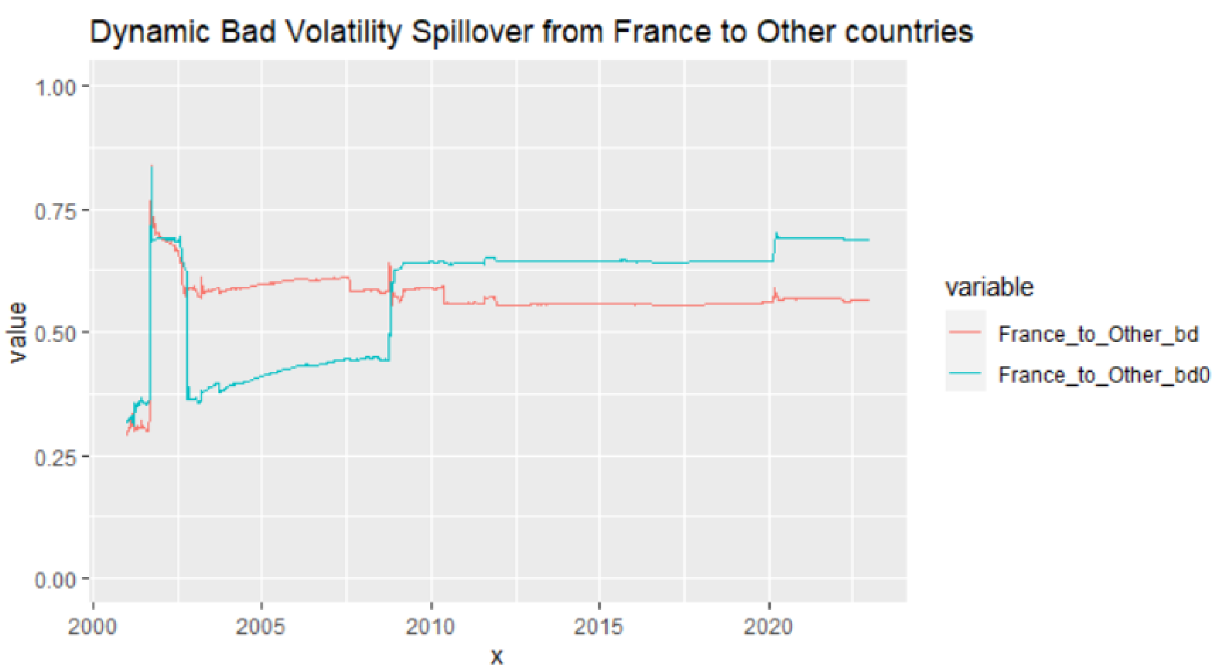


Fig 26. Bad volatility spillover from France to other countries

Spillover effect from other countries

In the following section, we will examine the spillover effects from other countries to a particular country, starting with the United States.

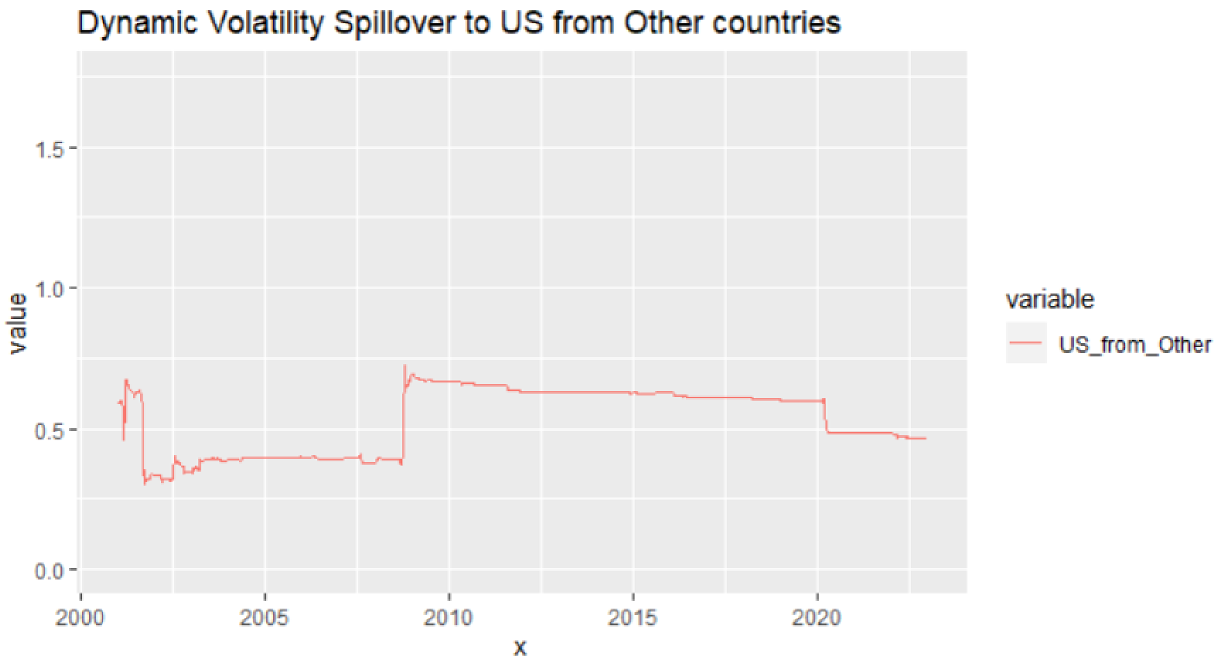


Fig 27. Volatility spillover to US from other countries

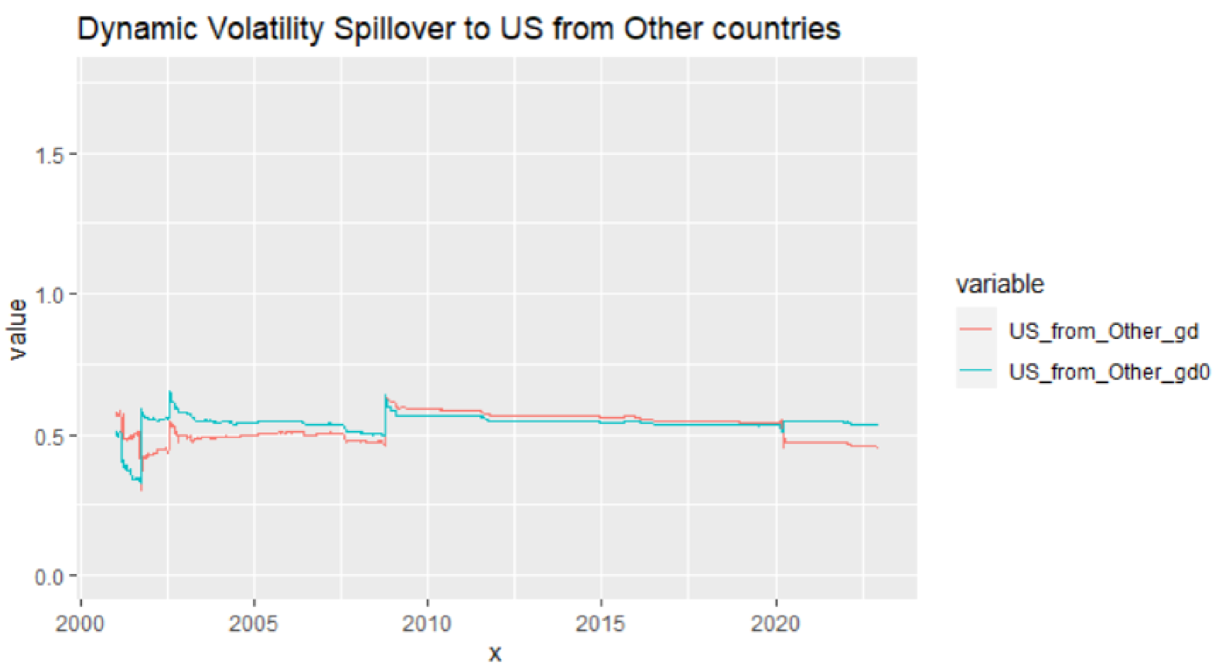


Fig 28. Good volatility spillover to US from other countries

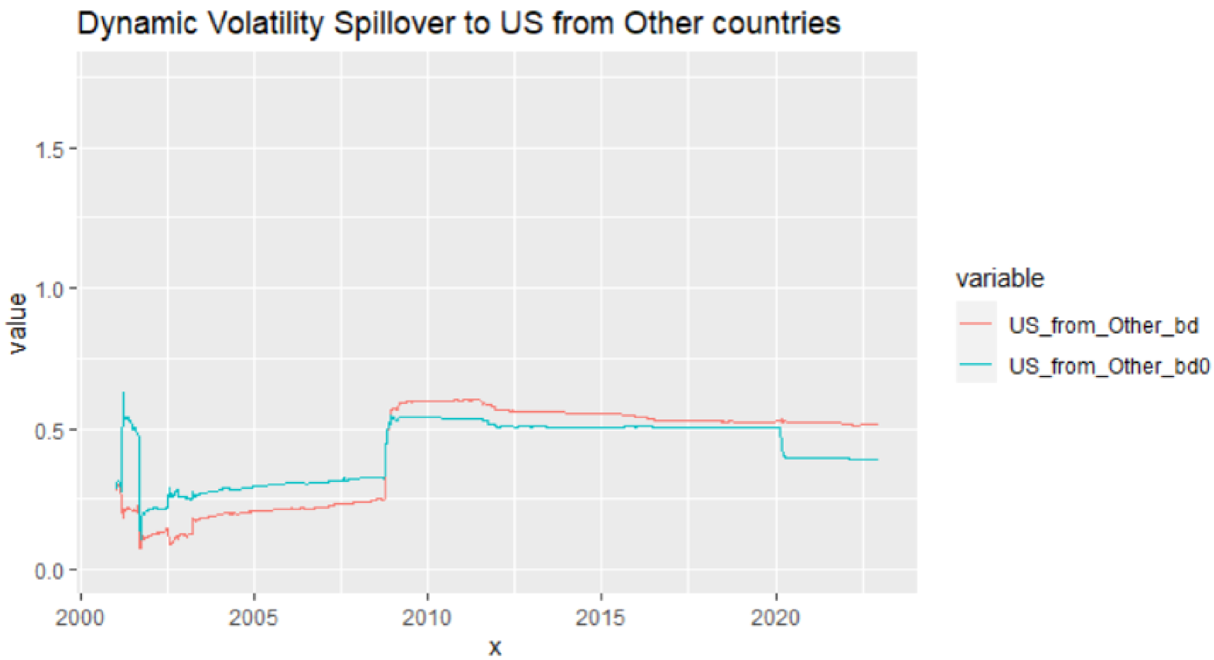


Fig 29. Bad volatility spillover to US from other countries

The next Country is Canada. Below we will see the spillover effect from other six countries to Canada.

For every country we can see the significant changes in volatility except for Canada. Canada's spillover has not changed a lot since 2000. The stock market of Canada is being overlooked by international investors and because of that the big global events did not affect Canada's volatility spillover a lot.

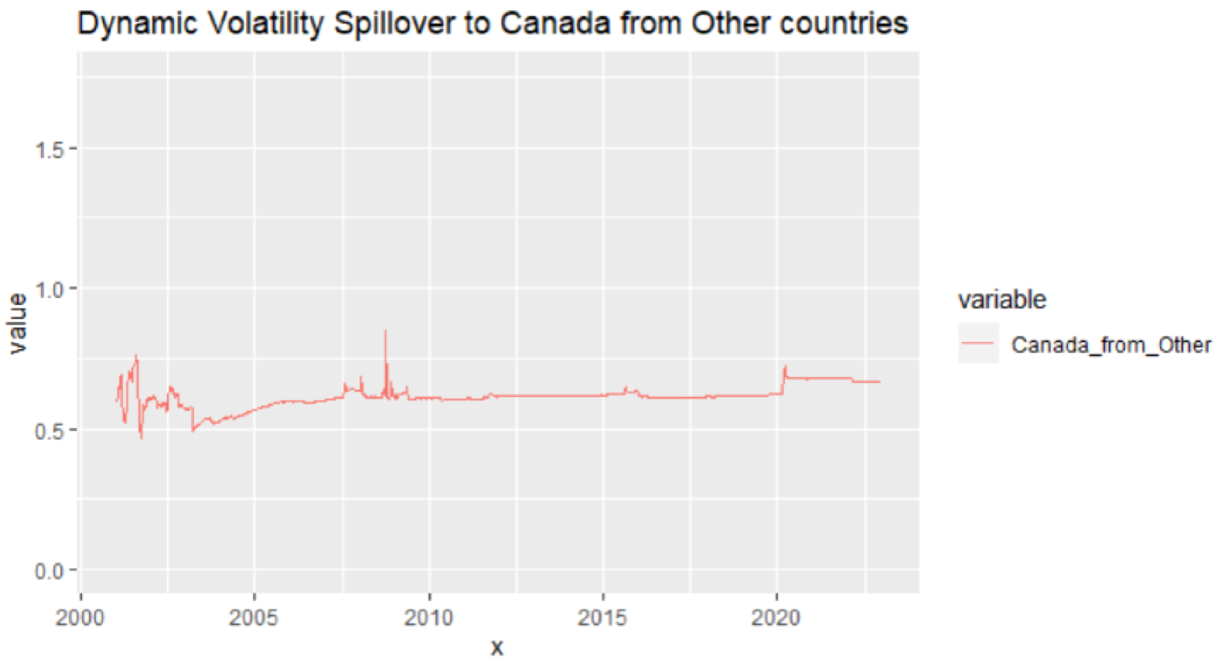


Fig 30. Volatility spillover to Canada from other countries

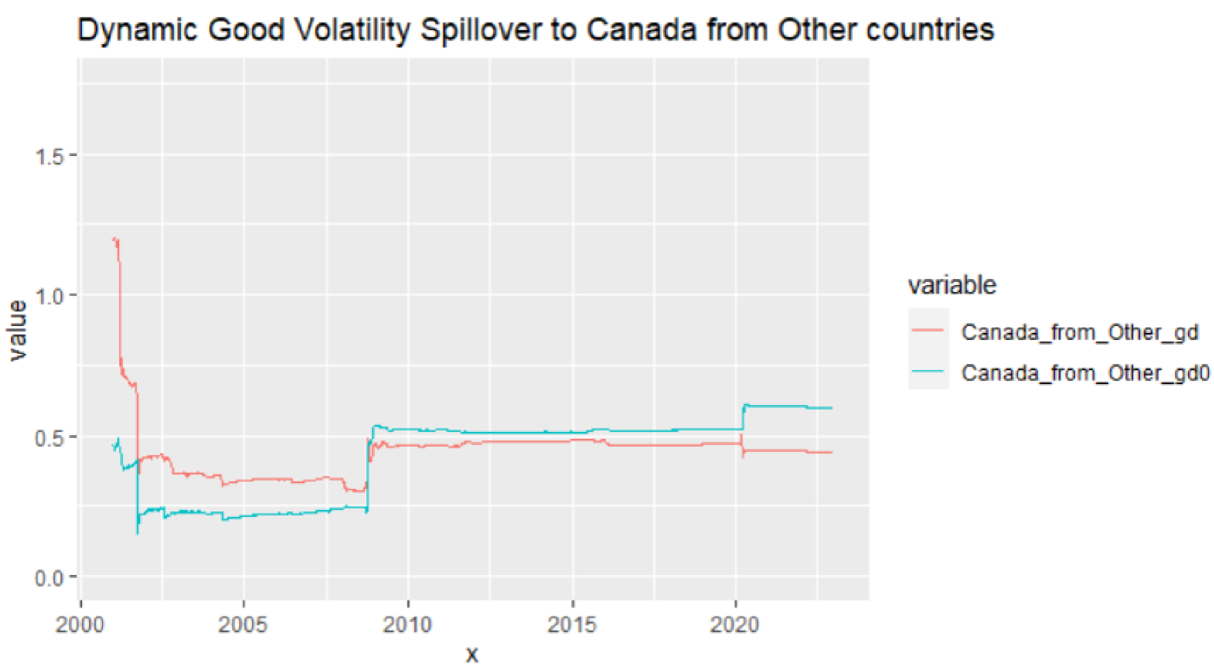


Fig 31. Good volatility spillover to Canada from other countries

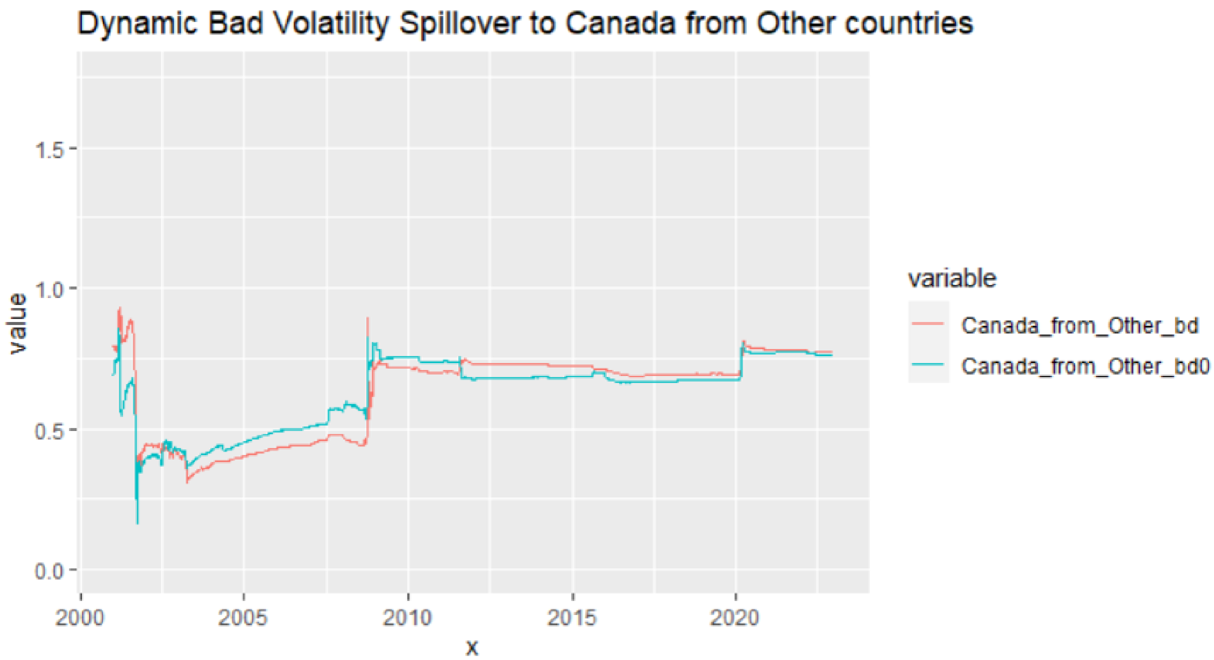


Fig 32. Bad volatility spillover to Canada from other countries

The next country will be Japan. Below we will see the figures of the spillover effect of other six countries to Japan.

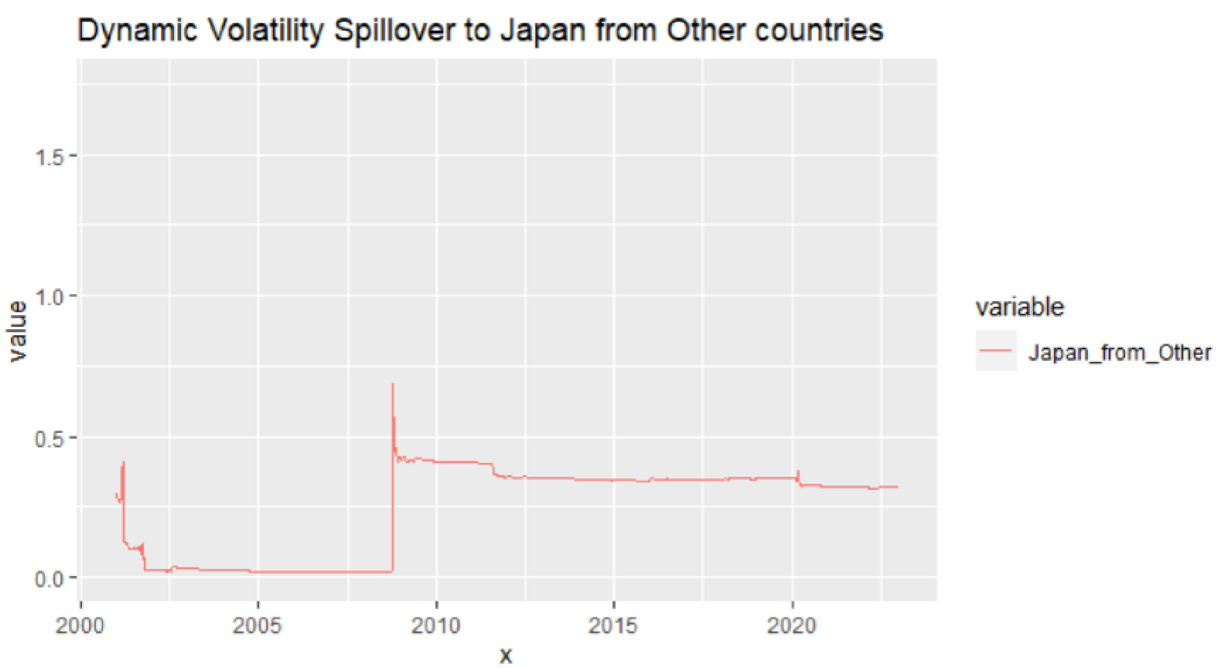


Fig 33. Volatility spillover to Japan from other countries

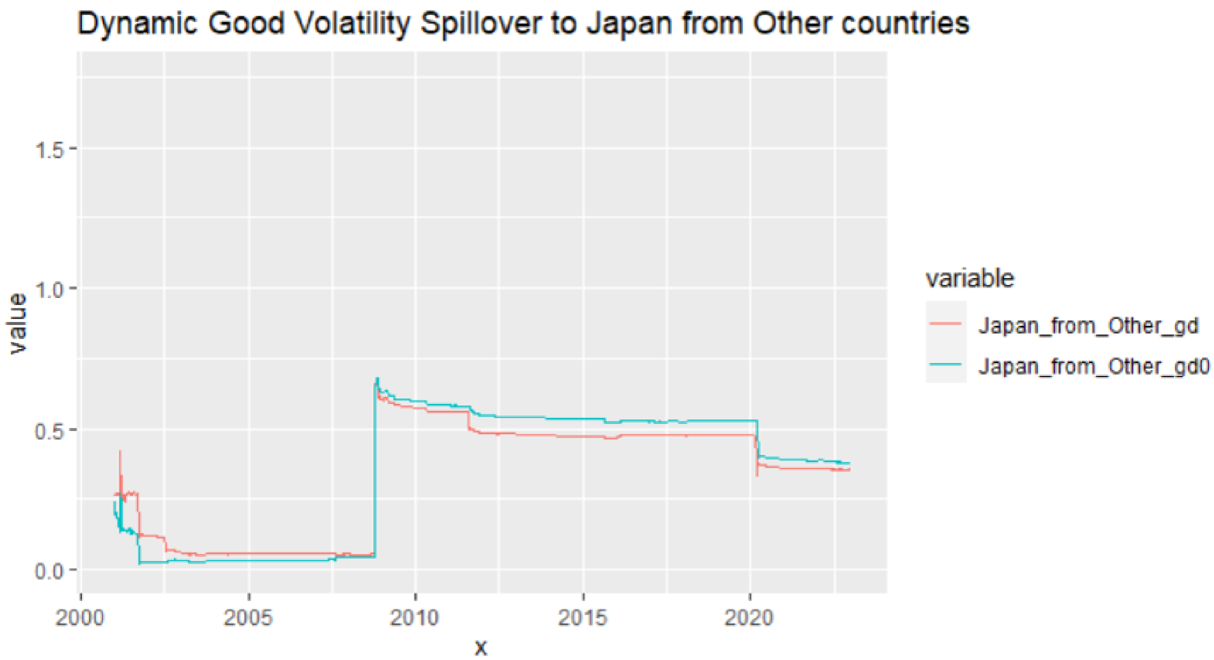


Fig 34. Good volatility spillover to Japan from other countries

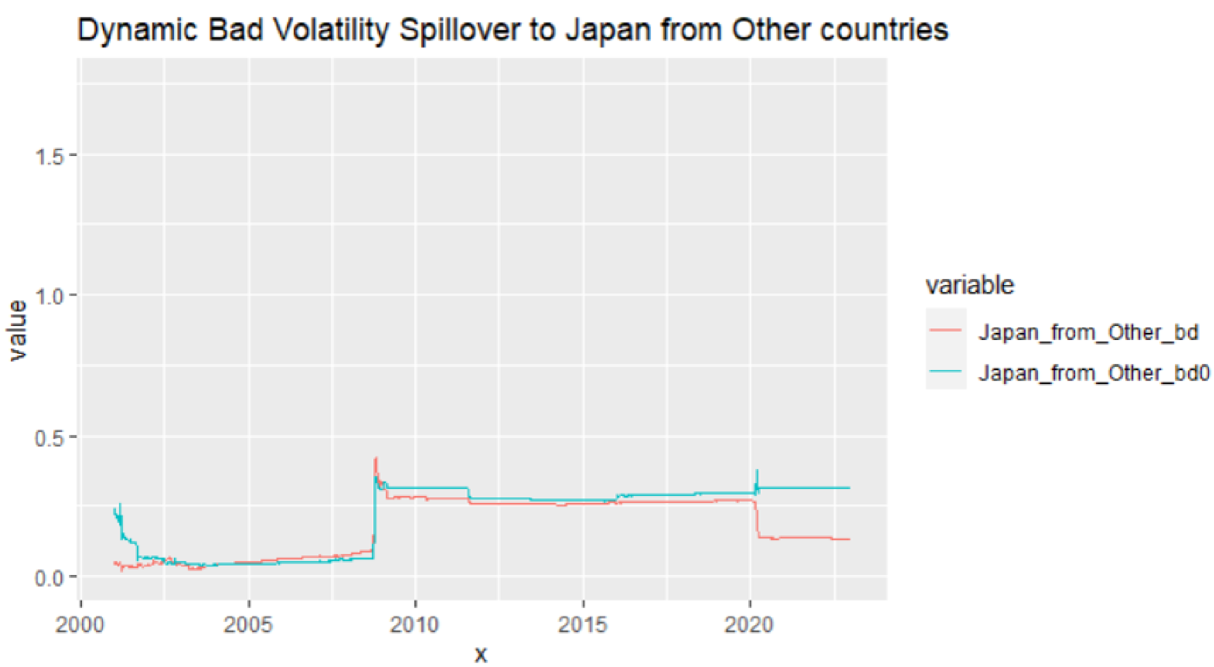


Fig 35. Bad volatility spillover to Japan from other countries

The fourth country will be Italy. Below we will see the spillover effect of other countries to Italy.

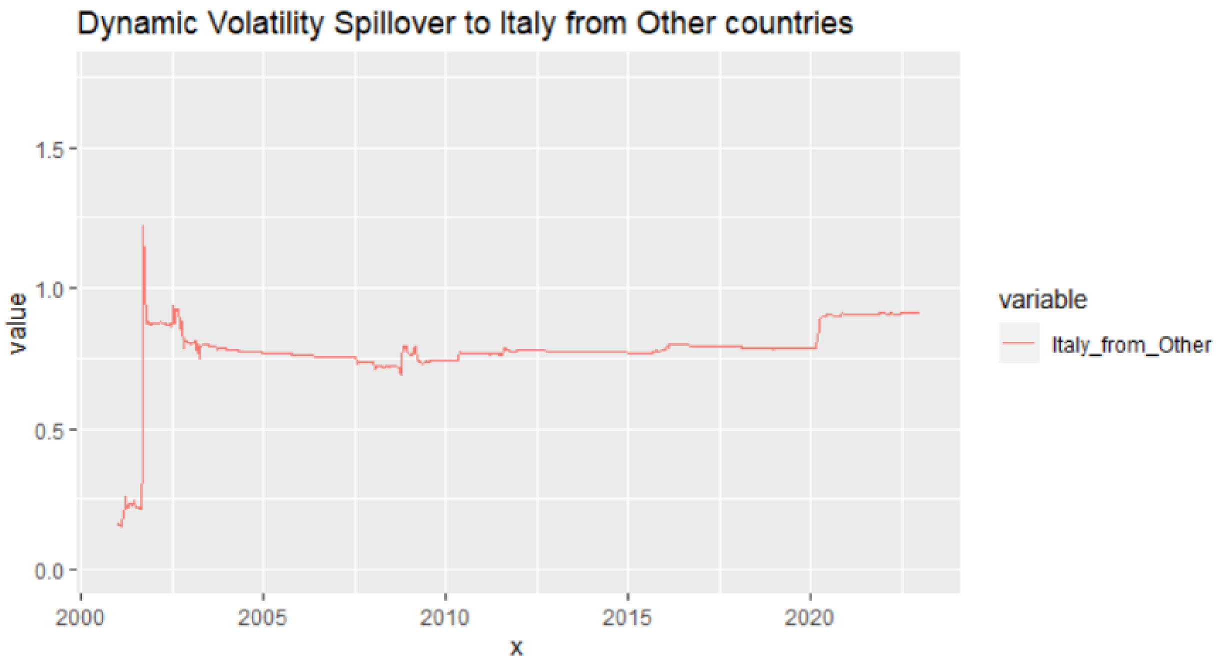


Fig 36. Volatility spillover to Italy from other countries

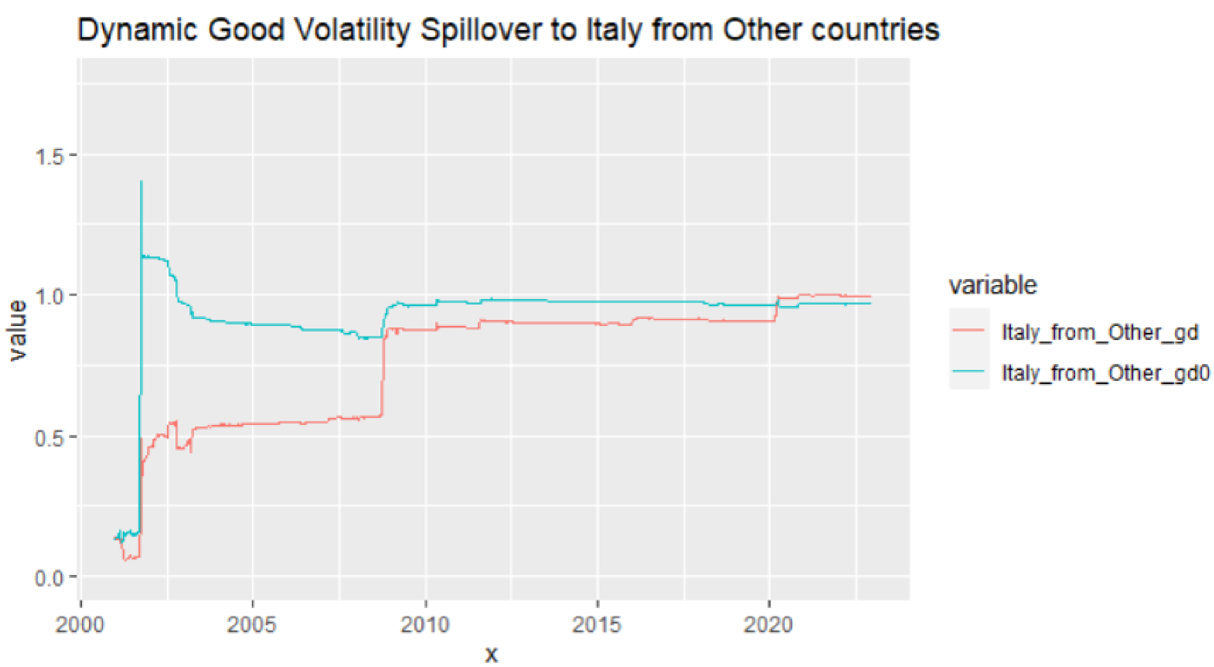


Fig 37. Good volatility spillover to Italy from other countries

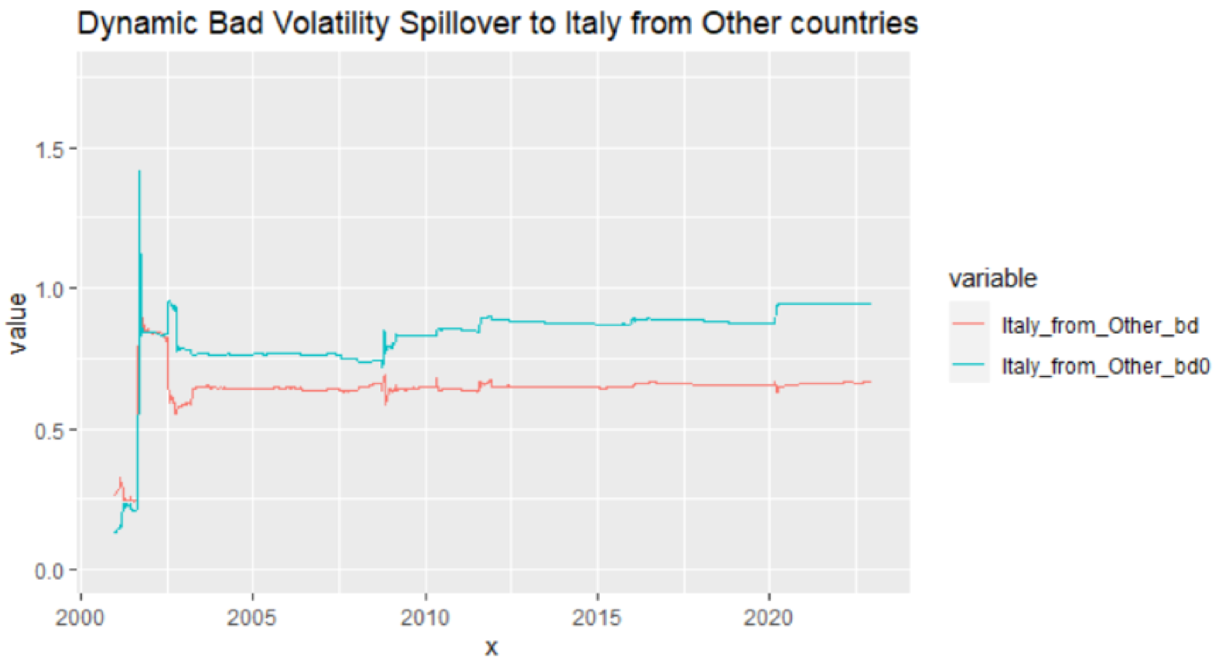


Fig 38. Bad volatility spillover to Italy from other countries

The next country will be Germany. Below we will see the spillover effect of other countries to Germany.

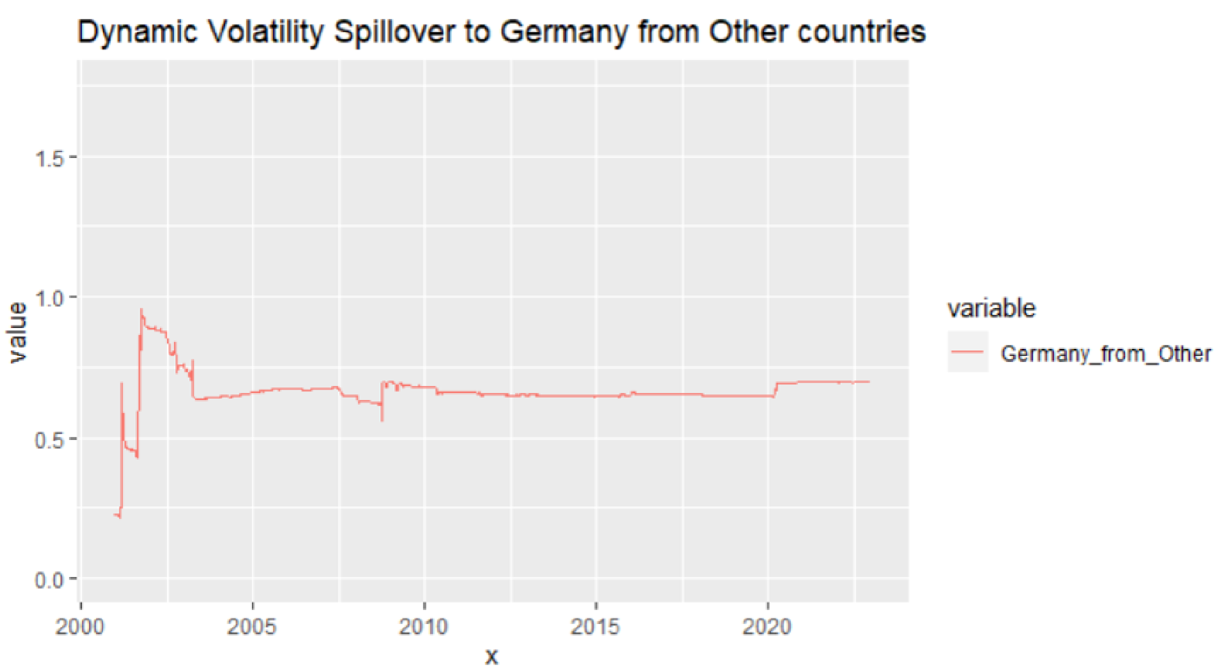


Fig 39. Volatility spillover to Germany from other countries

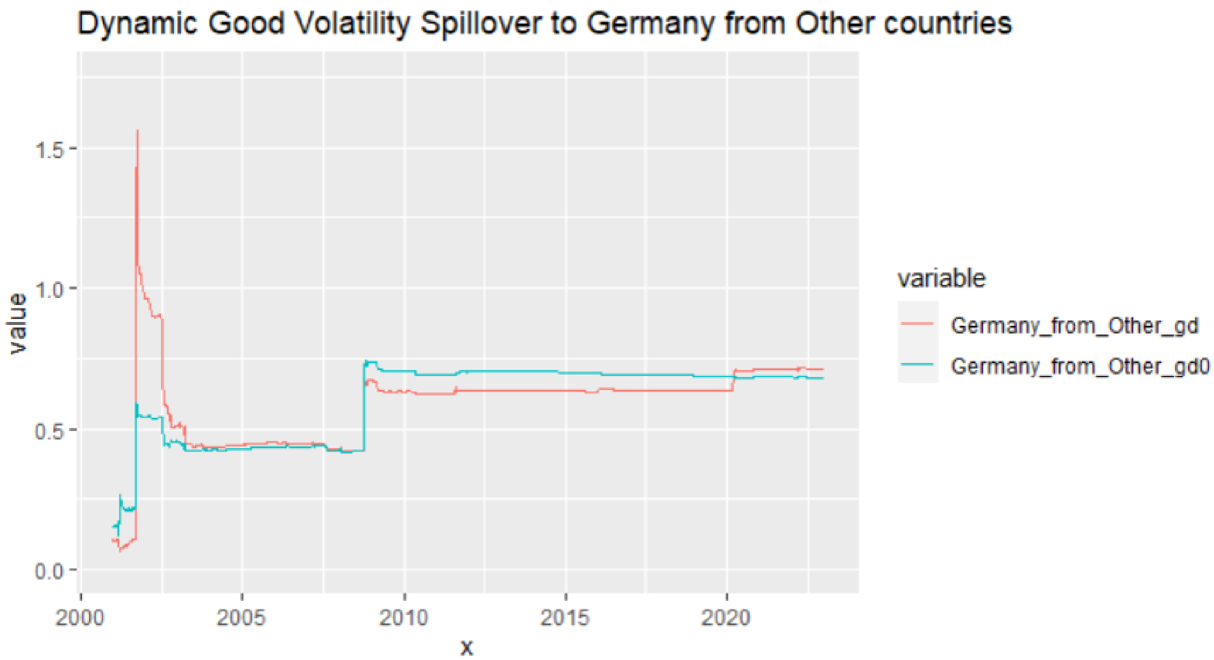


Fig 40. Good volatility spillover to Germany from other countries

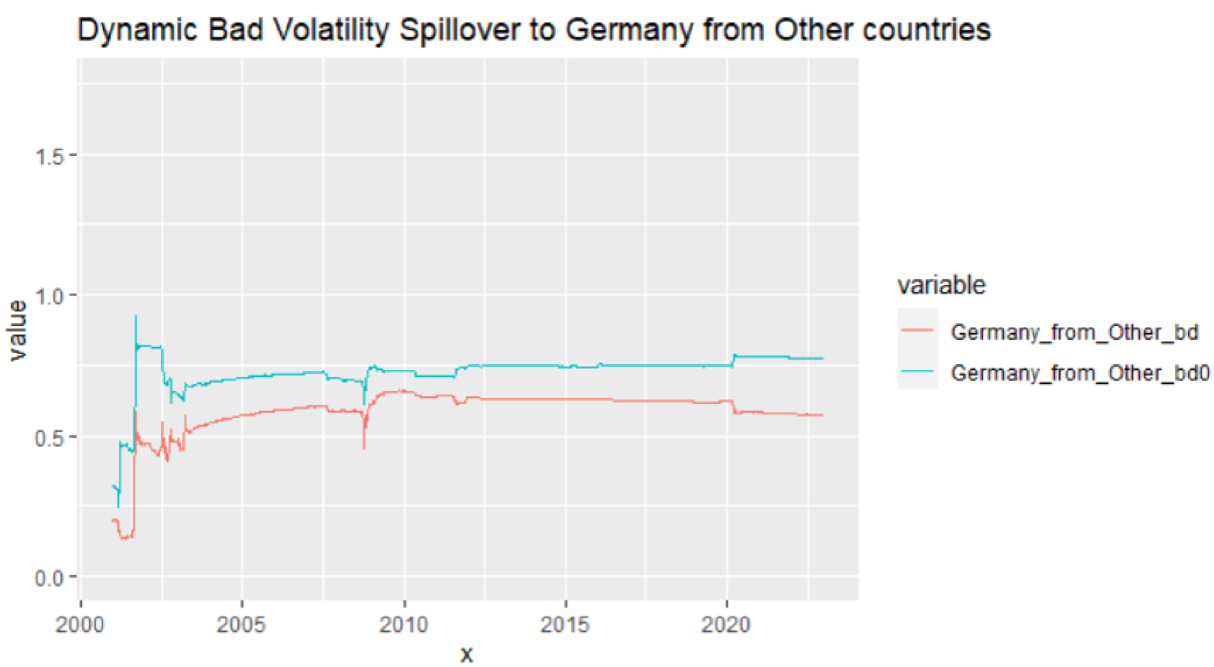


Fig 41. Bad volatility spillover to Germany from other countries

Below we will see the spillover effect figures of other countries to France.

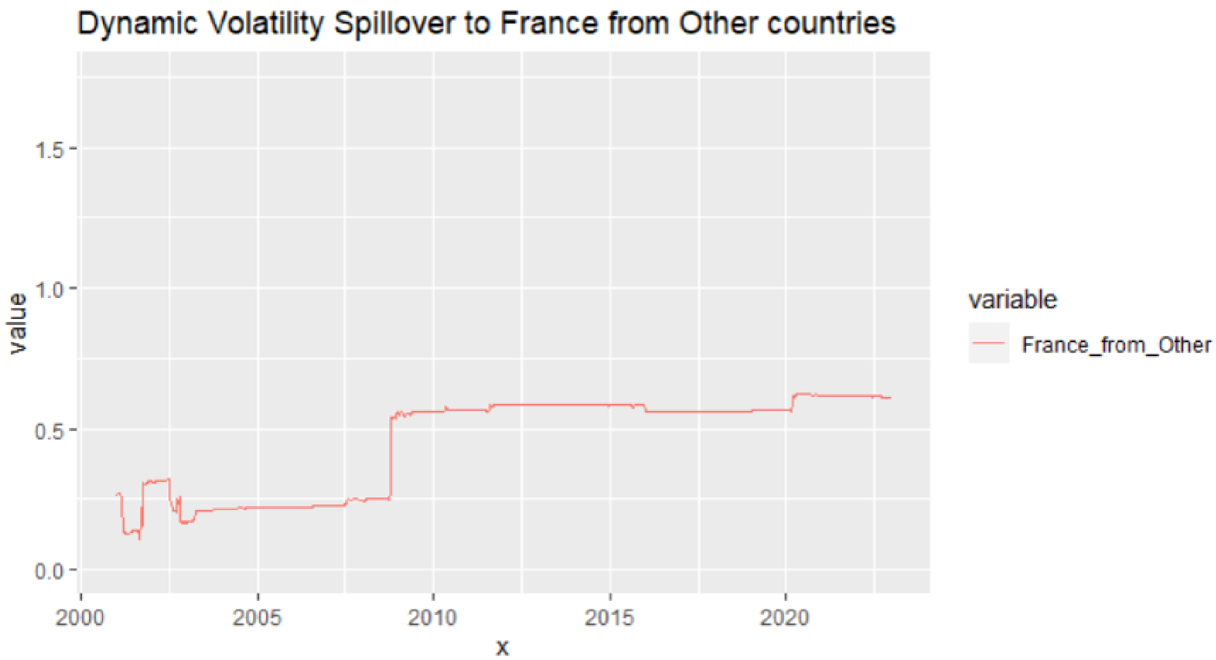


Fig 42. Volatility spillover to France from other countries

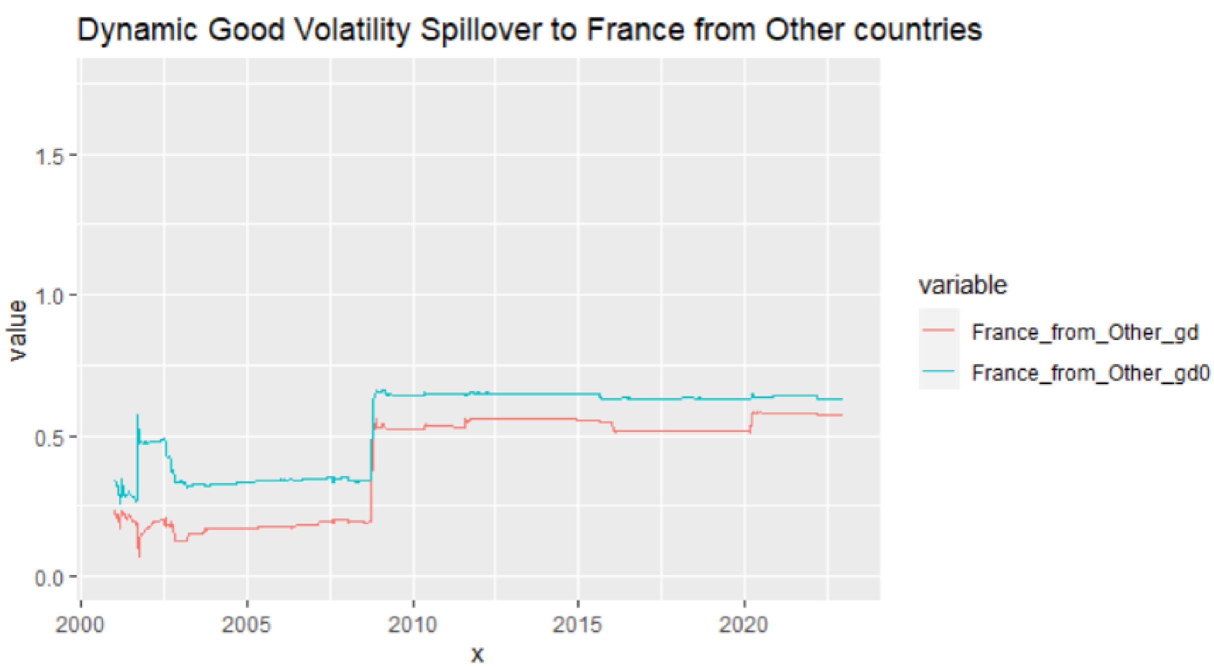


Fig 43. Good volatility spillover to France from other countries

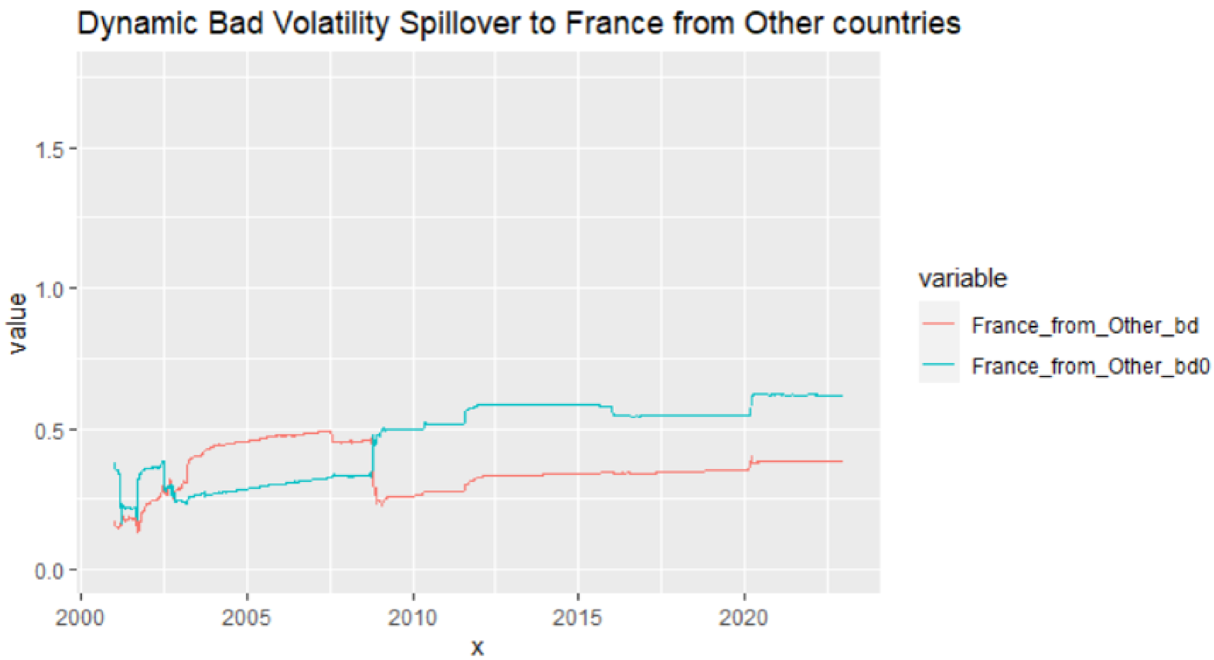


Fig 44. Bad volatility spillover to France from other countries

CHAPTER 5: DISCUSSION AND CONCLUSION

Contribution to the theory

We investigate the asymmetric volatility spillover effects in six major stock markets. We follow the techniques in Diebold and Yilmaz (2012) to measure volatility spillover effects. Using the Markov-switching GARCH model, we can capture the conditional volatility after controlling for time-varying expected return. Literature has suggested that ignoring the time-varying expectation will overestimate the conditional volatility. Hamilton and Susmel (1994) also show that controlling time-varying expectation is critical in the ARCH framework. Model selection criteria (Corrected Akaike Information Criteria) also indicates that our model outperforms the traditional GARCH model. The volatility spillover effects we measured demonstrate that the U.S. has a dominant role in spillover effects to other counties, while Japan has the smallest spillover effects from other countries which indicates that it is the most stable financial market among the six countries we considered.

The Markov-switching GARCH model in our paper not only can capture volatility more precisely, but it also can quantify the time-varying expected returns. A stylized fact in stock return is the asymmetries in volatility. Volatility is larger when the market is bad, and volatility reduced when the market recovers. It is interesting to see whether the same asymmetries also exist in volatility spillover effects. To investigate this, Bensaida (2019) proposes a GARCH model and uses 0 as constant expected return as well as the time-invariant threshold. We extend his research by allowing time-varying expected return and time-varying threshold for good/bad volatility. Our results are more consistent with the general understanding of stock markets. Our results also suggest a more dramatic difference between volatility spillover effects under good/bad volatility.

To further enhance this research we identified the following areas to expand upon Bensaida's work. We introduced time-varying expected returns that replaced a constant mean to refrain from overestimating volatility. In previous research, good and bad volatility was measured using zero as an absolute threshold which may not display the impact of good or bad news on investor expectations accurately. Instead, we used expected return for a more practical approach. We differentiated between bull and bear markets and analyzed how spillover effects of volatility differ between bull and bear markets. The results of this project include a bear market index which reveals the likelihood of each period being part of a bear market.

Although both methods are approximating investor's reactions, expected return and absolute threshold, our results show that sticking with a more practical approach such as expected return conception yields more direct results that are more consistent with the general understanding of stock markets. It was also observed that using zero as the threshold parameter tends to overstate the spillover effect, meaning it is not as reliable and realistic of an interpretation. Therefore, for greater reliability and accuracy when defining good and bad news, stockholders' expectations of returns should be taken into consideration.

Summary of Results

Volatility spillovers are shown to be asymmetric and have the largest percentage in its own market. Canada is found to have the least amount of impact on other countries' volatilities while Japan receives the least contribution from other countries. The US market appears to receive less volatility than most others and has a dominant role in affecting other markets according to investor's perspective. This differs from the results in Bensaida (2019) which places the U.S. in third in terms of market dominance. While Japan and the U.S. generally experience the least amount of volatility from other countries, Italy experiences the most. It is concluded that investors' expectations play a significant role when forecasting volatility.

These findings may benefit companies in understanding these probabilities and potential effects. This could be a highly beneficial tool in assessing when is most and least optimal for companies to make investment decisions as potential market fluctuations could reduce or increase returns on investments exponentially.

Results show that the U.S. has a strongly asymmetric impact on volatility for G6 markets–a one standard deviation shock in U.S. volatility can cause higher volatility in four other countries, compared to when a one standard deviation shock in the other countries increases U.S. volatility. As previously stated, we find that Japan and the U.S. receive the smallest contribution of volatility from other countries, while Italy is most impacted by external changes in volatility from other markets. Additionally, the findings suggest that investors expect great consequences in terms of the U.S.'s role when predicting future change in market volatility, heavily influencing current trends- distinctly different from results published by Bensaida (2019), where the U.S.'s position was weakened to under three dominant markets.

Recommendations to Business

By using the research presented, companies like JP Morgan can gain a better understanding of the characteristics of different capital markets and how spillovers may affect their business growth and investment strategies. Companies may use this knowledge to devise strategies and exploit favorable spillover opportunities. Companies can also use the bear market index to hedge financially when periods are more bearish. As an example, the results display an increase in spillover effects to the world during three major events that amplified the global economic downturns across multiple nations and industries. The 2000 recession and dotcom bubble, the 2008 financial crisis, and the Covid-19 pandemic all put significant pressure on financial systems which makes investing more volatile than normal.

As the industry becomes increasingly competitive through the use of capabilities such as data analytics and artificial intelligence, it is crucial for companies to leverage the proposed model for return maximization, risk management and hedging, and investment strategy (Deloitte Insights, 2022). Investing is becoming more complicated due to the increasing number of markets, investment options, and new technologies available. As a result, analyzing return and risk of investments extensively with a focus on portfolio management, has become essential to understand, anticipate, or minimize different risks involved. Since portfolio optimization depends on understanding expected return and risk of all the assets, studying the volatility of global stock market portfolios is necessary. The understanding of the volatility of stock markets in one country and how that volatility affects the volatility in other markets is important for investors to determine if they want to include such markets in their portfolio and to assess their risk appetite.

Visualizing expected return and conditional volatility in six stock markets involves determining the average return and risk of investing in each market. This is useful to investors or investment firms comparing investment opportunities across multiple markets. Analyzing how volatility of the stock market in one country will spillover to the other markets focuses on studying how changes in the levels of volatility in one market can cause changes in volatility in other markets. By studying this, companies can also see to what extent one market's volatility impacts other markets. This can help investment firms like Morgan Stanley determine their risk appetite and the exposure they are willing to take on for potential expected returns when they invest in foreign markets.

Investors can predict and quantify volatility spillover effects using rolling window analysis to anticipate when and where these events are occurring. In addition, investors can use this to assess correlation changes between markets and foresee systematic risk. Measuring the dynamics of volatility spillover effects during unusual events such as financial crises and pandemics aims to examine how these events impact stock market volatilities across all markets whether positively or negatively. In doing so, investors can assess the level of risk and be better equipped for decision making during such events.

Recommendations For Organizational Change

Based on current technology and capabilities leveraged by investment firms, implementing the model would require minimal changes to existing infrastructures. Execution of the model requires a data management system, data analysts, data scientists, machine learning engineers, a reliable technology platform, subject matter experts and a risk management system.

A reliable and robust data management system is required for an investment firm to properly implement advanced analytics. Having this ensures data is accurately presented to facilitate understanding of the data for effective decision making. The firm must also have data analysts who understand finance, the business of investing and the capabilities of advanced analytics technology to ensure that results from analytics are interpreted correctly. Furthermore, individuals with knowledge in advanced statistical methods and machine learning techniques are necessary. These individuals can analyze data and apply advanced analytics such as predictive modeling and forecasting. Reliable technology and software with the capacity to execute and automate the advanced analytics process is ideal considering the volume and velocity of market data. Artificial intelligence can also be used to identify trends, determine benchmarks, automation, evaluation of risk, forecasting and decision making. In addition, subject matter experts in various financial, economic, and quantitative fields are required for proper implementation and interpretation of advanced analytics. A comprehensive risk management system is essential when implementing advanced analytics for investing activities, to ensure proper oversight and compliance.

Markov-switching paper investigates whether MS-GARCH models provide risk managers with useful tools for improving the risk forecasts of the sorts of securities that are typically held by fund managers. Moreover, we investigate whether integrating the model's parameter uncertainty within the forecasts, via the Bayesian approach, improves the predictions.

Regarding the model, risk managers should extend their GARCH-type models with Markov-switching specifications in the case of investments in equities. Indeed, we find that Markov-switching GARCH models deliver better Value-at-Risk, expected shortfall, and left-tail distribution forecasts than their single-regime counterparts, especially for stock return data. Moreover, the improvements are more pronounced when the Markov-switching mechanism is applied to simple specifications such as the GARCH-Normal model. Second, accounting for parameter uncertainty helps for left-tail predictions independently of the inclusion of the Markov-switching mechanism. Moreover, larger improvements are observed when the parameter uncertainty is included in single-regime models. Overall, we recommend that risk managers rely on more flexible models and perform inference to account for parameter uncertainty.

Plans For Organizational Change

J.P. Morgan Chase Asset Management Organization, being a significant player in the financial industry, recognizes the crucial role of risk management in its daily operations and long-term strategies. The ongoing evolution in the business environment, however, has necessitated a review and enhancement of its current risk management policy. The aim is to introduce a robust, dynamic policy that reinforces cross-functional teamwork, leverages project management best practices, and encourages proactive leadership. This transformation will not only fortify its risk preparedness but also drive organizational resilience and competitiveness.

The change will be navigated through a meticulously crafted strategy, beginning with an in-depth analysis of the current risk management practices and the organization's culture. The new policy will be designed to address identified gaps and augment its strengths. Leadership will play an integral role in setting the tone for change, backed by a strong engagement plan that will keep all stakeholders informed, involved, and reassured. The strategy underscores the creation of cross-functional teams to encourage collaboration and cohesion across departments, while also adopting suitable project management methodologies to integrate the new risk policy seamlessly into the organization's workflow. Training will be provided to bridge knowledge gaps, ensuring that everyone is well-equipped to operate within the new policy framework.

Finally, the success of this transformation will be measured by carefully selected Key Performance Indicators (KPIs), with regular reviews and audits conducted to ensure adherence to the new policy and to identify areas of improvement. Potential challenges that might arise during the transition will be anticipated, and mitigation strategies will be prepared to address them promptly. This comprehensive change management plan, therefore, seeks to facilitate the successful implementation of a new risk management policy. By doing so, J.P. Morgan Chase Asset Management Organization will foster a culture of risk-aware decision making, cross-functional collaboration, and strong leadership, reinforcing our position as a resilient and trusted entity in the financial industry.

REFERENCES

1. Bekaert, G., Engstrom, E., Ermolov, A., (2015), "Bad environments, good environments: a non-Gaussian asymmetric volatility model," *Journal of Econometrics*, 186, 258-275.
2. Bekaert, G.,Wu, G., (2000), "Asymmetric volatility and risk in equity markets," *Review of Financial Studies*, 13, 1-42.
3. BenSaida, A., (2019), "Good and bad volatility spillovers: An asymmetric connectedness," *Journal of Financial Markets*, 43, 78-95.
4. Chen, X., Ghysels, E., (2011), "News-good or bad-and its impact on volatility predictions over multiple horizons," *Review of Financial Studies*, 24, 46-81.
5. Diebold, F.X. and Yilmaz, K., (2012), "Better to give than to receive: predictive directional measurement of volatility spillovers," *International Journal of Forecasting*, 28, 57-66.
6. Wu, G., (2001), "The determinants of asymmetric volatility," *Review of Financial Studies*, 14, 837-859.
7. Glosten, L.R., Jagannathan, R., Runkle, D.E., (1993), "On the relation between the expected value and the volatility of the nominal excess return on stocks," *Journal of Finance*, 48, 1779-1801.

8. Forbes, K.J. and Rigobon, R., (2002), "No Contagion, only interdependence: Measuring stock market comovements," *Journal of Finance*, 57, 2223-2261.

9. Kim, C.-J., (1994), "Dynamic linear models with Markov-switching," *Journal of Econometrics*, 60, 1-22.

10. King, M., Sentana, E. and Wadhwani, S., (1994), "Volatility and links between national stock markets," *Econometrica*, 62, 901-933.

11. Jones, H., (2021) "Why the U.S. will continue to dominate the global equity markets," *The National News*. 18 May.

12. Hamilton, J. D., & Susmel, R. (1994). Autoregressive conditional heteroskedasticity and changes in regime. *Journal of econometrics*, *64*(1-2), 307-333

13. Teräsvirta, T. (2006). *An introduction to univariate GARCH models. SSE*. EFI Working Papers in Economics and Finance (646).

14. Ang, A., & Timmermann, A. (2012). Regime changes and financial markets. *Annu. Rev. Financ. Econ.*, *4*(1), 313-337.

15. Fuess, R., Kaiser, D. G., & Adams, Z. (2007). Value at risk, GARCH modeling and the forecasting of hedge fund return volatility. *Journal of Derivatives & Hedge Funds*, *13*, 2-25.

16. Maheu, J. M., McCurdy, T. H., & Song, Y. (2012). Components of bull and bear markets: bull corrections and bear rallies. *Journal of Business & Economic Statistics*, *30*(3), 391-403.

17. Herbert, W. E., Ugwuanyi, G. O., & Nwaocha, E. I. (2019). Volatility clustering, leverage effects and risk-return trade-off in the Nigerian stock market. *Journal of Finance and Economics*, *7*(1), 1-13.

18. Deloitte Insights. (2022). 2023 Investment Management Outlook.

19. JPM-AM Market Insights. (2023). 2023 Mid-Year Investment Outlook.

20. JPM-AM Market Insights. (2022). The Investment Outlook for 2023.