# VOLATILITY SPILLOVERS BETWEEN U.S. AND EUROPEAN PRIMARY INDICES AND IMPACT OF MACROECONOMIC DETERMINANTS

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**Abstract**

The research study stock market influences through the last decades with the purpose of establishing if there is significant relationship between more developed stock markets and secondary ones. It is particularly useful in further analysis on portfolio diversification, especially during the times of turmoil in the markets. This analysis explores the connections between US and European primary indices and how this relationship is explained by macroeconomic variables. The study, by considering the returns of primary indices in 20 countries investigates the correlation between them and main primary index of US. The analysis uses DCC- GARCH model to provide insights into how information transmits and spills from each part of the financial world into another with capturing time-varying correlations. With combination of macroeconomic variables analysis provides the evidence of relationship between the spillover and development and how deeply it integrates with worldwide economies. Specifically, analysis contains main macroeconomic determinants such as Gross Domestic Product, Consumer Price Index, Trade Balance, Foreign Direct Investment, Industrial Production Index and recession cycles. The results provide observations into the interdependence of US and European financial hubs.

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# 1. Introduction

## 1.1. Background and Motivation.

The study of the influence of crashes across the markets has been the subject matter of various research for academics and analysts during recent times. The increasing global financial integration emphasizes the effect and research importance of the volatility spillovers in different financial markets. The stock market is to some extent mirroring the national economy which fully reflects the economic fluctuations of a country or region. Therefore, a study of the spillover effect of US stock market and foreign stock markets is significantly important in monitoring the transmission across financial markets, maintaining the safe operations of financial system and elevating economic development.

It is the nature of the markets to be volatile. The ups and downs of the financial markets are closely watched by the society, because of straightforward influence on households' finances. Public interest in market movements has intensified in the last decades, even more after the global financial crisis of 2007. When there is a sharp decline in the stock prices it attracts attention of the analysts and researchers and may sound confusing to people who are not familiar with this matter. Often the aftermath of the significant turmoil in the global markets is noticeable for wider public.

It is very challenging to time the market in short period of time. That is why many financial intermediaries offer solutions such as maintaining a long-term horizon and ignore the short-term fluctuations. However, this alternative may not fully explain how volatile markets are. Due to uncertainty and herd behaviour markets can experience disturbance which affects the gains even for long-term investors and the reaction to these events is crucial. The presence of volatility requires investors to develop ways to deal with it. Knowing the volatility behaviour would be extremely profitable to investors.

The aim of this paper is to investigate the relationship between the US S&P500 and European primary indices. More precisely, correlation and volatility spillovers between the primary index in United States, namely US S&P500 and the primary stock index returns of the 20 European countries, which are: ATX (Austria), BEL20 (Belgium), PX (Czech Republic), OMX Copenhagen AllShare (Denmark), OMX Helsinki 25 (Finland), CAC40 (France), DAX (Germany), BUX (Hungary), FTSE MidCap Index (Italy), AEX (Netherlands), OSEBX

Benchmark (Norway), WIG (Poland), PSI20 (Portugal), IBEX35 (Spain), OMX Stockholm Benchmark (Sweden), SMI (Switzerland),FTSE100 (United Kingdom), ISEQAllShare (Ireland), BIST100 (Turkey), LUXX (Luxembourg). The bivariate GARCH models are estimated using daily return data from January 3, 2008, to December 23, 2022. An additional objective is to use the macroeconomic variables to test for the relationship with the wider economy factors and find how the overall risk related to volatility is affected by S&P500 in each significant European primary index in the country. The results could be crucial for adjusting portfolios by macroeconomic variables to see the relationship between wider investment, trade policy, consumer price index, country's growth, industrial production and forecasting volatility between stock markets.

## 1.2. Research Objectives

Volatility Spillovers occur when the risk or uncertainty in one market affects the volatility in another market. The main objective of the study aims to study how the volatility of US primary index S&P500 influences the main European indices. It leads to determine whether the shocks in one market led to reaction in other market. The research aims to identify the time periods or events that intensify the spillovers, such as shocks related to policy change, political event or financial crises. It also aims to examine the presence of the volatility spillover as well as strength of it. It may differ due to integration in the market as well as significance of the economy of a specific country that includes particular important index on its stock exchange. Additionally, the study objective is to incorporate the GARCH models to analyse whether the results differ across various indices and estimate the conditional volatility and correlations between US and European indices. Furthermore, research aims to assess the impact of macroeconomic determinants on volatility spillovers. Macroeconomic variables such as GDP growth, inflation rates, industrial production index, foreign direct investment inflows are drivers of country's integration in worldwide economy and output. Investigation whether the specific macroeconomic factors have the most significant impact on the spillover might be due to potential interdependence of economies. Interdependence of economies could be associated with the trade balance between two countries. The time-varying nature of volatility and cycles of economic activity are also crucial to point the increased spillover in the markets. Understanding volatility spillovers and the influence of macroeconomic factors has implications on investors. It may provide the insights to diversification, portfolio management, risk management strategy based on the volatility spillover dynamics.

The study attempts to examine the spillovers among advanced European nations with significant stock market capitalisation in a Bivariate framework, to comprehend a holistic picture of linkages. For this purpose, daily returns are taken from January 1st, 2008, to December 31st, 2022.

## 1.3. Research Questions.

This thesis will investigate the relationship between US primary index (S&P 500) and twenty most recognised primary indices in twenty European countries, focusing on the volume of influence of S&P500. Additionally, the analysis will investigate the degree of relationship in which changes in macroeconomic determinants: affect the change in correlation between primary index of US and primary index of other countries. The analysis will try to answer: Is there connection between different European indices and main US financial index? How particular macroeconomic factors contribute to the transmission of volatility between global financial markets? How financial integrations affects volatility spillover?

## 1.4. Contribution of the study.

The inspiration for analysis of this subject, arise from the search for stock market influence in wider economy and attempt to explain why particular markets with similar background of financial markets history are more interconnected than others. In this case, the macroeconomic factors will be investigated. This thesis will contribute with using data from several wider in variety primary indices in European market. The study incorporates the role of key macroeconomic determinants into analysis at the same time. It gives a glimpse into the context of macroeconomic linkages which may potentially point out threshold of development which launch heightened volatility during crisis periods faster.

# 2. Literature Review

## 2.1. Volatility in Financial Markets

Stock exchange is a marketplace and infrastructure that facilitates equity trading. Stock market is a broader term encompassing all stocks traded within a specific region or country. It is often represented by an index or a collection of various stocks, such as the S&P 500 that connects companies and investors. It enables companies to raise capital by issuing equity shares that investors can buy. The funds raised are reinvested into the company, while investors aim to profit from their investments. Companies list their stocks on an exchange where buyers and sellers can trade. In the U.S., the two primary exchanges are the NYSE and Nasdaq. Companies listed on these exchanges must meet specific minimum requirements and adhere to baseline rules regarding their boards (Harper, D.R., 2024). Paper by Zhao (2010) mentions that “stock prices are generally interpreted as representing the present values of future cash flows of firms, reacting to exchange rate changes and forming the link among future income, interest rates, current investment and consumption decisions”. Equity markets offer opportunities for diversification and risk mitigation for investors, while also assisting policymakers in creating effective strategies and implementing legal framework to regulate them. Consequently, it is crucial to understand the co-movements and volatility transmissions that occur within these markets. Economic globalization is creating more opportunities for consumers and producers by facilitating trade in goods and services and promoting the internationalization of production, particularly through multinational corporations. The internationalization of financial markets is an integral part of modern research. The concept of volatility is captured from different academic perspectives but is analogous. Generally, in a wider economic perspective it refers to the frequency and magnitude of changes in the price of a financial instrument or market index (Engle, Rangel, 2008). It is also described as the degree of variation of a trading price series over time, usually measured by the standard deviation of logarithmic returns (Andersen et al. (2001). It is also referred to be used as a gauge of market risk (Jorion, 2007). The process where transmission of instability from market to market is defined as volatility spillover. It occurs when the volatility price change in one market causes a lagged impact on the volatility price in another market above the local effects of market. According to Obstfeld (1998), the relaxation of capital controls facilitated the free movement of funds between countries, enabling investors to diversify their portfolios internationally. This increased flow of capital has contributed to a deeper financial integration among markets, as investors seek opportunities globally to optimize returns and manage risk (Obstfeld, 1998).

In symposium Financial Market Volatility (1988), authors stated throughout the postwar period, stock markets, commodity markets, bond markets and foreign exchange markets have recorded sharp movements and again noted that these markets uncovered considerable volatility in 1987, during Black Monday- a global scale, largely unexpected and severe crash on October 19, 1987. Financial Market Volatility (1988) pointed that volatility in financial markets could have far-reaching ramifications. Participants of the symposium suggested that such volatility could disrupt domestic economic activity, unsettle international asset flows, and place strains on global supervisory efforts. The conference answered the question of: Through what channels can financial markets affect real economy by mentioning the paper by M. Gertler and G. Hubbard "Financial Factors in Business Fluctuations". According to their theory, financial markets fluctuations can affect the real economy through two channels: internal net worth of firms and availability of bank credit. By lowering the collateralizable net worth of the companies, economic downturns make it harder for these companies to borrow. In consequence, capital investment declines. Gertler and Hubbard (1988) stated that evidence support the theory. Historical events and background can have an impact on the investment of firms, particularly small ones, due to that the financial market fluctuations can affect the macroeconomy. As an example, to show this theory, the observation of little effect of 1987 market crash on economy is presented by the authors. Researchers stated that stock prices did show considerable variability in 1987, but it was not exceptionally consistent through the year. In this case, to the extent that changes in stock prices mirror changes in firms' collateralizable net worth, it did not change substantially for the year as a whole. It leads to realisation, that it had not much effect on investment, hence, overall economy. Eventually, Gertler and Hubbard (1988) mentioned that the crash of 1987, as compared to Great Depression, did not cause a significant restriction of bank credit, because of Federal Reserve involvement in providing liquidity. The subsequent point made by the symposium, related to international impact, a paper by C. Goodhart (1988) was summoned. Author claimed that, even though market participants should be cautious in adopting the view that financial market interdependence is on the rise, the international transmission can still play a significant role on key occasions. The crash of 1987 appeared to be one of them. Financial Market Volatility (1988) symposium participants, C. Goodhart and B. Quinn agreed that main worldwide stock markets during that time- London, Tokyo and New York are quite different in structure and expected to display different degree of international sensitivity.

The efficient markets hypothesis of financial economics states that the price of an asset reflects all relevant information that is available about the intrinsic value of asset. The EMH applies to all types of financial securities, discussions of the theory usually focus on one kind of security, namely, shares of common stock in a company. This theory developed by Eugene Fama (1970), suggests that financial markets are informationally efficient. In the financial markets, price of an asset fully reflects all available information at any given time. The author also depicts three versions. In a weak form, all past trading information (trading volume and historical prices) is already reflected in current prices. The technical analysis cannot contribute to obtaining an edge in returns as this information is already reflected. In a semi-strong form, all publicly available information such as news, financial reports are also reflected in asset's prices. This form adds that fundamental analysis as well as technical one mentioned in weak form, cannot create any excess in returns because it is already included in the prices Lastly, the strong form, shows that all knowledge, including insider information, is reflected in the asset's price (Fama, 1970). The implications on this theory for investors could mean that passive investing strategy and index fund offer better risk- adjusted returns and also a person doing research on their own has no more power in generating excess returns over a person who picks stocks randomly (Logue, 2024). EMH favours a passive investing strategy, where investors purchase and hold for long period. In a paper by B. G. Malkiel (2003) author mentioned that the intellectual dominance of the efficient market hypothesis had become far less universal and stated that researchers of this subject began to believe that stock prices are at least partially predictable. Malkiel (2003) emphasized psychological and behavioural features of stock-price determination and concluded that future stock prices are somewhat predictable on the basis of past stock price patterns as well as certain "fundamental" valuation metrics. Furthermore, Malkiel (2003) argued that collective judgment of investors will make mistakes that results in pricing irregularities and predictable patterns in stock returns can appear over time and even persist for short periods. Besides, he summoned the point stressed by Grossman and Stiglitz (1980) that market cannot be perfectly efficient or there would be no incentive for professionals to uncover the information that gets so quickly reflected in market prices. Additionally, research by Lo A. W. (2004) stems from EMH and introduces new approach which is Adaptive Market Hypothesis. For the reason of behavioural biases, innovations, change in market conditions and disturbances market efficiency evolves over time. The significant input into subject of volatility spillovers was introduced by Diebold and Yilmaz (2009) where authors introduced a framework for linkages in asset returns and return volatilities. Diebold and Yilmaz (2009) formulated measures of return spillovers and volatility spillovers based on notion of variance decomposition in vector autoregressions. It composes an index which study both crisis and non-crisis periods, including trends as well as bursts in spillovers. The index can be measured between financial markets, f.e. US and Asian countries. The methodology proposed by them has been widely adopted to analyse how shocks in one financial market affects volatility in other markets, especially during times of financial crises. The research portrays that global markets are interdependent (Diebold & Yilmaz, 2009). In research Modelling volatility spillovers from the US equity market to ASEAN stock markets by Vo X. V. and Tran T. A. (2019), authors studied the volatility spillovers in emerging markets as this specific area provide an ideal setting to study this subject. There is considerable number of reasons for that. It is assumed that they are more volatile, smaller in size and bigger in impact of small innovations than the developed equity markets. The results of the paper, show strong spread of volatility from US to ASEAN. Authors come to the conclusions that globalization and financial liberalization facilitates the cross-border capital movement, especially from mature to emerging markets. They point out the relevance of these observations for policymakers, especially to control excessive volatility spillovers. It has also practical importance for mitigating portfolio risk.

In the paper by Bartram S. M., Brown G., Stulz R. M. (2012), authors prepare global data set of firms from 50 countries between 1990-2006. They show that the stock returns of foreign firms are less volatile than the stock returns of comparable U.S. firms in the dataset. They attribute this difference mostly to foreign firms having lower idiosyncratic risk than comparable U.S. firms. It could be due to country and firm characteristics. Authors separate good and bad idiosyncratic volatility. Idiosyncratic volatility which is firm- specific and could be reduced by diversification, because it is uncorrelated with broader market movements. The study states the higher idiosyncratic volatility of the United States is associated with factors that are expected to be associated with greater economic welfare. In particular, they find that idiosyncratic volatility increases with investor protection, with stock market development, and with innovation. Authors also find that firm-level variables that are associated with innovation and growth opportunities are associated with greater idiosyncratic volatility. U.S. firms have a significantly higher share of research and development (R&D) in the sum of capital expenditures than comparable firms in foreign countries. This higher R&D

share contributes to the higher idiosyncratic volatility of U.S. firms. Some country characteristics that one would generally associate with higher economic and financial development are associated with lower volatility. In particular, authors find that idiosyncratic volatility falls with capital account openness and with bond market development. It can be high for reasons that are associated with greater economic welfare, for instance, greater incentives and ability of firms to take risks that lead to more innovation and growth. It can also be high for other reasons, such as political risk. Overall, volatility is high in the United States compared to the other countries for reasons that are associated with factors that contribute to economic growth (Bartram, Brown, Stulz, 2012).

In analysis by Forbes and Rigobon (2002) addresses the issue of financial contagion, which is often linked to volatility spillovers. The authors argue that what is often interpreted as contagion (i.e., the spread of market shocks from one region to another) may in fact be market interdependence—markets are inherently interconnected, and shocks in one market will naturally influence others. This paper challenges the idea that sudden spikes in volatility are always due to contagion, suggesting instead that global markets have a baseline level of interdependence, which is reflected in volatility movements. Due to deepening financial integration worldwide the interdependence of the world financial market is increasing naturally around it. The asset price fluctuation of one country's financial market often has a lag effect on the volatility of other countries' financial markets, therefore, it becomes a common feature across several financial markets (Zhong Y, Liu J., 2021).

In terms of practical approach, the paper by Engle (2002) introduces the Dynamic Conditional Correlation (DCC-GARCH) model, which has become a popular tool for analysing volatility spillovers. The DCC model allows for time-varying correlations between asset returns and is often used to study how volatility shocks in one market affect others over time. This analysis is significant in showing how inter-market relationships evolve and how correlations between markets change in response to volatility, especially during market turbulence. Diebold and Yilmaz (2009) highlight how financial crises exacerbate the interdependence between global markets. During periods of market turmoil, volatility spillovers increase, as investors reallocate their portfolios in response to changing conditions, causing contagion across borders. Demirer et al. (2018) applied DCC-GARCH models to demonstrate how volatility spillovers intensified during crises, with the US market often being the source of such volatility shocks that were transmitted globally. Dungey et al. (2014) applied a multivariate GARCH model to analyse spillovers between the US, UK, and Eurozone markets. Their findings suggested that while the

US market tends to lead in terms of volatility transmission, there is also feedback from European markets, especially during periods of financial turmoil. Studies by Kanas (1998) found significant volatility spillovers from the US to European stock markets, with evidence that the direction and magnitude of these spillovers depend on the economic environment. This paper examines the issue of volatility spillovers across the three largest European financial hubs stock markets (London, Frankfurt and Paris). To capture potential asymmetric effects of innovations on volatility author used Exponential Generalized Autoregressive Conditional Heteroscedasticity model. Yongdeng et al.,( 2024) found that stock market's role in driving volatility spillover, especially towards the Crude Oil market, changes markedly in the context of macroeconomic shocks. These shocks exert a more substantial impact on Crude Oil compared to other markets. In contrast, the Bond and Gold markets exhibit a lower level of volatility transmission and are less influenced by macroeconomic shocks, thereby reinforcing their roles as stabilizers within the financial system (Yongdeng et al., 2024). Volatility spillovers refer to the impact that events in one market may have on the volatility of other markets. When a market is in trouble, it will transmit the risk to other financial markets. The so called "domino effect" takes place. This risk spillover between financial markets gives information on how risk is transmitted and how this will improve the securities market's information efficiency. Identifying market volatility linkages, allows market participants to make inferences about the overall dynamics of the risk in the financial system (Naeem et al., 2023). Zhang, Yezhou, Yifan (2021) find that after the European Debt Crisis, the China-US Trade War, and the Covid-19 Pandemic, the global financial market's spillover network has been strengthened, and the volatility of net spillover has increased rapidly. When investors face adverse market fluctuations and co-movements in situation of uncertainty or crisis, recognising which markets are sources of risk spillovers of their holding assets, serve as convenient way to address their hedging strategies. For policymakers assessing the stability of markets and monitoring risk, would give them insights on how risk spills across different markets in response to geopolitical and health crises which can help formulating more effective policies. Therefore, it is important to understand the risk transmission and characteristics of the stock markets under the impact of the crisis (Zhang et al., 2021).

During crises, capital outflows can amplify financial instability, as seen during the 1997 Asian Financial Crisis and the 2008 Global Financial Crisis (Forbes & Warnock, 2012). For example, Bekaert and Harvey (1995) demonstrated that the liberalization of emerging markets led to increased correlations with developed markets, reducing the benefits of international diversification.

Covariance is a statistical tool that measures the directional relationship between the returns on two assets. Covariance is closely related to correlation, which standardizes the covariance by dividing it by the product of the standard deviations of the two assets (Hayes A., Investopedia, 2024). Covariance is often used in portfolio construction, risk management, and asset allocation (Markowitz, 1952). The discussion on portfolio diversification and the implications of correlation on portfolio risk draws from Modern Portfolio Theory (MPT) developed by Harry Markowitz (1952). Understanding dynamic correlations helps in assessing the changing diversification benefits.

Studies have revealed that more than half of the movement in the typical developed country's stock price index is unique to the country, but this percentage varies widely between them. Also, the more open the stock market is to capital flows, the higher will be the covariance between that market and the markets in other countries (Ripley, 1973). Special linkages brought about by financial ties, free capital movements and trade strengthens the common movement of stock prices (Ripley, 1973). Pirovano (2012) found that stock prices in Czech Republic, Hungary, Poland and Slovenia were significantly affected by Euro area monetary policy as compared to their own domestic monetary policy implying that financial integration resulted in the sensitivity of stock prices to external shocks. In the paper by Y. Zhong and J. Liu (2021) researchers used multivariate GARCH models to illustrate dynamic conditional correlation and the volatility spillovers. One of the models used was DCC-GARCH and they found that this model fits the data best and in further analysis is used to construct hedge ratios and optimal weights.

In the paper by Forbes & Rigobon (2002), authors point out that test for contagion based on cross-market correlation coefficient are problematic due to the bias introduced by changing volatility returns. "The study focuses on a definition of contagion such as: observed significant increase in cross-market linkages after a shock to one country or group of countries. Additionally, it concentrates on a conventional method of testing for contagion: it analyses if market correlation coefficients increase significantly after a crisis. If the cross-market correlations increase, this is interpreted as evidence of contagion." The study shows that the correlation coefficient underlying these tests is conditional on market volatility over the time period under consideration. It points out that during a crisis when a stock market volatility increases, estimates of cross-market correlations will be biased upward.

The authors in the paper specifically studied the 1997 East Asian crisis, 1994 Mexican peso devaluation, and 1987 U.S. stock market crash. The unconditional correlation coefficient is used in the test for contagion during these crises. It has shown no evidence of a significant increase in cross-market correlation coefficients during them. The results could be implying that there was no evidence on contagion while these particular periods occurred. Researchers, however, emphasize that it should not mean that markets were not linked. It is pointed out that a high level of market co-movement was present, which is called interdependence.

## 2.2. Literature on Macroeconomic Variables

Financial markets are heavily influenced by macroeconomic variables such as Gross Domestic Product (GDP), inflation, interest rates, and exchange rates. These variables play a crucial role in driving market expectations, investment decisions, and overall economic health. There are players in financial markets that try to follow certain patterns in the economy as a whole. The strategies are developed to recognise this patterns and forecasts based on these strategies are made. One of them is Global Macro Strategy in which a hedge fund bases its holdings primarily on political forecasts of macroeconomic principles that have high impact on the economies of those countries. Funds that employ such strategy build portfolios around predictions and projections of events on the country-wide or global scale. These entities make forecasts and analyse trends involving factors such as: international trade, currency exchange rates, interest rates (Chen J., 2024).

Macroeconomics is interpreted as the branch of economics that studies the behaviour and performance of an economy as a whole. It examines the aggregate changes in the economy such as inflation, unemployment, rate of growth, GDP, price levels, national income (Investopedia, 2023). In book by Freger and Jonung (2018) it is explained that the economies are reliant on corporations to drive the overall output. They show that corporations generate jobs, taxes and support domestic consumption. They are listed on the domestic stock market and their value is reliant on historical performance and future expectations. While extensive research on how macroeconomic determinants affect country market's return and volatility was conducted, there is a noticeable research gap in understanding their impact on spillovers and contagion between financial markets. Several empirical studies have confirmed the link between macroeconomic fundamentals and financial market volatility. For example, Flannery and Protopapadakis found that macroeconomic news related to inflation and industrial production have a significant impact on stock market volatility. Similarly, changes in monetary policy, as reflected in interest rate adjustments, have direct effects on both volatility and risk in financial markets. The paper by Chen (2008) investigated whether macroeconomic variables can predict recessions in the stock market. The author found from the empirical evidence from monthly data on the S&P 500 price index that among macroeconomic variables that were evaluated- yield curve spreads and inflation rates are the most useful predictors of bear markets in US stock market. Additionally, the author stated that comparing the bear market prediction (overall market or index decline of 20% or more over a sustained period of time- more than two months, Investopedia 2024) to the stock return predictability implied that it is easier to predict bear markets using macroeconomic variables. The result of this study demonstrated usefulness of forecasting bear markets rather than returns. The efficient market hypothesis theorizes that market is generally efficient in three different versions: weak, semi-strong and strong. The idea that publicly available information can be used to predict stock returns is a violation of the principle of semi-strong market efficiency (Downey L., 2024). One of the documented violations is found by Keim and Stambugh (1986) that several observable variables from bond and stock markets explain a substantial portion of future stock return movements. In the paper by Alzoubi (2022) it is explained that sudden changes in inflation affect firm's future cash flows and investors' required returns. For example, if inflation rate goes up, investors require inflation risk premium to compensate for the decline in the purchasing power. Firms may increase future cash flows in response to the increased inflation rate, otherwise stock prices should go down. Lee J. W and Brahmasrene T., (2018) mention that flow-oriented model (Dornbusch R., Fisher S., 1980) shows a positive linkage between selected macroeconomic variables and stock prices. The depreciation of local currency leads to greater competitiveness of the firms making their exports cheaper in international trade. Higher exports increase the domestic income and since the firms' stock prices are evaluated as the present value of the firms' future cash flows will increase. Paper by Chen and Shiu-Sheng (2009), suggests that yield curve spreads and inflation rates are the most useful predictors of recessions in the US market, also it is easier to predict bear market using macroeconomic variables. The analysis of the relationship of stock prices and macroeconomic variables by Peiro (2016) found that the industrial production index and interest rates affected stock prices in all France, Germany and United Kingdom.

# 3. Methodology.

## 3.1. Research method and data description

In this study, GARCH model is adopted to analyse a financial time series data to see for volatility spillover effects. This paper aims at investigating the issue of volatility spillovers across national stock markets for the period 2008 to 2022. This study is mainly based on data that have been collected from the database which collects daily prices. To test for the presence of volatility spillovers a return series is required which can be sampled. The study undertaken uses the closing prices as a measure of stock market return. Consequently, the return series for each market is chosen based on the market index which provides historical daily time-series. Twenty globally traded stock market indices were selected to test the versatility and robustness of the approach for volatility spillover. The stock indices data used in this paper are daily and are obtained from FactSet. The methodology requires matched observations between all the markets. Furthermore, the sample period commences from January 3rd, 2008, to December 30th, 2022. For the sake of facilitating forecast, I have chosen the daily returns of these indices and matched them in USD. In any time series data, the volatility or changes in some periods may be due to some event. To neutralize the impact of this event on the time series analysis include dummy variable. A dummy variable can take the value of either 0 or 1. The transformation of indices to change in logarithms has the advantage that it produces series that are of greater theoretical interest. The returns for each market are calculated by the following formula: Return= LN (Return t / Return t-1). As a step to perform DCC GARCH fitting the GARCH (1,1) is required. Volatility spillovers between different time zones as well as use of the closing price of the indices any common influence from the one market will first reveal itself in the next opening market and then in the next succeeding market. Therefore, a common stock market factor will induce an association between current day markets of two stock exchanges. Therefore, it is advisable to use intra-day data sampled at the open and close of each market. This would help in accurately distinguishing between effects. The advantage of using closing data as stated is that spillover effects may be the strongest at the opening prices. As closing prices incorporate noise generated during the trading period, the use of closing prices provides a stronger test for spillover effects (Natarajan V. K., Singh A. R. R., Priya N. C., Examining mean-volatility spillovers across national stock markets, 2014).

### 3.1.1. ARCH models

The ARCH (Autoregressive Conditional Heteroskedasticity) model, introduced by Robert Engle in 1982, is designed to model time series data where the variance of the error terms varies over time. This model is foundational for understanding volatility clustering, a common phenomenon in financial data where periods of high volatility are followed by more periods of high volatility.

In ARCH equation the conditional variance of returns σt2 depends on past squared residuals (errors):

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 \epsilon_{t-2}^2 + \cdots + \alpha_q \epsilon_{t-q}^2$$

Where:

$\sigma_t^2$ is the conditional variance at time *t*,

$\epsilon_{t-i}^2$ are past squared errors,

$\alpha_0 > 0, \alpha_i \geq 0$ are the model's parameters

ARCH introduced the idea of volatility depending on past shocks. It allowed for periods of high volatility followed by periods of calm (volatility clustering).

### 3.1.2. GARCH models

In 1986 Tim Bollerslev extended the ARCH model to the GARCH- Generalized ARCH model. The GARCH added an autoregressive term to the conditional variance equation, making it more flexible and parsimonious than high-order ARCH models. This model allows current volatility to depend not only on past squared residuals but also on past volatility.

The GARCH equation is defined as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

$\sigma_t^2$ is the conditional variance at time *t*,

$\sigma_{t-j}^2$ are past conditional variances

$\epsilon_{t-i}^2$ are the past squared errors

$\alpha_0 > 0, \alpha_i \geq 0, \beta_i \geq 0$ are model's parameters

The Generalized Autoregressive Conditional Heteroskedasticity model, introduced by Bollerslev (1986) as an extension of the ARCH model (Engle, 1982), has become a cornerstone in financial econometrics for modelling time-varying volatility. The GARCH is the type of models that are especially suited for financial data, which often exhibit volatility clustering-periods of high volatility followed by more high volatility, and periods of low volatility followed by more low volatility (Mandelbrot, 1963). Volatility, or the conditional variance, changes over time and is particularly crucial in risk management, portfolio allocation, and derivative pricing. The basic GARCH (1,1) model assumes that today's volatility depends on yesterday's volatility and the error term. There are many advantages of GARCH. To main ones are such as it is a flexible model and can fit different types of time series data with different volatility patterns. It has ability to model volatility heteroscedasticity of time series, which can improve the accuracy of forecasts. It can be also used to estimate the value at risk and the conditional value at risk of an investment portfolio. On the other hand, there are few disadvantages. It requires large amount of data to accurately estimate the model parameters. It is sensitive to the model specification and can be difficult to work if it is not specified correctly (nixtlaverse.nixtla.io, 2024). The GARCH also does not consider extreme or unexpected events in the time series, which can affect the accuracy of the predictions in situations of high volatility. It also assumes that the time series are normally distributed, which might not be true in practice. It can produce inaccurate estimates of volatility if the errors are not normally distributed(Bollerslev,1986).

### 3.1.3. Multivariate GARCH Models (BEKK-GARCH, DCC-GARCH)

While the standard GARCH model is widely applied, there are several extensions to account for different characteristics of financial data, including asymmetric responses to shocks and cross-market volatility spillovers. Two advanced models most recognised in the study on volatility are BEKK-GARCH and DCC-GARCH.

The Baba, Engle, Kraft, and Kroner (BEKK) GARCH model (Engle & Kroner, 1995) is a multivariate extension of the GARCH model that models the volatility and covariances of multiple time series. The BEKK-GARCH model is designed to ensure the positive definiteness of the covariance matrix. The general form of the BEKK model is given by:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$

Where:

- Ht is the conditional covariance matrix at time t,
- εt−1 is the vector of residuals from the previous time period,
- A and B are parameter matrices,
- C is a constant matrix ensuring the positive definiteness of Ht.

Mean Equation:

$$rt = \mu + \epsilon t$$

Residuals:

$$\epsilon_t = \mathbf{H}_t^{1/2}\mathbf{z}_t$$

The BEKK model can be extended to the general BEKK(p,q) model, but the BEKK(1,1) form is the most commonly used due to its simplicity and ease of estimation (https://cran.r-project.org/web/packages/BEKKs/BEKKs.pdf.)

The BEKK model is advantageous because it accounts for cross-market volatility spillovers and ensures that the covariance matrix remains positive definite, which is crucial for multivariate applications. The BEKK formulation is computationally intensive due to the large number of parameters, but it provides a flexible framework for modelling the joint dynamics of returns from different assets or markets.

The BEKK-GARCH model is particularly useful in examining volatility spillovers between markets or assets. For instance, it has been applied to study the transmission of volatility between stock markets in different countries (Beirne et al., 2009). Univariate GARCH are used to model volatility of one time series. Multivariate GARCH models are used to forecast several time series to portray if linkages between them can be observed. The main objective of the study is to find whether volatility of US primary index is influencing other European primary indices. From computational perspective, it is better to estimate pairwise bivariate GARCH models, between S&P 500 and each of the country's main index. GARCH models provide a more flexible way to model volatility clustering and persistence in financial time series. It reduces the number of parameters by incorporating past variables. There have been many extensions of GARCH model since it was first developed. Another variant of GARCH model is DCC-GARCH (Dynamic Conditional Correlation). Due to conflicting results in the research BEKK was dropped. Based on the literature on the subject more suitable method is Dynamic Conditional Correlation GARCH. The model was introduced by Engle in 2002 to model time-varying correlations between multiple financial time series. It extends GARCH to bivariate or multivariate approach, allowing conditional correlations to change over time. The DCC GARCH model separates the modelling variances and correlations. The equation proposed by Engle (2002) can be written as:

$$
\begin{aligned}
\mathbf{y}_t &= \mathbf{C}\mathbf{x}_t + \boldsymbol{\epsilon}_t \\
\boldsymbol{\epsilon}_t &= \mathbf{H}_t^{1/2}\boldsymbol{\nu}_t \\
\mathbf{H}_t &= \mathbf{D}_t^{1/2}\mathbf{R}_t\mathbf{D}_t^{1/2} \\
\mathbf{R}_t &= \mathrm{diag}(\mathbf{Q}_t)^{-1/2}\mathbf{Q}_t\mathrm{diag}(\mathbf{Q}_t)^{-1/2} \\
\mathbf{Q}_t &= (1-\lambda_1-\lambda_2)\mathbf{R} + \lambda_1\widetilde{\boldsymbol{\epsilon}}_{t-1}\widetilde{\boldsymbol{\epsilon}}'_{t-1} + \lambda_2\mathbf{Q}_{t-1}
\end{aligned}
$$

where:

$H_t$ is the time-varying covariance matrix,

$D_t$ is the diagonal matrix of conditional variances,

$R_t$ is a matrix of conditional quasicorrelations,

$\mathbf{y}_t$ is *m x* l vector of dependent variables,

$\mathbf{C}$ is *m x k* matrix of parameters,

$\mathbf{x}_t$ is k x l vector of independent variables, which may contain lags of $\mathbf{y}_t$ ,

$\boldsymbol{\nu}_t$ is *m x* l vector of normal, independent, and identically distributed innovations

DCC GARCH estimates the parameters of dynamic conditional correlation (DCC) multivariate generalized autoregressive conditionally heteroskedastic models in which the conditional variances are modelled as univariate generalized autoregressive conditionally heteroskedastic models and the conditional covariances are modeled as nonlinear functions of the conditional variances. The conditional quasicorrelation parameters that weight the nonlinear combinations of the conditional variances follow the GARCH-like process specified in Engle (2002), (DCC GARCH, Stata). The results of DCC- GARCH represent the time-varying correlations between US and 20 different countries over time (daily, 2008-2022). Other models assume constant correlations which may not hold true over time, while DCC allows to capture those correlations that evolve over time showing changing relationships between US primary index and other countries' indices. It also analyses financial markets co-movement by observing how correlation changes. It shows how closely different foreign indices move in respect to US index.

## 3.2. OLS Assumptions

To ensure consistent and unbiased estimates, the model needs to meet certain assumptions. There are key assumptions of the linear regression model and the methods for testing them. Ordinary Least Squares (OLS) is a method of estimating the parameters in a linear regression. The model aims to find the best-fitting line through the data points by minimizing the sum of the squared differences between the observed values and the values predicted by the model. It assumes a potential linear relationship between dependent variable and independent variables and estimates the coefficients. There are four main assumptions that analysis aims to fulfil (Greene, 2012).

### 3.2.1. Heteroscedasticity

Homoskedasticity assumption states that the variance of the unobserved error, *u*, conditional on the explanatory variables is constant. Heteroscedasticity arises when the variance of the residuals in a regression model is not constant across all levels of the independent variables (Wooldridge, 2016). If the values of the independent variables change, the spread or dispersion of the residuals also changes. This violates the homoscedasticity assumption, which expects residuals to have constant variance throughout. Such an issue can severely undermine the reliability of a linear regression model. Ideally, residuals should exhibit homoscedasticity to ensure that statistical inferences are valid. However, heteroscedasticity is often observed in financial data, where variability tends to fluctuate. Detecting heteroscedasticity is important because it can lead to inefficient estimates, such as inaccurate standard errors, which in turn affect the precision of hypothesis tests and confidence intervals. Various tests are available to check for this assumption such as Breusch-Pagan test, which evaluates whether the variance of the residuals is related to the independent variables. If the p-value from this test is below a significance level (typically 0.05), it indicates significant heteroscedasticity. Other methods include the Goldfeld-Quandt test, Harvey-Collier test, White test, and visual analysis using residual scatterplots.

### 3.2.2. Normality

Normality refers to the assumption that a set of data follows a normal distribution (Gaussian). Assessing the normality of residuals is crucial for the analysis. In financial data, nonnormal residual distributions are common due to volatility (Brooks, 2019). However, violation of the assumption is often not a problem, due to the central limit theorem. The central limit theorem states that the sample means of moderately large samples are often well-approximated by a normal distribution even if the data are not normally distributed (Central limit theorem and the normality assumption, 2024). In the analysis the Jarque-Bera test and Q-Q plots are applied to check residual normality.

### 3.2.3. Autocorrelation

The regression assumes that error terms are independent. Autocorrelation occurs when the error terms in a regression model are correlated with their past values. It means that information about past shocks can be used to predict current shocks. Assumption stating that there is no autocorrelation between errors should be fulfilled. The estimated standard errors tend to underestimate the true standard error. P value might be lower (The Intuition behind the Assumptions of Linear Regression Algorithm, 2021). Breusch- Godfrey test is performed to verify this assumption.

### 3.2.4. Linearity

The relationship between the independent and dependent variables must be linear.
A linear regression model assumes that the average outcome is linearly related to each term in the model when holding all others fixed. If the relationship is linear, the model fulfils the assumption (Appendix, figure X). Linearity can be tested through visual inspections using

scatter or residual plots, as well as the Rainbow test to check the linearity; in this test, a significant p-value (< 0.05) indicates a departure from linearity (Nahhas R. W., 2024).

# 4. Data description

## 4.1. Financial Data (Indices).

The daily (from 03 January 2008 to 30 December 2022) closing stock prices of the S&P 500 and the main European indices. The primary indices were retrieved from Factset database and converted to US Dollar.

Table 1. Data description

| Acronym | Data | Source |
|---|---|---|
| ^GSPC | S&P 500 (USA) | Factset database |
| UKX | FTSE100 (United Kingdom) | Factset database |
| GDAXI | DAX (Germany) | Factset database |
| FCHI | CAC40 (France) | Factset database |
| AEX | AEX (Netherlands) | Factset database |
| FTFSTHM | FTSEMidCap (Italy) | Factset database |
| BVLG | PSIAllShare (Portugal) | Factset database |
| SMI | SMI (Switzerland) | Factset database |
| OMXS30 | OMX Stockholm Benchmark (Sweden) | Factset database |
| OSEBX.OL | OSEBX (Norway) | Factset database |
| OMXH25 | OMX Helsinki (Finland) | Factset database |
| ISEQ | ISEQAllShare (Ireland) | Factset database |
| OMXC25 | OMX Copenhagen (Denmark) | Factset database |
| BFX | BEL20 (Belgium) | Factset database |
| IBEX | IBEX35 (Spain) | Factset database |
| XU 100.IS | BIST100 (Turkey) | Factset database |
| ^WIG | WIG (Poland) | Factset database |
| ^ATX | ATX (Austria) | Factset database |
| LUXXX | LUXX (Luxembourg) | Factset database |
| ^BUX.BD | BUX (Hungary) | Factset database |
| SE PX | PX (Czech Republic) | Factset database |

Many of the companies presented in the indices are internationally focused companies, therefore index's movements can be affected. Due to that they do not always are a fairly good indicator of how the economies of the host countries perform as a whole. Most of the companies placed on the flagship indices are regarded as blue-chip stocks. Blue chip stock is capital stock of a stock corporation with national reputation for quality, reliability, and the ability to operate profitably in both good and bad times. The outlook of the company is that it will operate in the future. The term blue chip derives from the colloquial language that it holds the highest value (Chen J., 2024). The S&P 500 is widely regarded as the best single gauge of large-cap U.S. equities. The index includes 500 leading companies and covers approximately 80% of available market capitalization. FTSE100 Is the most famous stock market index in United Kingdom with the 100 most highly capitalised blue-chip stocks listed on London Stock Exchange. It consists of the largest 100 UK companies by full market value. The German index DAX consists of the 40 major German blue-chip companies trading on Frankfurt Stock Exchange. The 40 largest companies are picked in terms of order to book volume and market capitalization. The CAC40 is a benchmark French stock market index which represents a capitalization-weighted measure of the 40 most significant stocks among largest total value of a publicly traded company's outstanding shares on the Euronext Paris. AEX is an index composed of 25 Dutch companies' most frequently traded securities. FTSE Italia Mid Cap index consists of the next 60 largest shares listed on Italian Bourse- Euronext Milan and Euronext MIV Milan markets, after the 40 included in the FTSE MIB. PSIAllShare is a benchmark stock market index of companies that trade on Euronext Lisbon, the main stock exchange of Portugal. The index tracks the prices of the twenty listings with the largest market capitalisation SMI is Switzerland's main index made up of largest and most liquid stocks. OMX Stockholm consist of selection of the largest and most traded stocks, with representation from majority of super sectors. OSEBX Norway is a benchmark index consisting of 70 major companies. OMX Helsinki is its stock exchange leading index, which consists of 25 most actively traded stocks on the exchange and is used as the benchmark index for management of diversified Finnish stock portfolios. ISEQ AllShare is one of the most famous indices of Ireland composed of 26 companies. OMX Copenhagen consists of 25 most-traded stock classes as of market value weighted index. BEL20 is the benchmark stock market index of Euronext Brussels which tracks the performance of 20 most capitalized and liquid stocks traded in Belgium. IBEX35 is the main benchmark of the Spanish stock market, composed of the 35 most liquid companies with largest market capitalization. This index reflects the performance of the shares of these companies and is key indicator for evaluating the economic and financial health of Spain. BIST 100 is the most recognised Turkish stock index; it provides information on the share price performance of the 100 largest companies on the Istanbul Stock Exchange. It reflects the Turkish blue chips companies' performance. WIG index is the first exchange index of Poland, and it comprises all companies listed at Warsaw Stock Exchange list that meet the base eligibility criteria. ATX index of Austria tracks the price trends of the 20 blue chips on Vienna Stock Exchange. The Luxembourg LUXX index is weighted index of the most capitalized and liquid stocks. It is a major stock index which tracks performance of ten most valuable companies on stock exchange. BUX is the major stock index of Budapest SE which tracks performance of large, actively traded shares of 17 companies. PX is the official index of the Prague Stock Exchange and is made up of the most actively traded blue chips in Czech Republic (Collective information on brief background of each primary index was obtained from Investing.com, Euronext Live Markets, Bloomberg database).

## 4.2. The choice of primary stock indices.

The main assumption behind the choice of the sample of countries, was to assess the connectedness of the between US stock market and European ones. Therefore, the S&P 500 was defined as primary index for US. In terms of European counterparts, the study took into consideration the market capitalisation to pick the countries with highest ones. To produce valid outcome, the study was estimated across twenty countries in Europe with an aforementioned requirement of significant market capitalisation.

Table 2. Indices arranged in terms of Stock Exchange Capitalisation.

| Exchange | Primary Index Used | Stock Exchange Capitalization (USD) |
|---|---|---|
| New York Stock Exchange | S&P 500 | 28.42 trillion |
| Euronext | CAC40 (France)<br>BEL20 (Belgium)<br>AEX (Netherlands)<br>ISEQAllShare (Ireland)<br>FTSEMidCap (Italy)<br>PSIAllShare (Portugal)<br>OSEBX (Norway) | 7.22 trillion |
| London Stock Exchange | FTSE100 | 3.42 trillion |
| Deutsche Boerse AG | DAX | 2.37 trillion |
| SIX Swiss Exchange | SMI | 1.95 trillion |
| Nasdaq Nordic | OMXC Benchmark (Denmark)<br>OMX Stockholm Benchmark (Sweden)<br>OMX Helsinki (Finland) | 1.3 trillion |
| BME Spanish Exchanges | IBEX35 | 741.64 billion |
| Borsa Istanbul | BIST100 | 385.23 billion |
| Warsaw Stock Exchange (GPW) | WIG | 349.31 billion |
| Wiener Borse | ATX | 147.565 billion |
| Luxembourg Stock Exchange | LUXX | 50.897 billion |
| Budapest Stock Exchange | BUX | 44.4 billion |

| | | |
|---|---|---|
| Prague Stock Exchange | PX | 20.15 billion |

Source: CEIC Database (accessed in July, 2024, retrieved the last updated values), adjusted with the data from ceoworld.biz, GlobalEconomicData, SimplyWallSt).

## 4.3. Macroeconomic Variables

In this chapter the importance of macroeconomic variables will be discussed. This study is mainly based on data that have been collected from the macroeconomic database of IMF and OECD.

### 4.3.1. Gross Domestic Product (PPP).

Gross Domestic Product is one of the most fundamental indicators in macroeconomic analysis. GDP measures the total monetary value of final goods and services, which are bought by the final user and produced in a country in each given period. It amounts whole output generated within the economy (country). In this analysis data for Gross Domestic Product based on Purchasing Power Parity which is a measure of the price of specific goods in different countries to compare the purchasing power of the currency in the country. Purchasing power parity is an economic term invented to measure the prices in different locations (Krugman & Obstfeld, 2009). GDP can be approached from three perspectives: production (or output), income, and expenditure, all of which in theory should provide the same value. GDP is critical because it provides a comprehensive snapshot of a nation's economic health. It reflects the overall economic activity and is used to portray the performance of an economy. As an aggregate measure, GDP helps in assessing whether the economy is expanding or contracting, which can influence investment decisions, fiscal policies, and monetary policies. GDP as a variable in a model is essential for understanding the broader economic context and testing hypotheses related to economic growth (Callen T., IMF).

### 4.3.2. Consumer Price Index.

Inflation is an increase in the prices of goods and services. The Consumer Price Index (CPI) is the most well-known one. CPI is measuring the weighted average of prices of a basket of consumer goods and services, such as transportation, food and medical care. It is calculated by taking price changes for each item in the predetermined basket of goods and averaging them. Changes in the CPI show changes in the cost of living. CPI is one of the most frequently used statistics for identifying periods of inflation or deflation (Fernando J., 2024). CPI is a measure used by Central Banks in its inflation targeting. It is a goals-based approach to monetary policy whereby a central bank seeks a specific annual rate of inflation for a country's economy, normally around 2% or 3% per year (Reserve bank of Australia, 2024).

Inflation is measured in terms of the annual growth rate and index base year (2015) with a breakdown for food, energy and total excluding food and energy. Inflation measures the erosion of living standards (Fernando J., 2024). Consumer price index is estimated as a proportional change in the prices of a fixed set of consumer goods and services of constant quantity paid for by the population. The CPI measures the average change in prices paid by consumers for goods and services over time. It is a critical measure of inflation, reflecting changes in the cost of living (OECD, 2024). It is used by policymakers to adjust monetary policy, such as interest rates, and to index social benefits and wages. A rising CPI indicates inflationary pressures, while a falling CPI may suggest deflation. It is used to measure the price changes not the level and is also used to measure changes in the cost of living. CPI is also used to adjust nominal values to real terms, providing a clearer picture of economic trends. The Consumer Price Index (CPI) measures the monthly change in prices paid by consumers and is grouped to three broad categories: demand-pull, cost-push and inflation expectations. Demand- pull is due to developments on the demand side of the economy. It arises when the total demand for goods and services increases to exceed the supply of goods and services that can be sustainably produced. On the other hand, cost-push inflation occurs due to fall of total supply of goods and services (Reserve Bank of Australia, 2024).

### 4.3.3. Industrial Production Index.

Industrial production refers to the output of industrial establishments and covers sectors such as mining, manufacturing, electricity, gas and steam and air-conditioning. This indicator is measured in an index based on a reference period that expresses change in the volume of production output for the base year of 2015. The Industrial Production Index (IPI) measures the output of the industrial sector, including manufacturing, mining, and utilities. It reflects changes in the volume of production and is an important indicator of economic activity. IPI provides insights into the health of the industrial sector and overall economic performance. It helps in assessing the level of industrial activity and its contribution to GDP. Changes in IPI can indicate shifts in economic cycles and business conditions. IPI is used in regression models to examine how industrial production affects or is affected by other macroeconomic variables. It helps in analysing the relationship between industrial activity and economic growth, investment, and trade balance. IPI can also be used to forecast economic trends and assess the impact of economic policies (OECD, Industrial production index definition). The index is compiled on a monthly basis to show changes in industrial production. It measures movements in production output and highlights structural developments in the economy.

### 4.3.4. Trade Balance.

The trade balance, defined as the difference between the value of a country's exports and imports, is a key indicator of international economic performance. A positive trade balance indicates a surplus, while a negative trade balance signifies a deficit. The trade balance provides insights into a country's international economic relations and competitiveness. A persistent trade deficit might indicate underlying issues such as declining competitiveness or structural imbalances, while a surplus may suggest strong economic performance or issues with currency undervaluation. All OECD countries record their activity in terms of worldwide trade (Kenton W., 2024).

### 4.3.5. Foreign Direct Investment.

FDI refers to investments made by a firm or individual in one country in business interests in another country, in the form of either establishing business operations or acquiring business assets. FDI is crucial for economic development as it brings capital, technology, and management expertise into the host country. It can lead to improved productivity, increased employment, and enhanced economic integration with global markets. In regression analysis, FDI is often examined to understand its impact on economic growth, productivity, and sectoral performance. It is used to test hypotheses about the benefits and risks of FDI inflows, and how they interact with other macroeconomic variables such as GDP and trade balance (Hayes A., 2024). While FDI can cause risks for the host economy, it is generally associated with being an indicator of a country's attractiveness as an investment destination. It creates job opportunities, higher wages which transforms the living standards and reduce poverty (UNCTAD, 2010). In order to host FDI, a country usually has to be relatively developed, has to have stable political environment and modern legal framework and also advanced financial system (L. Alfaro et al. 2004). FDI is also related to enhanced trade which affects relationship with countries seeking products and services imported from the economy of hosting country. It can contribute to long-term growth due to competitiveness in terms of wages and labour skill. It is also one of the initial attempts to integrate the country into wider global market and new connections. It is also associated with improvements in productivity and efficiency (Lipsey, 2002).

### 4.3.6. Recession

Generally, recession does not have official definition but is recognised as a period of decline in economic activity. Very short periods of decline are not considered recessions. Widely used and recognised one is two consecutive quarters of decline in a country's real (inflation-adjusted) gross domestic product (GDP)—the value of all goods and services a country produces. This definition has its drawbacks. A focus on GDP alone is narrow, and it is often better to consider a wider set of measures of economic activity to determine whether a country is indeed suffering a recession. Using other indicators can also provide a timelier gauge of the state of the economy (Claessens S,  Ayhan Kose M., 2024).

In the United States, the private institution- National Bureau of Economic Research (NBER), which maintains a chronology of the beginning and ending dates of US recessions, uses a broader definition and considers several measures of activity to determine the dates of recessions. The NBER's Business Cycle Dating Committee defines a recession as "a significant decline in economic activity spread across the economy, lasting more than a few months, normally visible in production, employment, real income, and other indicators. A recession begins when the economy reaches a peak of activity and ends when the economy reaches its trough." Consistent with this definition, NBER focuses on a comprehensive set of measures as GDP, employment, income, sales, and industrial production in order to analyse the trends in economic activity. Although an economy can show signs of weakening months before a recession begins, the process of determining whether a country is in a true recession is timely. The decision process by NBER involves establishing a broad decline in economic activity over an extended period, after compiling and sifting through many variables, which are often subject to revisions after their initial announcement. In addition, different measures of activity may exhibit conflicting behaviour, making it difficult to identify whether the country is indeed suffering from a broad-based decline in economic activity (NBER).

Understanding the sources of recessions can be challenging due to many determinants of it and it is a broad subject that is studied in a continued manner, because of variety of reasons recessions take place. Some are associated with sharp changes in the prices of the inputs used in producing goods and services. For example, a steep increase in oil prices can be a harbinger of a recession. As energy becomes expensive, it pushes up the overall price level, leading to a decline in aggregate demand (Claessens S., Ayhan Kose M., 2024, IMF). A recession can also be triggered by a country's decision to reduce inflation by employing contractionary monetary or fiscal policies. The misspecification of implementing policies can also lead to a decline in demand for goods and services (Claessens S., Ayhan Kose M., 2024,  IMF).

Recession from 2007 is rooted in financial market problems. In the article by Ayhan Kose and Claessens, authors mentioned that sharp increases in asset prices and a speedy expansion of credit often coincide with rapid accumulation of debt. When corporations and households face difficulties in meeting their debt obligations, they reduce investment and consumption, which in turn leads to a decrease in economic activity. Not all such crises end up in recessions, but when they do, these recessions are often more costly than others. Recessions can be the result of a decline in external demand, especially in countries with strong export sectors. Adverse effects of recessions in large countries such as Germany, Japan, and the United States are rapidly felt by their regional trading partners, especially during globally synchronized recessions (Claessens S., Ayhan Kose M., 2024). Because of various causes, it is a challenge to predict them. The behavioural patterns of numerous economic variables including credit volume, asset prices, and the unemployment rate that come to the attention followed by recessions have been documented. Sometimes causes of the recessions can be labelled as results of recessions. When institutions such as NBER use a large set of variables to forecast the future behaviour of economic activity, none has proved a reliable predictor of whether a recession is going to take place. Furthermore, Ayhan Kose and Claessens state that changes in some variables such as asset prices, the unemployment rate, certain interest rates, and consumer confidence appear to be useful in predicting recessions, but economists still fall short of accurately forecasting recessions as well as predicting their severity in terms of duration and outcome.

The NBER's definition emphasizes that a recession involves a significant decline in economic activity that is spread across the economy and lasts more than a few months. The institution also mentions that the event must fulfil various requirements to be labelled and recognised as recession. There are three main criteria: depth, diffusion, and duration. While each criterion needs to be met individually to some degree, extreme conditions revealed by one criterion may partially offset weaker indications from another. For example, in the case of the worldwide crisis which happened subsequently after February 2020 peak in economic activity, the committee concluded that this drop in activity had been so sever and so widely diffused throughout the economy that, even if it proved to not be long lasting, the downturn should be classified as a recession. (Business Cycle Dating, NBER).

Table 3. Latest recessions approved by NBER and the cycles.

| Peak Month (Quarter) | Through Month (Quarter) | Contraction | Expansion | Cycle | |
|---|---|---|---|---|---|
| November 1973 (Q4) | March 1975 (Q1) | 16 | 36 | 52 | 47 |
| January 1980 (Q1) | July 1980 (Q3) | 6 | 58 | 64 | 74 |
| July 1981 (Q3) | November 1982 (Q4) | 16 | 12 | 28 | 18 |
| July 1990 (Q3) | March 1991 (Q1) | 8 | 92 | 100 | 108 |
| March 2001 (Q1) | November 2001 (Q4) | 8 | 120 | 128 | 128 |
| December 2007 (Q4) | June 2009 (Q2) | 18 | 73 | 91 | 81 |
| February 2020 (2019 Q4) | April 2020 (Q2) | 2 | 128 | 130 | 146 |

Source: (Business Cycle Dating, NBER).

Table 3 shows historical U.S. business cycles, including peak months/quarters, trough months/quarters, and the durations of the different phases of economic cycles. Peak indicates the highest point in the business cycle, after which the economy begins to contract or enter a recession. Through indicates the lowest point in the business cycle, marking the end of a recession and the start of an economic recovery or expansion. Contraction points to the length of time (in months) the economy was in recession, which is the period between the peak and trough. Expansion shows how long the economy experienced growth, measured from the trough (end of the recession) to the next peak (start of the next recession). Cycle is the overall cycle length. It combines both the contraction and expansion phases (NBER Business Cycle Dating).

# 5. Analysis and results.

## 5.1. Descriptive Statistics.

The first step in the statistical investigation is to obtain descriptive statistics for the datasets. This step summarizes the data used for variables used in the model. It highlights characteristics of the data. In table 1 the data for logarithmic results is presented which is used to obtain dynamic conditional correlations between the primary indices as first step in the overall analysis. The data consists of 3741 observations. The data collected equals the fifteen consecutive years' time span of daily closing prices for twenty countries.

Table 4. Descriptive statistic for logarithmic returns on closing prices of each index.

Table: Descriptive Statistics for Log Returns

| Country | N | Mean | Median | Min | Max | Std_Dev | Variance | Skewness | Kurtosis |
|:---|---:|---:|---:|---:|---:|---:|---:|---:|---:|
| Austria | 3741 | -0.0000979 | 0.0004754 | -0.1467452 | 0.1202104 | 0.0162756 | 0.0002649 | -0.4662109 | 7.885073 |
| Belgium | 3741 | -0.0001143 | 0.0002358 | -0.1708075 | 0.1043802 | 0.0154107 | 0.0002375 | -0.5364609 | 8.853323 |
| Czech | 3741 | -0.0001721 | 0.0001827 | -0.1763501 | 0.1147510 | 0.0171927 | 0.0002956 | -0.5969936 | 12.634229 |
| Denmark | 3741 | 0.0002199 | 0.0006780 | -0.1283247 | 0.1016009 | 0.0141361 | 0.0001998 | -0.3752669 | 6.368447 |
| Finland | 3741 | 0.0000411 | 0.0005008 | -0.1243164 | 0.1064828 | 0.0166383 | 0.0002768 | -0.1194882 | 5.077640 |
| France | 3741 | -0.0000449 | 0.0005711 | -0.1485159 | 0.1213880 | 0.0168562 | 0.0002841 | -0.1752783 | 8.075219 |
| Germany | 3741 | 0.0000638 | 0.0004540 | -0.1480811 | 0.1236482 | 0.0165082 | 0.0002725 | -0.1693835 | 7.470200 |
| Hungary | 3741 | -0.0000675 | 0.0004831 | -0.1895367 | 0.1837760 | 0.0210112 | 0.0004415 | -0.2704205 | 9.224567 |
| Ireland | 3741 | -0.0000802 | 0.0005512 | -0.1514812 | 0.0994849 | 0.0169408 | 0.0002870 | -0.6901175 | 7.685689 |
| Italy | 3741 | -0.0001546 | 0.0006578 | -0.1913917 | 0.0996013 | 0.0171338 | 0.0002936 | -0.7220966 | 7.819679 |
| Luxembourg | 3741 | -0.0002190 | -0.0001487 | -0.1294287 | 0.0954079 | 0.0173370 | 0.0003006 | -0.4367878 | 5.171750 |
| Netherlands | 3741 | -0.0000055 | 0.0006413 | -0.1312985 | 0.1230883 | 0.0157563 | 0.0002483 | -0.2401667 | 9.221290 |
| Norway | 3741 | 0.0000762 | 0.0006079 | -0.1497349 | 0.1436805 | 0.0197408 | 0.0003897 | -0.5240815 | 6.871968 |
| Poland | 3741 | -0.0001459 | 0.0001498 | -0.1670655 | 0.1278110 | 0.0184443 | 0.0003402 | -0.6354889 | 8.597659 |
| Portugal | 3741 | -0.0003030 | 0.0001963 | -0.1263889 | 0.1167883 | 0.0154742 | 0.0002395 | -0.3623823 | 6.166505 |
| Spain | 3741 | -0.0002466 | 0.0000868 | -0.1690444 | 0.1496619 | 0.0178472 | 0.0003185 | -0.3609727 | 8.645021 |
| Sweden | 3741 | 0.0000569 | 0.0003999 | -0.1488701 | 0.1454673 | 0.0179713 | 0.0003230 | -0.0713376 | 6.522721 |
| Switzerland | 3741 | 0.0001133 | 0.0003379 | -0.1176705 | 0.1001566 | 0.0120335 | 0.0001448 | -0.2168414 | 8.078723 |
| Turkey | 3741 | -0.0001278 | 0.0009449 | -0.1895785 | 0.2580664 | 0.0225215 | 0.0005072 | -0.2661475 | 10.864297 |
| UK | 3741 | 0.0000400 | 0.0004162 | -0.1151249 | 0.0938434 | 0.0120392 | 0.0001449 | -0.3428552 | 10.108913 |
| US | 3741 | 0.0002608 | 0.0006365 | -0.1276511 | 0.1095793 | 0.0131500 | 0.0001729 | -0.4991572 | 12.140937 |

The summary statistics for the daily log returns of the five national stock markets are reported in table 4. The means of returns range between -0.0003030 (Portugal) and 0.002608 (USA). The standard deviation of returns ranges between 0.012 (UK) and 0.0225 (Turkey). This indicates that the Turkey stock market is the most volatile and the UK market is the least volatile. The high kurtosis in some markets suggests that their daily return series have a fat-tailed distribution. Tables 5-9 show descriptive statistics for independent variables. The datasets also consist of fifteen-year time span for twenty countries but for monthly values. The number of observations is 180.

Table 5. Descriptive statistics for Consumer Price Index variable.

Table: Descriptive Statistics for Monthly CPI

| Country | N | Mean | Median | Min | Max | Std_Dev | Variance | Skewness | Kurtosis |
|:---|---:|---:|---:|---:|---:|---:|---:|---:|---:|
| Austria | 180 | 100.56500 | 100.05 | 86.9 | 125.5 | 8.745901 | 76.490779 | 0.5769393 | 0.1088551 |
| Belgium | 180 | 101.74278 | 100.10 | 88.1 | 127.1 | 8.440426 | 71.240786 | 0.6754071 | 0.3982098 |
| Czechia | 180 | 103.06556 | 100.00 | 89.9 | 138.5 | 10.853011 | 117.787857 | 1.4810970 | 2.2026490 |
| Denmark | 180 | 99.76167 | 100.05 | 88.2 | 117.6 | 5.736001 | 32.901707 | 0.4723367 | 0.8886816 |
| Finland | 180 | 99.69000 | 100.10 | 89.0 | 117.4 | 5.881598 | 34.593196 | 0.4022488 | 0.4801545 |
| France | 180 | 100.52556 | 100.15 | 91.9 | 114.3 | 4.998806 | 24.988058 | 0.5100873 | 0.1390848 |
| Germany | 180 | 100.64500 | 99.80 | 90.9 | 119.9 | 6.452614 | 41.636232 | 0.7520946 | 0.4511793 |
| Greece | 180 | 100.84000 | 100.70 | 91.2 | 114.4 | 4.067621 | 16.545542 | 0.6414422 | 1.8240093 |
| Hungary | 180 | 102.34944 | 100.40 | 80.2 | 152.0 | 13.261043 | 175.855251 | 1.0656164 | 1.9571637 |
| Ireland | 180 | 100.75111 | 100.40 | 94.4 | 115.6 | 3.764395 | 14.170669 | 1.8220641 | 4.8029589 |
| Italy | 180 | 99.72444 | 100.00 | 89.5 | 119.0 | 5.544191 | 30.738058 | 0.6163789 | 1.4164261 |
| Luxembourg | 180 | 100.20056 | 100.00 | 87.2 | 118.0 | 7.148344 | 51.098827 | 0.3040482 | -0.2109413 |
| Netherlands | 180 | 100.66333 | 100.00 | 87.6 | 128.3 | 8.312365 | 69.095408 | 0.9061662 | 0.9601363 |
| Norway | 180 | 102.01667 | 100.00 | 86.7 | 126.0 | 10.106364 | 102.138603 | 0.4705811 | -0.7634380 |
| Poland | 180 | 102.12167 | 100.60 | 85.5 | 139.1 | 10.456846 | 109.345617 | 1.3822933 | 2.6383697 |
| Portugal | 180 | 100.25722 | 100.20 | 91.5 | 116.7 | 5.225122 | 27.301903 | 0.5867994 | 1.0867669 |
| Spain | 180 | 100.80333 | 100.80 | 90.6 | 118.0 | 5.957802 | 35.495408 | 0.7946962 | 1.1039446 |
| Sweden | 180 | 102.56611 | 100.40 | 93.9 | 126.4 | 6.045851 | 36.552309 | 1.4105771 | 2.4295615 |
| Switzerland | 180 | 101.24000 | 101.20 | 99.0 | 105.0 | 1.129572 | 1.275933 | 1.1250411 | 2.2586850 |
| Turkey | 180 | 127.72278 | 99.90 | 56.4 | 433.0 | 80.010629 | 6401.700763 | 2.0327938 | 4.1070608 |
| United Kingdom | 180 | 100.73000 | 100.10 | 84.1 | 125.3 | 9.149649 | 83.716078 | 0.3374123 | -0.2227343 |

For table 5, the CPI variable shows that most countries have a median close to the mean, indicating quite symmetric distribution. Skewness measures the asymmetry of distribution and kurtosis, if higher than 3 indicates more extreme outliers. The country that stands out in the presented descriptive statistics for CPI is Turkey with having much larger mean, largest spread between minimum and maximum values, higher standard deviation, high variability.

Other countries have more moderate ranges. These results indicate unstable inflation rates for Turkey.

Table 6. Descriptive statistics for Trade Balance variable.

Table: Descriptive Statistics for Monthly Trade Balance (TB)

| Country | N | Mean | Median | Min | Max | Std_Dev | Variance | Skewness | Kurtosis |
|:---|---:|---:|---:|---:|---:|---:|---:|---:|---:|
| Austria | 180 | -0.6202377 | -0.633823 | -1.4131 | 0.3486 | 0.2858245 | 0.0816956 | 0.3465287 | 0.7981097 |
| Belgium | 180 | 1.0114456 | 1.032250 | -0.3130 | 1.9557 | 0.3542690 | 0.1255065 | -0.5285948 | 1.0363699 |
| Czechia | 180 | -0.1776983 | -0.179350 | -0.3800 | -0.0328 | 0.0681715 | 0.0046474 | -0.2321288 | -0.2525514 |
| Denmark | 180 | -0.4779528 | -0.447050 | -1.0785 | -0.1344 | 0.1857843 | 0.0345158 | -0.8420862 | 0.6710021 |
| Finland | 180 | -0.2771784 | -0.252650 | -0.7442 | -0.0020 | 0.1371299 | 0.0188046 | -0.7153388 | 0.2769705 |
| France | 180 | -1.2154956 | -1.198000 | -2.8316 | 0.0139 | 0.4809741 | 0.2313361 | -0.3840513 | 0.1478438 |
| Germany | 180 | -4.9753256 | -5.304500 | -8.3047 | -1.1810 | 1.3677964 | 1.8708670 | 0.5159373 | -0.1667931 |
| Greece | 180 | 0.0030867 | -0.012750 | -0.1137 | 0.5205 | 0.0694844 | 0.0048281 | 2.9922768 | 16.7276515 |
| Hungary | 180 | -0.2334372 | -0.236950 | -0.6308 | -0.0447 | 0.1144259 | 0.0130933 | -0.5506498 | 0.1267304 |
| Ireland | 180 | -3.1392956 | -2.731150 | -6.6160 | -1.1046 | 1.2674455 | 1.6064182 | -0.7341032 | -0.4578913 |
| Italy | 180 | -2.2161989 | -2.231000 | -4.4620 | -0.8557 | 0.7731557 | 0.5977697 | -0.4307251 | -0.2846363 |
| Luxembourg | 180 | 0.0750850 | 0.058900 | -0.0519 | 0.3830 | 0.0677366 | 0.0045882 | 1.5473336 | 2.9839502 |
| Netherlands | 180 | 1.7941011 | 1.743500 | 0.3027 | 4.4859 | 0.6106508 | 0.3728943 | 1.4639489 | 4.7990973 |
| Norway | 180 | -0.1747900 | -0.160150 | -0.6520 | 0.2337 | 0.1716498 | 0.0294637 | -0.2497989 | -0.0208751 |
| Poland | 180 | -0.1283768 | -0.140550 | -0.5985 | 0.4345 | 0.1443557 | 0.0208386 | 0.3388359 | 0.9121661 |
| Portugal | 180 | -0.1529161 | -0.158350 | -0.4780 | 0.0718 | 0.0906527 | 0.0082179 | -0.0229617 | 0.7021453 |
| Spain | 180 | -0.1188140 | -0.109800 | -0.6724 | 0.7440 | 0.2723467 | 0.0741727 | 0.2969619 | -0.0129294 |
| Sweden | 180 | -0.5471817 | -0.550450 | -1.0559 | -0.0073 | 0.1762819 | 0.0310753 | -0.3803092 | 0.4427935 |
| Switzerland | 180 | -1.1379317 | -0.720300 | -10.9872 | 1.5538 | 1.7537593 | 3.0756718 | -2.2480596 | 7.7090866 |
| Turkey | 180 | 0.1917500 | 0.207450 | -0.7217 | 1.1024 | 0.3664556 | 0.1342897 | -0.0447530 | -0.1617778 |
| United Kingdom | 180 | 0.1652294 | 0.125250 | -1.4756 | 1.9011 | 0.6201157 | 0.3845435 | 0.3096925 | -0.0412529 |

Table 6 shows the trade balance between United States and each European country. It points out that the average trade balance of most countries exhibits negative mean, which suggests that these countries recorded a trade deficit during the years in which this analysis was conducted. Higher variance indicates more fluctuation while lower more consistent values. Table 7 shows the data for Industrial Production Index. The means exhibit the values showing how the country performed in the specified time period, with most countries having stable values over time relative to the base period set at 100. Countries like Ireland, Poland and Turkey show high variability in their industrial production, mirroring economic changes in their economies due to either higher demand, commodity prices or shifts in policies. The negative skewness might indicate presence of more declines and positive the presence of more appreciation in IPI values.

Table 7. Descriptive statistics for Industrial Production Index variable.

Table: Descriptive Statistics for Monthly Industrial Production Index (IPI)

| Country | N | Mean | Median | Min | Max | Std_Dev | Variance | Skewness | Kurtosis |
|:---|---:|---:|---:|---:|---:|---:|---:|---:|---:|
| Austria | 180 | 104.34444 | 100.30 | 85.3 | 128.6 | 10.799298 | 116.624829 | 0.5360313 | -0.6294609 |
| Belgium | 180 | 105.90389 | 102.75 | 85.7 | 140.0 | 10.740938 | 115.367750 | 0.8920850 | 0.4688305 |
| Czech Republic | 180 | 100.07667 | 99.65 | 75.8 | 117.8 | 11.348424 | 128.786715 | -0.1309919 | -1.2135912 |
| Denmark | 180 | 105.77500 | 103.25 | 89.8 | 149.1 | 9.260856 | 85.763450 | 1.5748198 | 3.2265822 |
| Finland | 180 | 108.47944 | 107.45 | 97.3 | 128.2 | 6.916192 | 47.833709 | 0.7470726 | 0.0822539 |
| France | 180 | 100.25833 | 99.90 | 68.1 | 115.3 | 4.737782 | 22.446578 | -1.5854008 | 13.0015392 |
| Germany | 180 | 97.10056 | 98.40 | 71.3 | 107.7 | 6.604827 | 43.623743 | -1.4398552 | 2.1826908 |
| Greece | 180 | 110.29167 | 107.65 | 95.3 | 147.8 | 10.676628 | 113.990377 | 1.2170049 | 1.3229350 |
| Hungary | 180 | 98.86611 | 97.90 | 71.7 | 128.3 | 14.981061 | 224.432197 | 0.1624511 | -1.0644908 |
| Ireland | 180 | 93.62167 | 92.95 | 54.2 | 226.0 | 37.404977 | 1399.132321 | 1.3191116 | 1.4127125 |
| Italy | 180 | 104.17111 | 103.95 | 58.3 | 131.7 | 7.796314 | 60.782513 | -0.1767613 | 9.6898413 |
| Luxembourg | 180 | 98.74389 | 99.10 | 68.5 | 119.0 | 6.558155 | 43.009404 | -0.2459147 | 3.6856416 |
| Netherlands | 180 | 102.66889 | 102.90 | 91.4 | 113.2 | 3.073227 | 9.444725 | -0.3765182 | 1.3317051 |
| Norway | 180 | 101.98278 | 101.30 | 90.8 | 115.6 | 4.990850 | 24.908584 | 0.6130091 | 0.2711043 |
| Poland | 180 | 104.24722 | 99.30 | 71.3 | 154.4 | 21.401792 | 458.036696 | 0.6546735 | -0.3739108 |
| Portugal | 180 | 101.96111 | 101.85 | 74.4 | 123.2 | 5.948423 | 35.383731 | -0.1443260 | 5.0788075 |
| Spain | 180 | 103.44278 | 103.65 | 70.1 | 133.8 | 7.645922 | 58.460115 | 1.1181734 | 6.4150453 |
| Sweden | 180 | 105.45667 | 105.15 | 91.0 | 125.6 | 7.159493 | 51.258335 | 0.1606084 | -0.7757969 |
| Switzerland | 180 | 105.96222 | 101.00 | 93.4 | 136.6 | 10.763725 | 115.857783 | 1.0106748 | -0.0831199 |
| Turkey | 180 | 99.13278 | 99.25 | 57.0 | 149.4 | 23.883623 | 570.427467 | 0.2031390 | -0.8235967 |
| UK | 180 | 99.50167 | 99.50 | 88.6 | 113.3 | 5.544210 | 30.738265 | 0.2971008 | -0.3495669 |

Table 8 contains the data for GDP, it is possible to compare relative economic performance. It shows the pace of growth, maturity and stability. The positive skewness might implicate periods of growth.

Table 8. Descriptive statistics for Gross Domestic Product variable.

Table: Descriptive Statistics for Monthly Gross Domestic Product (GDP)

| Country | N | Mean | Median | Min | Max | Std_Dev | Variance | Skewness | Kurtosis |
|:---|---:|---:|---:|---:|---:|---:|---:|---:|---:|
| Austria | 180 | 449145.29 | 428466.90 | 327870.8 | 660099.5 | 86746.15 | 7.524894e+09 | 0.5605923 | -0.5684712 |
| Belgium | 180 | 545436.75 | 519257.95 | 392952.6 | 815637.7 | 112226.94 | 1.259489e+10 | 0.6676919 | -0.4376891 |
| Czechia | 180 | 386977.97 | 357676.97 | 274003.8 | 586471.3 | 90233.62 | 8.142106e+09 | 0.6001995 | -0.9365283 |
| Denmark | 180 | 301178.78 | 277051.35 | 214769.9 | 471929.3 | 68010.52 | 4.625431e+09 | 0.8941459 | -0.1034223 |
| Finland | 180 | 251865.28 | 233028.23 | 201969.7 | 352433.4 | 42472.38 | 1.803903e+09 | 0.8199043 | -0.4577833 |
| France | 180 | 2863718.77 | 2711947.12 | 2196920.2 | 4037749.3 | 510904.54 | 2.610235e+11 | 0.6078410 | -0.7527897 |
| Germany | 180 | 4054054.24 | 3870033.35 | 2976539.6 | 5683901.1 | 767347.66 | 5.888224e+11 | 0.3529046 | -1.0285493 |
| Greece | 180 | 315562.86 | 308766.38 | 274105.8 | 418474.5 | 32323.97 | 1.044839e+09 | 1.1145502 | 1.1016386 |
| Hungary | 180 | 279234.26 | 261854.40 | 193237.4 | 427090.3 | 62783.39 | 3.941754e+09 | 0.7356321 | -0.5167608 |
| Ireland | 180 | 345102.74 | 331183.90 | 184709.9 | 735983.7 | 154012.26 | 2.371978e+10 | 0.8350312 | -0.2987851 |
| Italy | 180 | 2417433.10 | 2225206.30 | 2008941.3 | 3376944.4 | 353325.34 | 1.248388e+11 | 1.0135762 | 0.1565151 |
| Luxembourg | 180 | 63009.78 | 61688.07 | 40899.6 | 96978.2 | 15539.02 | 2.414611e+08 | 0.5192419 | -0.6699390 |
| Netherlands | 180 | 915639.21 | 851196.33 | 725304.3 | 1363559.2 | 167057.31 | 2.790814e+10 | 0.9697561 | -0.0055875 |
| Norway | 180 | 358749.17 | 334587.48 | 263136.8 | 788509.1 | 99056.71 | 9.812231e+09 | 2.4385991 | 5.8307560 |
| Poland | 180 | 1078760.58 | 1010800.77 | 647969.7 | 1738048.1 | 289266.24 | 8.367496e+10 | 0.6372365 | -0.5256264 |
| Portugal | 180 | 329395.16 | 305985.57 | 271513.2 | 481251.9 | 53631.79 | 2.876368e+09 | 1.0028221 | 0.0745290 |
| Spain | 180 | 1724407.51 | 1610886.60 | 1472590.4 | 2414027.6 | 259076.39 | 6.712057e+10 | 0.8403112 | -0.4015877 |
| Sweden | 180 | 496162.38 | 477685.67 | 371493.0 | 711175.1 | 96658.96 | 9.342955e+09 | 0.6157158 | -0.6745819 |
| Switzerland | 180 | 547465.59 | 539339.00 | 389998.6 | 813988.6 | 108114.02 | 1.168864e+10 | 0.6152707 | -0.2655078 |
| Türkiye | 180 | 1947669.28 | 2013331.70 | 1043906.3 | 3423931.6 | 579916.47 | 3.363031e+11 | 0.3027210 | -0.4750780 |
| United Kingdom | 180 | 2826889.00 | 2759264.70 | 2170431.7 | 3921247.2 | 491825.54 | 2.418924e+11 | 0.4698912 | -0.8468930 |

Table 9. Descriptive statistics for Foreign Direct Investment variable.

Table: Descriptive Statistics for Monthly Foreign Direct Investment (FDI)

| Country | N | Mean | Median | Min | Max | Std_Dev | Variance | Skewness | Kurtosis |
|:---|---:|---:|---:|---:|---:|---:|---:|---:|---:|
| Austria | 180 | -0.1109911 | 0.0693609 | -14.7994005 | 18.6300577 | 3.4406105 | 1.183780e+01 | 0.9680337 | 9.3108226 |
| Belgium | 180 | 2.6456734 | 0.6765580 | -24.9836034 | 21.7974290 | 7.8977716 | 6.237480e+01 | 0.0851878 | 0.5516254 |
| Czechia | 180 | 0.7117847 | 0.7146724 | 0.0520321 | 1.4739357 | 0.2693544 | 7.255180e-02 | -0.2789628 | 0.0886431 |
| Denmark | 180 | 0.3792581 | 0.2694123 | -8.4327209 | 7.8533518 | 1.8949014 | 3.590651e+00 | -0.5335022 | 6.0757222 |
| Finland | 180 | 0.6315596 | 0.8282103 | -24.5138319 | 25.3356803 | 4.4910310 | 2.016936e+01 | -0.1535757 | 14.6561307 |
| France | 180 | 3.9055706 | 3.0580810 | 0.1593425 | 12.5951720 | 2.5313513 | 6.407739e+00 | 1.0742980 | 0.6575538 |
| Germany | 180 | 6.6948877 | 5.7338799 | 0.7682952 | 17.8069660 | 3.5545839 | 1.263507e+01 | 0.9802471 | 0.7868462 |
| Greece | 180 | 0.2846965 | 0.2609596 | 0.0152051 | 0.7397836 | 0.1716590 | 2.946680e-02 | 0.7342356 | -0.0887526 |
| Hungary | 180 | 1.9887211 | 0.3091980 | -17.4875490 | 33.8981282 | 6.4641354 | 4.178505e+01 | 1.6595919 | 5.2131421 |
| Ireland | 180 | 5.0118193 | 5.3221171 | -40.0498210 | 32.2776166 | 8.1930827 | 6.712660e+01 | -1.3230446 | 9.0294435 |
| Italy | 180 | 1.6043875 | 1.4398303 | -6.2278456 | 9.1077163 | 2.3804669 | 5.666623e+00 | -0.2761207 | 1.4827421 |
| Luxembourg | 180 | -0.2363357 | 1.2324342 | -53.0482543 | 44.2437178 | 10.5772015 | 1.118772e+02 | -1.2793337 | 10.2699418 |
| Netherlands | 180 | 8.5093893 | 12.0211920 | -121.7161374 | 66.6597250 | 22.7841192 | 5.191161e+02 | -2.3795870 | 9.9218917 |
| Norway | 180 | 0.6614888 | 0.7535829 | -7.3508253 | 6.4067721 | 1.6418449 | 2.695655e+00 | -1.2215972 | 5.5288651 |
| Poland | 180 | 1.4917215 | 1.4455461 | 0.0229215 | 3.8432056 | 0.7851985 | 6.165367e-01 | 0.7478096 | 0.7454580 |
| Portugal | 180 | 0.7790498 | 0.7657386 | 0.0216481 | 2.3709114 | 0.4061253 | 1.649377e-01 | 1.1214200 | 2.5724938 |
| Spain | 180 | 3.2141411 | 2.8806554 | 0.1942216 | 10.2773346 | 1.6112697 | 2.596190e+00 | 1.2290876 | 2.8722708 |
| Sweden | 180 | 1.3332492 | 0.9783594 | -3.7619831 | 6.5295103 | 1.7541287 | 3.076967e+00 | 0.6477901 | 0.4239037 |
| Switzerland | 180 | 0.1773312 | 1.5796780 | -766.5593482 | 770.0598635 | 126.0335955 | 1.588447e+04 | 0.0319583 | 22.4846352 |
| Türkiye | 180 | 1.0826397 | 1.0879841 | 0.4467262 | 2.2358266 | 0.3174658 | 1.007845e-01 | 0.8994165 | 1.2695531 |
| United Kingdom | 180 | 6.7783823 | 4.3697557 | -42.7360149 | 46.0344752 | 11.4422628 | 1.309254e+02 | 0.4687578 | 4.4092714 |

In table 9, the data for FDI is presented, broad overview shows which countries have more stable investment trends. There are values which bring attention, such as the standard deviation for Switzerland, indicating that there are more volatile investment flows over time. The data for Switzerland might point to the presence of outliers for particular year, as can be observed in minimum, maximum and standard deviation. Mean values show that UK, Germany, Ireland and Netherlands exhibit higher FDI inflows.

## 5.2. Augmented Dickey- Fuller Test

To ensure the stationarity of the time series data, the Augmented Dickey-Fuller (ADF) test was employed. The ADF test helps detect the presence of unit roots in a time series, where the null hypothesis states that the data has a unit root (non-stationary), and the alternative hypothesis indicates stationarity. Stationarity is essential for the reliability in GARCH that assume constant mean, variance, and covariance over time. The Augmented Dickey- Fuller test (ADF) is a statistical test used to determine whether a time series is stationary, meaning that the properties such as mean and variance, do not change over time. It is an extension of the Dickey-Fuller test, which includes lagged terms of the dependent variable to account for autocorrelation in the data. The ADF test is used to check for unit roots in a time series. It helps to identify if a time series needs differencing to become stationary, requirement for time series models such as GARCH models (Dickey, D. A., & Fuller, W. A., 1979).

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \epsilon_t$$

Where:

$\Delta y_t$ is the change in the series,

$\alpha$ is a constant,

$\beta t$ is a time trend,

$\gamma y_{t-1}$ is the lagged level of the series

$\delta_i \Delta y_{t-i}$ represents the lagged differences of the series

$\epsilon_t$ is the error term

The hypotheses:

Null hypothesis H0: Time series contains unit root (it is not stationary),

Alternative hypothesis H1: Time series is stationary

Table 10. ADF test results for monthly values of Dynamic Conditional Correlation.

| Country | ADF Statistic | P-value | Conclusion |
|---|---|---|---|
| Austria | -6,579 | 0,01 | Stationary |
| Belgium | -7,013 | 0,01 | Stationary |
| Czech | -5,899 | 0,01 | Stationary |
| Denmark | -7,944 | 0,01 | Stationary |
| Finland | -7,091 | 0,01 | Stationary |
| France | -7,341 | 0,01 | Stationary |
| Germany | -7,101 | 0,01 | Stationary |
| Hungary | -7,145 | 0,01 | Stationary |
| Ireland | -6,731 | 0,01 | Stationary |
| Italy | -6,663 | 0,01 | Stationary |
| Luxembourg | -5,665 | 0,01 | Stationary |
| Netherlands | -6,242 | 0,01 | Stationary |
| Norway | -5,256 | 0,01 | Stationary |
| Poland | -6,239 | 0,01 | Stationary |
| Portugal | -6,862 | 0,01 | Stationary |
| Spain | -7,622 | 0,01 | Stationary |
| Switzerland | -8,838 | 0,01 | Stationary |
| Sweden | -5,99 | 0,01 | Stationary |
| Turkey | -8,372 | 0,01 | Stationary |
| UK | -7,884 | 0,01 | Stationary |

Based on the ADF test results, all variables eventually were found to be stationary at the 5% significance level. Non-stationary variables required further transformation, such as differencing, to make them suitable for further time series analysis. This operation is crucial for ensuring that spurious regressions are avoided in further modelling. Stationarity is a prerequisite for applying certain time series models. A stationary time series is one whose statistical properties do not depend on the time at which the series is observed (Kwiatkowski et al, 1992). Time series with trends, or with seasonality, are not stationary the trend and seasonality will affect the value of the time series at different times. Time series with cyclic behaviour (but with no trend or seasonality) is stationary. This is because the cycles are not of a fixed length, so before observing the series it should not be possible to predict the peaks and throughs of the cycles. In general, a stationary time series will have no predictable patterns in the long-term. The presence of non-stationary data for at least one country in any of the variables required transformation through first differencing. This step ensures the robustness of the subsequent volatility spillover analysis between US and European markets, as non-stationary data could lead to misleading inferences. Figures 18- 22 in the appendix illustrate the ADF test results for macroeconomic variables after first differencing for FDI, TB, IPI and second differencing for GDP and CPI. Obtaining dynamic conditional correlations required checking for stationarity at each stage. While at logarithmic returns and daily DCC stage observations were stationary, at averaged to monthly DCC values showed non-stationarity, which required differencing. The results are shown above in the table 10.

## 5.3. DCC GARCH results

The DCC monitor conditions of global markets during periods of financial disturbances, such as 2008 financial crisis. As a model it helps to identify these periods of increased global market synchronization, as correlations between markets often increase during that time. The results are interpreted as values between 0 and 1. 0 shows no correlation between the country creating and the country receiving spillover at the point in time. This means that markets move independently. Values closer to 0 means less correlation. 1 shows perfect positive correlation, implying that markets move together in the same direction at the same magnitude. The closer the correlation is to 1, the stronger is the relationship between the markets. Increase in correlation that typically occurs during global crises or major economic events (e.g., the 2008 financial crisis, COVID-19 pandemic), can reflects how markets tend to become more correlated during periods of heightened volatility. On the other hand, the decrease in correlation should happen during more stable or calm periods when markets are less synchronized and behave accordingly to local situation and country-specific factors.

Volatility Clustering is related to periods where the correlations suddenly spike or drop, these could be linked to significant macroeconomic events, policy changes, or market shocks. High correlation means that adding that country to the portfolio may not significantly reduce risk since it moves closely with the US market. Volatility clustering is a phenomenon observed in financial markets where periods of high volatility tend to be followed by periods of high volatility and low volatility is followed by low volatility (Nguyen et al. 2020). Low correlation means adding that country's assets could provide diversification benefits, reducing overall portfolio risk. In Stable Periods correlations may drop, reflecting independent market movements driven by domestic economic factors. Figure 1 display correlations showing that these values are quite high and during the around recession timeframes exhibits trends. From 2008 and onwards the correlation exceeds 0,5 and reaches 0,6 which corresponds to global financial crisis of 2008-09. The correlation gradually declines with time as the market start to recover and becoming less dependent on each other. The periods of high correlation persisted longer than June of 2009 (last month qualified as recession by NBER), up till 2011. This persistence could be associated with another crisis but less severe one- European debt crisis. However, the initial spike is clearly related to the 2008-09 global financial crisis.

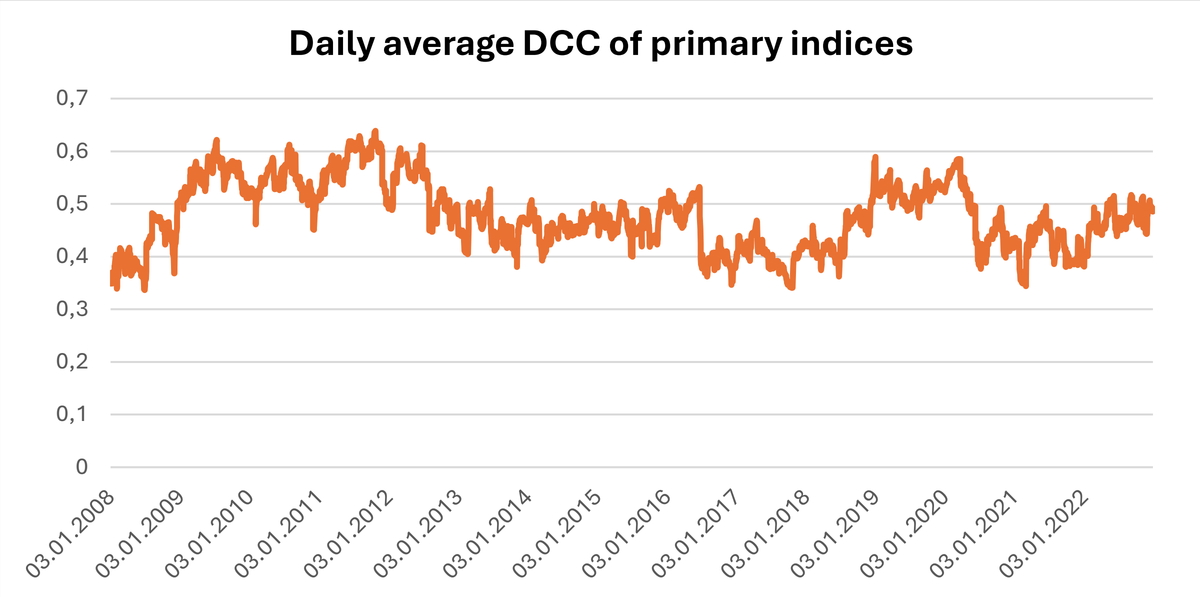



Fig 1. Daily average dynamic conditional correlation for all European indices.

Moreover, correlations decreased to the values of 0,3-0,4 until again in 2019 spikes in values occurred to the levels from 2009. The difference in persistence can also be observed, it is due to less effect of the global turmoil, which mirrors NBER's data. The sharp rise in correlation in 2019/20 coincide with pandemic. After the peak it diverges, implying recovery. Dynamic Conditional Correlation plots differ between countries as can be seen in the plots for the pair of countries (Appendix). Considerable values that overstate the average values can be noticed in countries with more developed and historical financial hubs. Especially, for France, Germany, Netherlands, Sweden and UK (>0.7, during crises).

## 5.4. Regression model of the Study

An OLS regression model is employed to assess how the macroeconomic variables, along with recession, influence dynamic conditional correlation between US primary index and other European primary indices. The model is presented as follows:

Correlation US-Country= $\beta0 + \beta1 \cdot GDP + \beta2 \cdot CPI + \beta3 \cdot FDI + \beta4 \cdot IPI + \beta5 \cdot TB + \beta6 \cdot Recession + \epsilon$

Dependent variable: Dynamic Conditional Correlation

Independent variables:

$\beta1$ GDP= Gross Domestic Product,

$\beta2$ CPI= Consumer Price Index,

$\beta3$ FDI= Foreign Direct Investment,

$\beta4$ IPI= Industrial Production Index,

$\beta5$ TB= Trade Balance,

Dummy variable: Recession (stated by independent source- NBER as 0- no recession during that month, 1- recession)

$\beta0$= Intercept

$\epsilon$ = Error term.

## 5.5. Initial Regression Results

This part examines whether macroeconomic determinants significantly influence correlation between the indices.

Firstly, initial OLS regression was performed to evaluate the variables and check for significance.

Table 11. Results of the regression (Dependent variable: Dynamic Conditional Correlation; R-squared= 0.01249; Adjusted R-squared= 0.01081; **p-value<0.01, *p- value<0.05).

| Explanatory Variables | Coefficients (Beta) | Std. Error | t-Statistics | Significance (p- Value) |
|---|---|---|---|---|
| Intercept | 2,053E-04 | 6,872E-04 | 0,299 | 0,765106 |
| GDP | -1,844E-04 | 4,348E-08 | -4,231 | 0,0000228** |
| TradeBalance | 5,664E-04 | 1,436E-03 | 0,394 | 0,693319 |

| | | | | |
|---|---|---|---|---|
| CPI | 2,111E-03 | 7,053E-04 | 2,993 | 0,002782** |
| IPI | 3,171E-05 | 3,195E-05 | 0,993 | 0,320993 |
| FDI | -7,804E-05 | 3,220E-05 | -2,424 | 0,015413* |
| recession | -7,558E-03 | 2,162E-03 | -3,497 | 0,000477** |

The results from the OLS regression on macroeconomic variables show that DCC is significantly influenced by four variables. Gross Domestic Product (GDP), Foreign Direct Investment (FDI) and recession show a negative relationship with DCC, with coefficient of -0,0001844 for GDP, -0,00007804 for FDI and -0,007558 for recession. Additionally, Consumer Price Index (CPI), show a positive relationship with DCC with coefficient of 0,002782. The recession dummy variable has a negative coefficient within significance levels, suggesting that DCC decreases during recessions.

Table. 12. VIF results for the variables in the initial regression.

| Variance Inflation Factor | |
|---|---|
| GDP | 1.006630 |
| TradeBalance | 1.000441 |
| CPI | 1.000344 |
| IPI | 1.002116 |
| FDI | 1.000011 |
| recession | 1.007047 |

### 5.5.1. Diagnostic Testing.

The result from your Breusch-Godfrey test for serial correlation is as follows: LM test statistic = 289.65, degrees of freedom = 4 and p-value = 2.2e-16.

Table. 13. Breusch- Godfrey test for Autocorrelation.

| **Breusch- Godfrey test** | | |
|---|---|---|
| **LM test statistic** | **DF** | **P-Value** |
| 289.65 | 4 | 2.2e-16 |

Null Hypothesis ($H_0$): The Breusch-Godfrey test assumes the null hypothesis that no serial correlation exists in the residuals of the regression model. The test statistic (LM = 289.65) is used to assess whether there is serial correlation. Values of the test statistic show evidence against the null hypothesis (no serial correlation). The p-value is reported as 2.2e-16. This is close to 0, meaning the null hypothesis of no serial correlation is rejected at any significance level (0.05, 0.01). This indicates that there is significant autocorrelation in the residuals. The presence of autocorrelation suggests that the error terms are not independent of each other. In regression models, this can lead to inefficient estimates, inflated standard errors, and incorrect inferences. It violates one of the key assumptions of ordinary least squares (OLS) regression.

Table 14. Rainbow test for Linearity.

| Rainbow test | | | |
|---|---|---|---|
| **Rainbow test** | **DF1** | **DF2** | **P-Value** |
| 0.97758 | 1770 | 1763 | 0.6831 |

The Rainbow test is a statistical test that checks for the linearity of a regression model. Test statistic = 0.97758 and p-value = 0.6831. Test statistic is close to 1, which is often indicative of no significant non-linearity in the model. P-value of 0.6831 is high and is well above 0.05, therefore it fails to reject the null hypothesis of the Rainbow test. The null hypothesis in the Rainbow test is that the model is correctly specified, meaning that it is linear in its parameters. It suggests that there is no evidence of non-linearity in the model. Additionally figure 2 (Appendix) shows that there are no non-linear patterns. This test result indicates that model does not have issues with linearity, and the linear relationship between the independent variables and the dependent variable is likely appropriate.

Table 15. Breusch-Pagan test for Heteroscedasticity.

| Breusch- Pagan test | | |
|---|---|---|
| **BP** | **DF** | **P-Value** |
| 6.334 | 6 | 0.3868 |

The Breusch-Pagan test results in show insight into whether heteroscedasticity (non-constant variance) is present in regression model. BP = 6.334: A higher test statistic suggests greater evidence against the null hypothesis. p-value = 0.3868: The p-value is high, indicating that failure to reject the null hypothesis of homoscedasticity.

The null hypothesis of the Breusch-Pagan test is that the variance of the residuals is constant (homoscedasticity). A p-value > 0.05 means there is not enough evidence to reject the null hypothesis. In this case, the high p-value (0.3868) suggests that the residuals have constant variance, and there is no significant evidence of heteroscedasticity in the model. The model's residuals exhibit homoscedasticity (constant variance), which is favourable for the assumptions of linear regression. Figure 3 (Appendix) Residuals vs. Fitted Values with constant spread across the range and does not point to heteroskedasticity either.

Table 16. Jarque-Bera test for Normality.

| Jarque Bera Test for Normality | | |
|---|---|---|
| X-squared | DF | P-Value |
| 911.54 | 2 | 2.2e-16 |

The results show a statistical test used to check whether the residuals of a regression model are normally distributed. X-squared (Test statistic) is 911.54. The Jarque-Bera test statistic quantifies the difference of the skewness and kurtosis of the sample data from a normal distribution. The larger this value, the more the data deviates from normality and p-value equals 2.2e-16, which means it is extremely small. Null hypothesis states that the residuals are normally distributed and alternative hypothesis that residuals are not normally distributed. Since the p-value is much smaller than common significance levels (e.g., 0.05 or 0.01), this indicates that the residuals are not normally distributed, which suggests a violation of the normality assumption in the model. Non-normality in residuals is often observed in financial data due to factors like volatility clustering. While this may not necessarily invalidate the model for predictions, it does affect hypothesis testing, confidence intervals, and the reliability of the model's coefficients.

In conclusion, the regression analysis through diagnostic tests identified several violations. Breusch- Pagan test for heteroscedasticity showed p-value of 0.3868, indicating that there is no violation of the assumption. Additionally, p-value of 0.6831 from Rainbow test is above 0.05 significance level, therefore it fails to reject the null hypothesis of the Rainbow test. Consequently, model is correctly specified, meaning that it is linear in its parameters. However, the Jarque-Bera test exhibit that the p-value is much smaller than common significance levels (e.g., 0.05 or 0.01), this indicates that the residuals are not normally distributed, which suggests a violation of the normality assumption in the model.
Besides, the p-value in Breusch-Godfrey test for autocorrelation is reported as 2.2e-16. This is close to 0, meaning the null hypothesis of no serial correlation is rejected at any significance level (0.05, 0.01). This indicates that there is significant autocorrelation in the residuals. In order to mitigate these violations, the corrective measures need to be applied.

## 5.6. Updated regression results.

The initial diagnostic tests revealed several issues with the regression model. Specifically, the Breusch-Godfrey test showed autocorrelation, and the Jarque-Bera test revealed non-normality in the residuals. Furthermore, regression results indicate that multicollinearity issue might be present. Multicollinearity occurs when independent variables in a regression model are highly correlated, meaning they share a potential linear relationship. This issue leads to unreliable coefficient estimates, making it difficult to assess the individual effects of each independent variable on the dependent variable. Additionally, VIF results were presented with values for each variable oscillating around 1, indicating no correlation between the independent variable and other ones. Moderate autocorrelation starts from values exceeding 5. The correlation matrices were also included to check for correlations between the variables for each country (Appendix). Although they did not show any significant correlation between the variables (highest being the positive correlation 0.47), the corrective measure will be applied, because the results in the software stated otherwise. In order to mitigate this issue one of the variables with high significance should be dropped from the model. To correct for both normality and autocorrelation, the Huber robust regression was completed. Huber regression is a type of robust regression that is aware of the possibility of outliers in a dataset and assigns them less weight than other examples in the dataset (J. Brownlee, 2020). Huber regression is a robust algorithm that combines both advantages of the least squares method and the absolute deviation method. It is designed to be less sensitive to outliers compared to ordinary least squares regression (Rahul S., 2023). By iteratively updating the coefficients using the Huber loss function, the HuberRegressor algorithm finds a set of coefficients that minimize the overall loss while being less influenced by outliers compared to OLS regression (Rahul S., 2023). It is useful when dealing with datasets where robustness to outliers is desired also financial data. The updated results summary in table 17 are summarized below.

Table 17. Updated regression results (without the GDP variable, Huber robust regression). **p-value<0.01, *p- value<0.05).

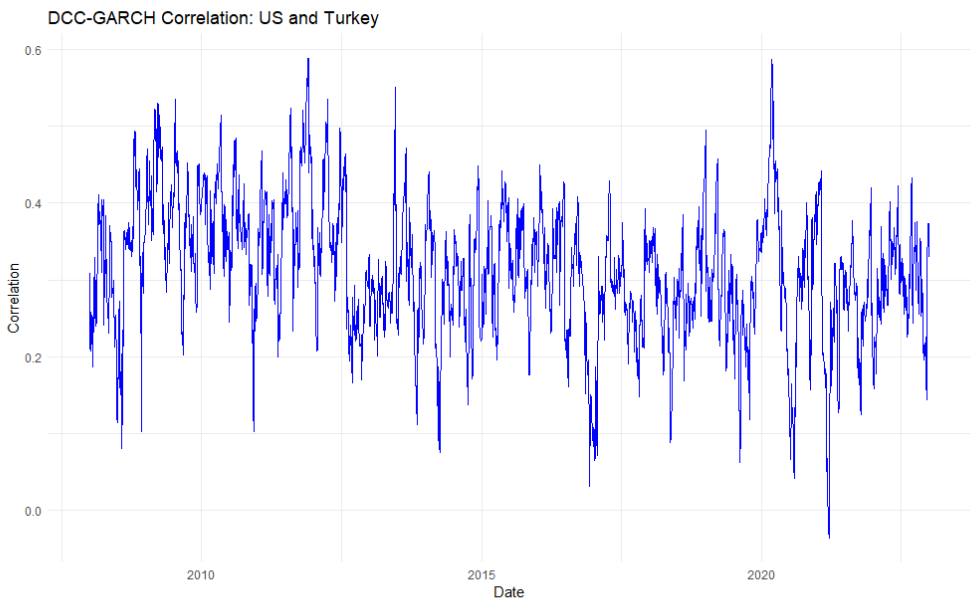
| Explanatory Variables | Coefficients (Beta) | Std. Error | t-Statistics | Significance (p- Value) |
|---|---|---|---|---|
| constant | -0,0005 | 0,001 | -0,856 | 0,392 |
| TradeBalance | 0,0004 | 0,001 | 0,335 | 0,738 |
| CPI | 0,0022 | 0,001 | 3,487 | 0,000** |
| IPI | 0,00002471 | 0,0000286 | 0,863 | 0,388 |

| | | | | |
|---|---|---|---|---|
| FDI | -0,00007019 | 0,0000289 | -2,432 | 0,015* |
| recession | -0,0054 | 0,002 | -2,817 | 0,005** |

# 6. Discussion

The study's findings, based on the theories and methodology discussed in previous parts shows clear relationship, especially during crises. In the first step the DCC model was introduced and helped to understand the changing relationship between the US market and other countries over time, especially in response to external shocks, economic crises. During this time, there were two long lasting events which can be labelled as recession by NBER. The increased volatility followed around the recession cycle. The DCC-GARCH results help to understand how relationships between the US market and other countries have evolved over time and assessing the degree of global market integration. Higher correlations during crises indicate less diversification benefit across countries. This suggests that portfolio managers may need to adjust their risk strategies during volatile times since markets tend to move in together. Lower correlations imply better diversification potential, meaning holding assets across different countries could reduce risk. Eventually, all the markets aim for openness and strong financial markets. While Turkey is becoming more connected it is still led by country specific background and stands out in terms of spillovers with the lowest correlation.

Fig. 43. Dynamic Conditional Correlation between US and Turkey.



Secondly, the robust regression, adjusted for violations of initial regression. The results highlighted three variables: CPI, FDI and recession to be significant. There is significant positive relationship as coefficient for Consumer Price Index is 0.0022 and the p-value is very low. For the variable FDI the coefficient is -0,00007019, with p-value 0,015 showing that there is significant negative relationship. Furthermore, recession shows statistically significant negative relationship with dependent variable. The other variables Trade Balance and IPI were not statistically significant. Contrary to the assumptions the variable recession shows negative impact on DCC, meaning that presence of the dummy variable recession might decrease cross-market correlations. Additionally, FDI shows negative coefficient with DCC suggesting that increase in FDI reduces dynamic conditional correlation, which stands for less interdependence of the primary indices. CPI has positive relationship with market correlations. Even though, overall adjusted robust model captures significant relationships of dependent variable with CPI, FDI and recession, the economic significance and explanatory power is very low. The results stand contrary to the initial assumptions.

# 7. Conclusion

Engle's work on the DCC model forms the foundational theory for Dynamic Conditional Correlations. This model is commonly used to assess the time-varying nature of correlations between different markets or asset classes. It is useful mainly in describing risk assessment to check how diversification benefits change over time, especially during market stress. The investors can exploit it through diversification of portfolio within the less integrated financial markets such as Czech Republic and Turkey. These countries, especially Turkey are subject to different local economic forces. It can be observed in the initial phase of the analysis that variables for Turkey are very unstable. In descriptive statistics macroeconomic variables such as CPI, IPI stood out. On the other hand, there are leading countries in Europe which somehow incorporated the trends from US primary indices during global events in the past. These countries also exhibit strong economic background in terms of trade, industrial production and growth. While all countries in this analysis, to some extend display connection to S&P 500, there is still a gap between more connected "Western Europe" and CEE countries (DCC Correlations, Appendix). This distinction could be associated with the late international integration into global market economy. As these countries are either still developing, transitional economies or became newly identified as developed ones in the past decade. This classification is linked to the pace in which those countries started participating in global

economy. Therefore, there is still a gap between the countries exhibiting strong macroeconomic foundations, as well as being home to the distinct financial hubs and so called “latecomer” countries in terms of implementing various market-based systems and external opening. From the global financial market perspective, it determines how connected the US market is to each country's market. High and consistent correlations over time may suggest increasing economic interdependence. Furthermore, the primary indices hosted by stock exchanges with higher market capitalization, show higher connectedness to S&P 500.
The results on macroeconomic variables pointed to statistical significance but lacked economic significance in terms of the variables. The contagion is clearly visible during 2008 global crisis recession dates and around Covid-19 recession dates.

## 7.1. Limitations

Further refinement of the model or inclusion of additional variables may be necessary for greater economic explanatory power. Model might show some misspecifications due to the data preparation. The FDI and GDP variables were obtained from IMF database on a quarterly basis. The data is published every quarter, and the analysis used monthly values for all variables. To address missing values for FDI and GDP, linear interpolation was implemented. Interpolation creates estimated values that could influence the further analysis. Due to the lack of stationarity, differencing was required which amplified changes in the data. Interpolation allowed further analysis, because it mitigated the lack of data. Applying interpolation has its drawbacks because it exaggerates trends in the differenced series, potentially impacting the interpretation of relationship between the variables. Therefore, these variables should be interpreted with caution. With the experience on working with the data, an alternative emerged in terms of switching to the data on quarterly basis and averaging other variables to quarters instead of months and extending the time interval to obtain considerable number of observations. Checking for other variables could be useful, such as exchange rates, unemployment rates or growth rates. Narrowing the number of countries in the analysis might be useful in order to perform multivariate GARCH.

## 7.2. Further research

Overall, study examined the relationship between dynamic conditional correlations and macroeconomic variables, and it points to various opportunities for greater research. Funds often employ strategy on building portfolios around predictions and projections of events on the country-wide or global scale. These entities make forecasts and analyse trends involving macroeconomic factors such as: international trade, currency exchange rates, interest rates. Based on the literature review, further study on interconnectedness and contagion between US and developing countries in Asia and Arab countries to look for more potential portfolio diversification options. From perspective of investors, new emerging markets might be used as a refuge for capital allocation during the time of turmoil in US, Europe or other bigger financial hubs. Furthermore, adding variables capturing to behavioural finance or creating monetary policy variable effect on the recovery could point to useful outcomes. Focusing on deeper banking industry spillovers in during crisis could lead to benefits for policymakers.

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# APPENDIX:

Fig. 2. Q-Q Plot of Residuals.

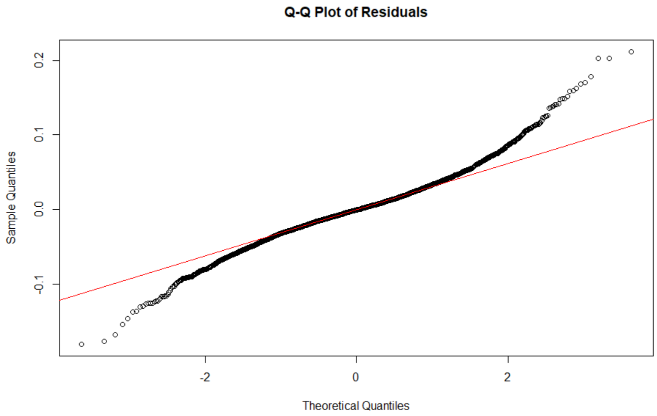



Fig. 3.  Residuals vs Fitted Values.

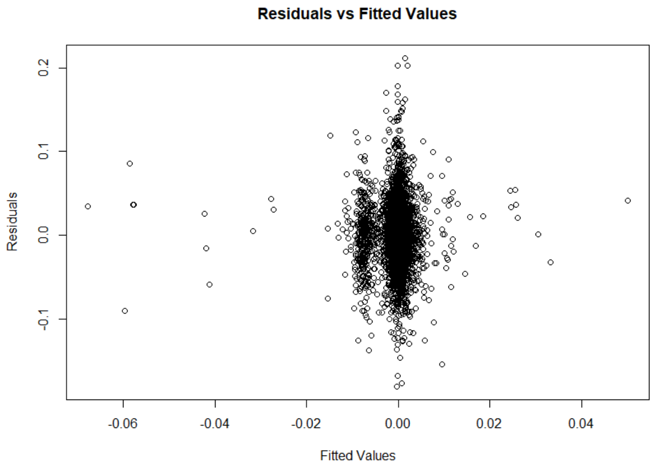



Fig. 4. Leverage Plot.

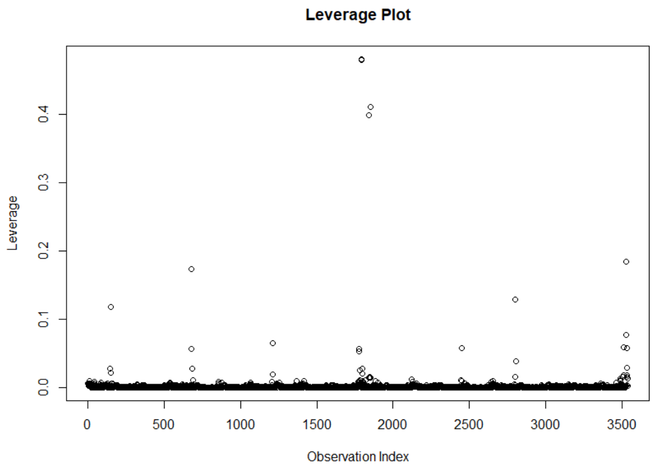



Fig. 5. Standardized Residuals.

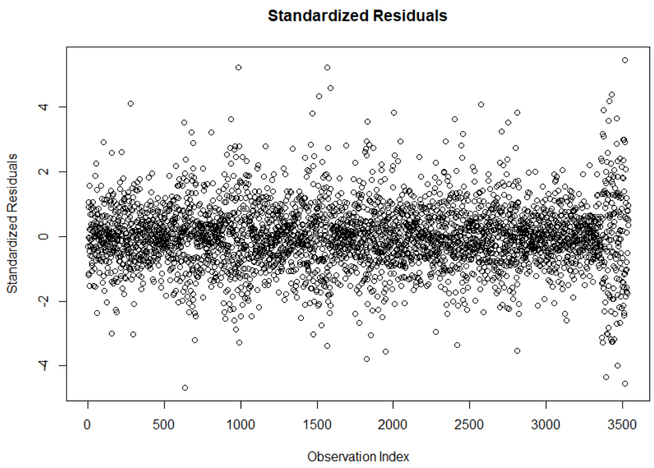



Table 18. ADF test results for Industrial Production Index.

| Country | ADF Statistic | P-value | Conclusion |
|---|---|---|---|
| Austria | -6,823 | 0,01 | Stationary |
| Belgium | -5,502 | 0,01 | Stationary |
| Czech | -6,719 | 0,01 | Stationary |
| Denmark | -5,873 | 0,01 | Stationary |
| Finland | -4,979 | 0,01 | Stationary |
| France | -6,719 | 0,01 | Stationary |
| Germany | -5,699 | 0,01 | Stationary |
| Hungary | -7,158 | 0,01 | Stationary |
| Ireland | -6,836 | 0,01 | Stationary |
| Italy | -6,526 | 0,01 | Stationary |
| Luxembourg | -5,799 | 0,01 | Stationary |
| Netherlands | -6,635 | 0,01 | Stationary |
| Norway | -7,8 | 0,01 | Stationary |
| Poland | -6,949 | 0,01 | Stationary |
| Portugal | -7,827 | 0,01 | Stationary |
| Spain | -6,481 | 0,01 | Stationary |
| Switzerland | -9,128 | 0,01 | Stationary |
| Sweden | -5,594 | 0,01 | Stationary |
| Turkey | -6,26 | 0,01 | Stationary |
| UK | -7,658 | 0,01 | Stationary |

Table 19. ADF test results for Gross Domestic Product.

| Country | ADF Statistic | P-value | Conclusion |
|---|---|---|---|
| Austria | -12,18 | 0,01 | Stationary |
| Belgium | -10,353 | 0,01 | Stationary |

| | | | |
|---|---|---|---|
| Czech | -9,99 | 0,01 | Stationary |
| Denmark | -9,617 | 0,01 | Stationary |
| Finland | -10,757 | 0,01 | Stationary |
| France | -10,351 | 0,01 | Stationary |
| Germany | -12,092 | 0,01 | Stationary |
| Hungary | -10,432 | 0,01 | Stationary |
| Ireland | -8,68 | 0,01 | Stationary |
| Italy | -9,836 | 0,01 | Stationary |
| Luxembourg | -8,85 | 0,01 | Stationary |
| Netherlands | -10,302 | 0,01 | Stationary |
| Norway | -6,954 | 0,01 | Stationary |
| Poland | -9,896 | 0,01 | Stationary |
| Portugal | -12,149 | 0,01 | Stationary |
| Spain | -9,795 | 0,01 | Stationary |
| Switzerland | -9,594 | 0,01 | Stationary |
| Sweden | -9,311 | 0,01 | Stationary |
| Turkey | -10,249 | 0,01 | Stationary |
| UK | -12,202 | 0,01 | Stationary |

Table 20. ADF test results for Trade Balance.

| **Country** | **ADF Statistic** | **P-value** | **Conclusion** |
|---|---|---|---|
| Austria | -9,325 | 0,01 | Stationary |
| Belgium | -8,202 | 0,01 | Stationary |
| Czech | -6,715 | 0,01 | Stationary |
| Denmark | -8,621 | 0,01 | Stationary |
| Finland | -8,714 | 0,01 | Stationary |
| France | -7,019 | 0,01 | Stationary |
| Germany | -7,698 | 0,01 | Stationary |
| Hungary | -8,923 | 0,01 | Stationary |
| Ireland | -9,782 | 0,01 | Stationary |
| Italy | -7,934 | 0,01 | Stationary |
| Luxembourg | -10,392 | 0,01 | Stationary |
| Netherlands | -6,838 | 0,01 | Stationary |
| Norway | -7,573 | 0,01 | Stationary |
| Poland | -7,046 | 0,01 | Stationary |
| Portugal | -7,546 | 0,01 | Stationary |
| Spain | -7,086 | 0,01 | Stationary |
| Switzerland | -7,159 | 0,01 | Stationary |
| Sweden | -8,631 | 0,01 | Stationary |
| Turkey | -7,701 | 0,01 | Stationary |
| UK | -8,343 | 0,01 | Stationary |

Table 21. ADF test results for Foreign Direct Investment. .

| **Country** | **ADF Statistic** | **P-value** | **Conclusion** |
|---|---|---|---|

| | | | |
|---|---|---|---|
| Austria | -5,889 | 0,01 | Stationary |
| Belgium | -6,656 | 0,01 | Stationary |
| Czech | -4,81 | 0,01 | Stationary |
| Denmark | -5,26 | 0,01 | Stationary |
| Finland | -6,788 | 0,01 | Stationary |
| France | -5,021 | 0,01 | Stationary |
| Germany | -4,731 | 0,01 | Stationary |
| Hungary | -5,692 | 0,01 | Stationary |
| Ireland | -5,927 | 0,01 | Stationary |
| Italy | -6,524 | 0,01 | Stationary |
| Luxembourg | -4,78 | 0,01 | Stationary |
| Netherlands | -6,016 | 0,01 | Stationary |
| Norway | -6,29 | 0,01 | Stationary |
| Poland | -4,634 | 0,01 | Stationary |
| Portugal | -4,505 | 0,01 | Stationary |
| Spain | -5,799 | 0,01 | Stationary |
| Switzerland | -6,51 | 0,01 | Stationary |
| Sweden | -5,665 | 0,01 | Stationary |
| Turkey | -5,318 | 0,01 | Stationary |
| UK | -6,078 | 0,01 | Stationary |

Table 22. ADF test results for Consumer Price Index.

| **Country** | **ADF Statistic** | **P-value** | **Conclusion** |
|---|---|---|---|
| Austria | -11,15 | 0,01 | Stationary |
| Belgium | -8,587 | 0,01 | Stationary |
| Czech | -7,141 | 0,01 | Stationary |
| Denmark | -8,038 | 0,01 | Stationary |
| Finland | -9,557 | 0,01 | Stationary |
| France | -8,435 | 0,01 | Stationary |
| Germany | -8,426 | 0,01 | Stationary |
| Hungary | -7,273 | 0,01 | Stationary |
| Ireland | -7,44 | 0,01 | Stationary |
| Italy | -8,365 | 0,01 | Stationary |
| Luxembourg | -11,038 | 0,01 | Stationary |
| Netherlands | -11,517 | 0,01 | Stationary |
| Norway | -10,461 | 0,01 | Stationary |
| Poland | -7,577 | 0,01 | Stationary |
| Portugal | -9,472 | 0,01 | Stationary |
| Spain | -10,14 | 0,01 | Stationary |
| Switzerland | -7,908 | 0,01 | Stationary |
| Sweden | -11,744 | 0,01 | Stationary |
| Turkey | -5,574 | 0,01 | Stationary |
| UK | -9,685 | 0,01 | Stationary |

Fig. 6. Correlation Matrix between variables for Sweden.

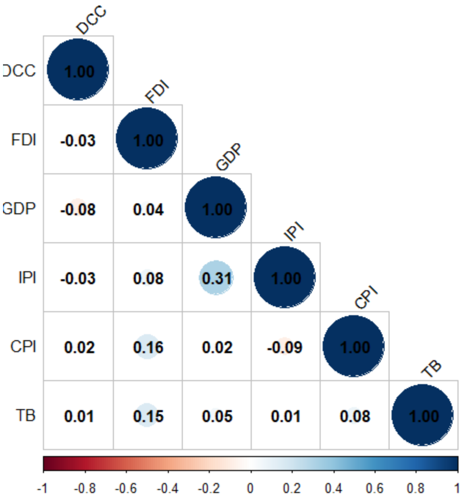



Fig. 7. Correlation Matrix between variables for Portugal.

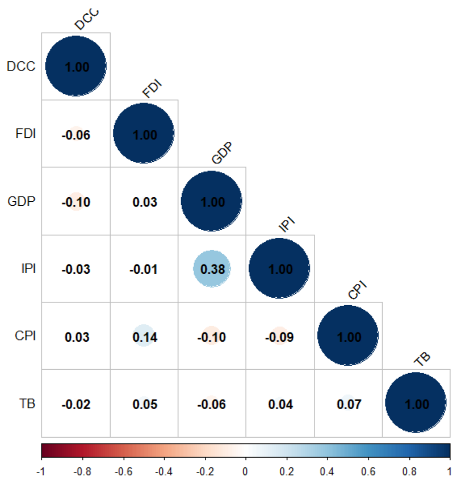



Fig. 8. Correlation Matrix between variables for Germany.

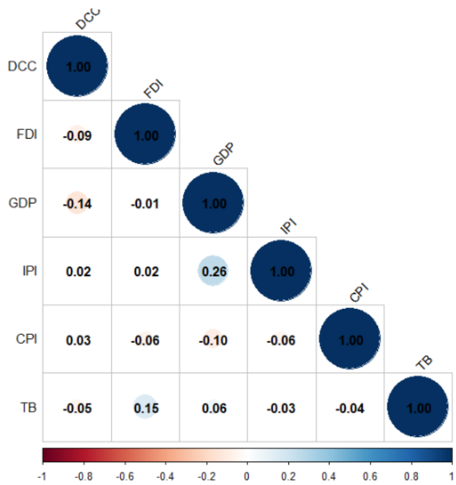



Table. 9. Correlation Matrix between variables for UK.

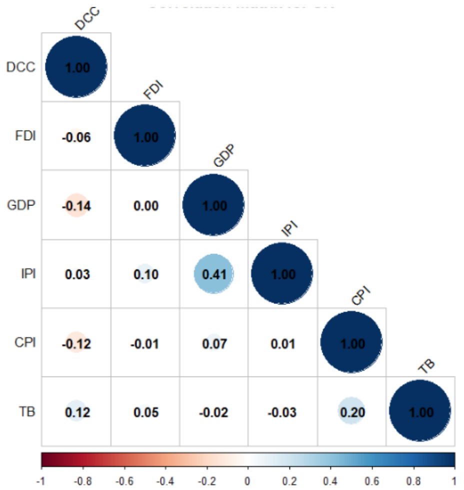



Table. 10. Correlation Matrix between variables for Poland.

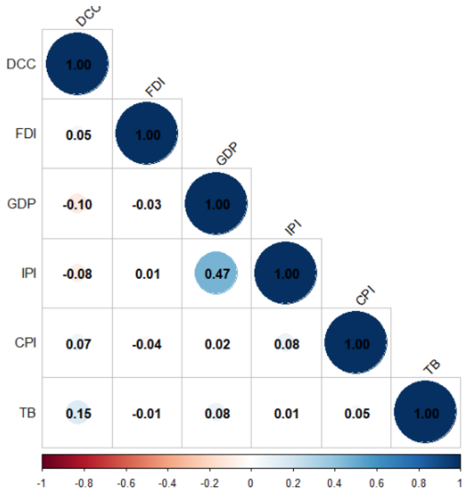



Table. 11. Correlation Matrix between variables for Hungary.

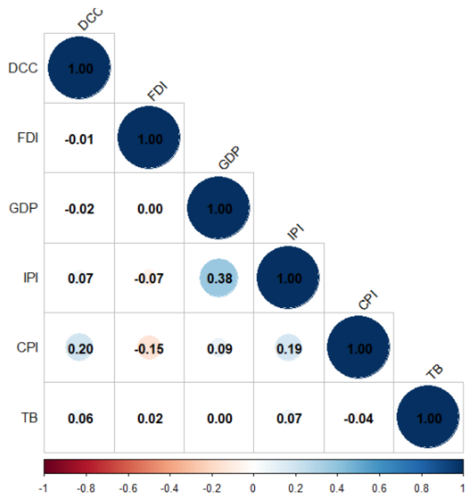


Table. 12. Correlation Matrix between variables for Italy.

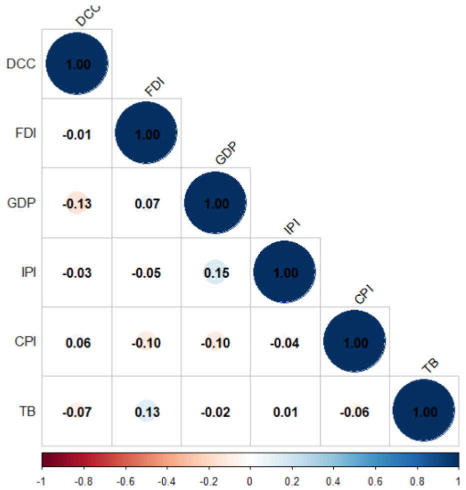



Table. 13. Correlation Matrix between variables for Netherlands.

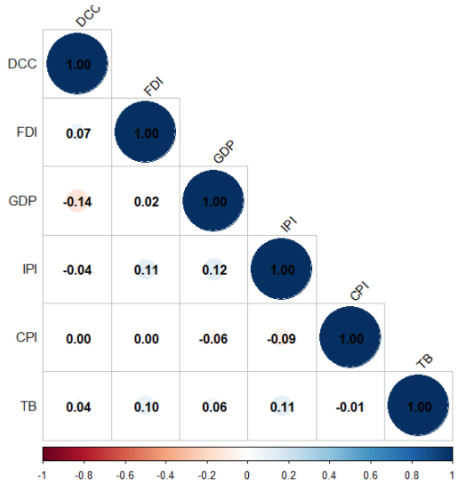



Table. 14. Correlation Matrix between variables for Belgium.

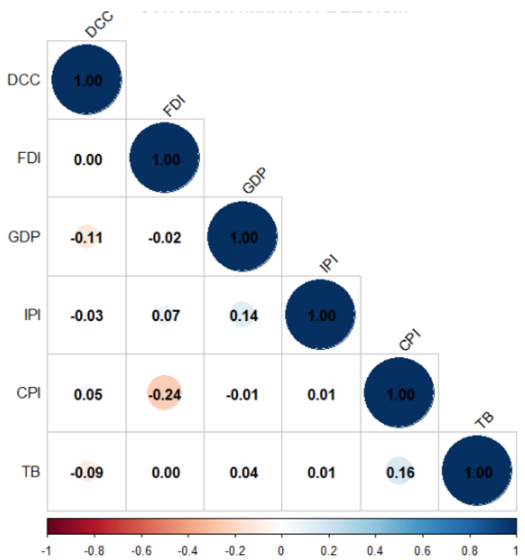


Table. 15. Correlation Matrix between variables for Denmark.

| | DCC | FDI | GDP | IPI | CPI | TB |
|---|---|---|---|---|---|---|
| DCC | 1.00 | | | | | |
| FDI | 0.09 | 1.00 | | | | |
| GDP | -0.11 | 0.02 | 1.00 | | | |
| IPI | -0.04 | 0.06 | 0.06 | 1.00 | | |
| CPI | 0.03 | -0.06 | 0.02 | -0.11 | 1.00 | |
| TB | -0.05 | 0.07 | 0.02 | 0.08 | -0.07 | 1.00 |

Table. 16. Correlation Matrix between variables for Switzerland.

| | DCC | FDI | GDP | IPI | CPI | TB |
|---|---|---|---|---|---|---|
| DCC | 1.00 | | | | | |
| FDI | -0.17 | 1.00 | | | | |
| GDP | -0.06 | -0.03 | 1.00 | | | |
| IPI | 0.06 | 0.00 | 0.01 | 1.00 | | |
| CPI | -0.01 | 0.03 | 0.02 | 0.00 | 1.00 | |
| TB | 0.04 | -0.01 | 0.05 | 0.02 | -0.24 | 1.00 |

Table. 17. Correlation Matrix between variables for Norway.

| | DCC | FDI | GDP | IPI | CPI | TB |
|---|---|---|---|---|---|---|
| DCC | 1.00 | | | | | |
| FDI | 0.05 | 1.00 | | | | |
| GDP | 0.06 | 0.03 | 1.00 | | | |
| IPI | 0.02 | 0.13 | 0.08 | 1.00 | | |
| CPI | -0.03 | 0.03 | 0.17 | 0.12 | 1.00 | |
| TB | -0.03 | -0.02 | -0.02 | -0.15 | -0.06 | 1.00 |

Table. 18. Correlation Matrix between variables for Ireland.

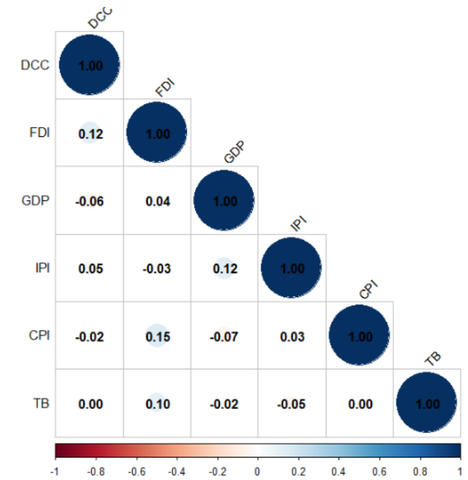



Table. X=19. Correlation Matrix between variables for Spain.

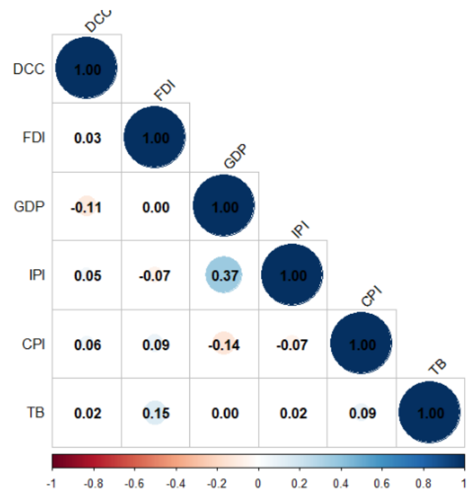



Table. 20. Correlation Matrix between variables for Czech.

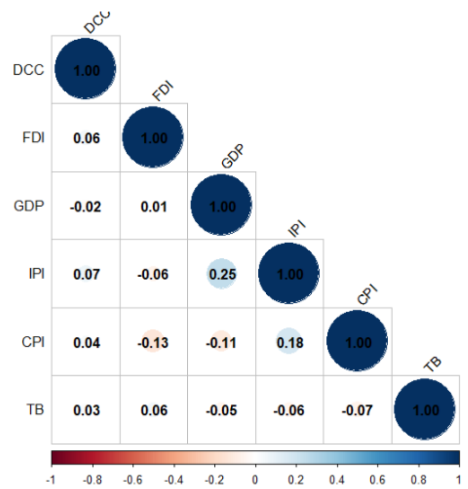



Table. 21. Correlation Matrix between variables for France.

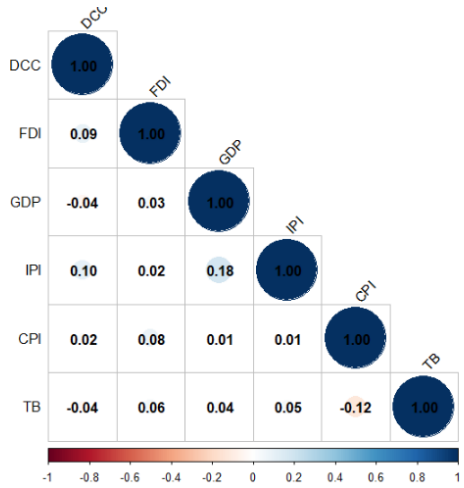



Table. 22. Correlation Matrix between variables for Finland.

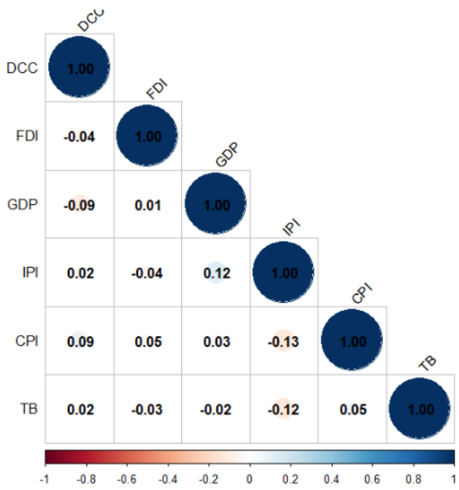



Table. 23. Correlation Matrix between variables for Luxembourg.

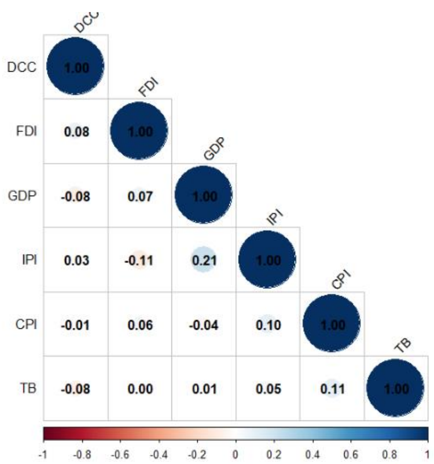



Table. 24. Correlation Matrix between variables for Austria.

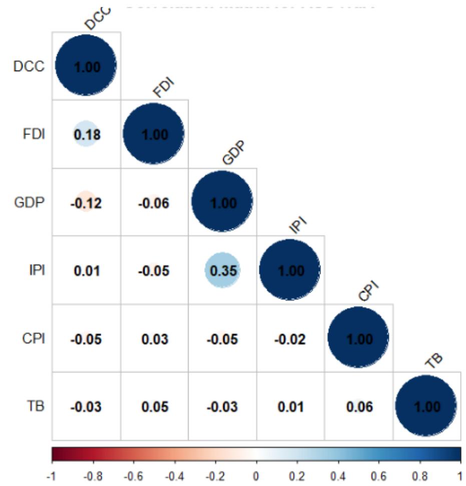



Table. 25. Correlation Matrix between variables for Turkey.

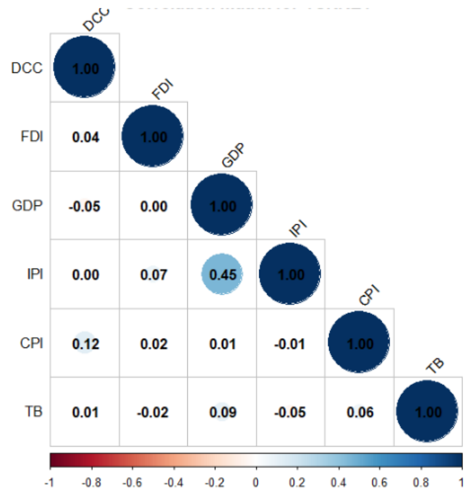



Fig. 26. Dynamic Conditional Correlation between US and Austria.

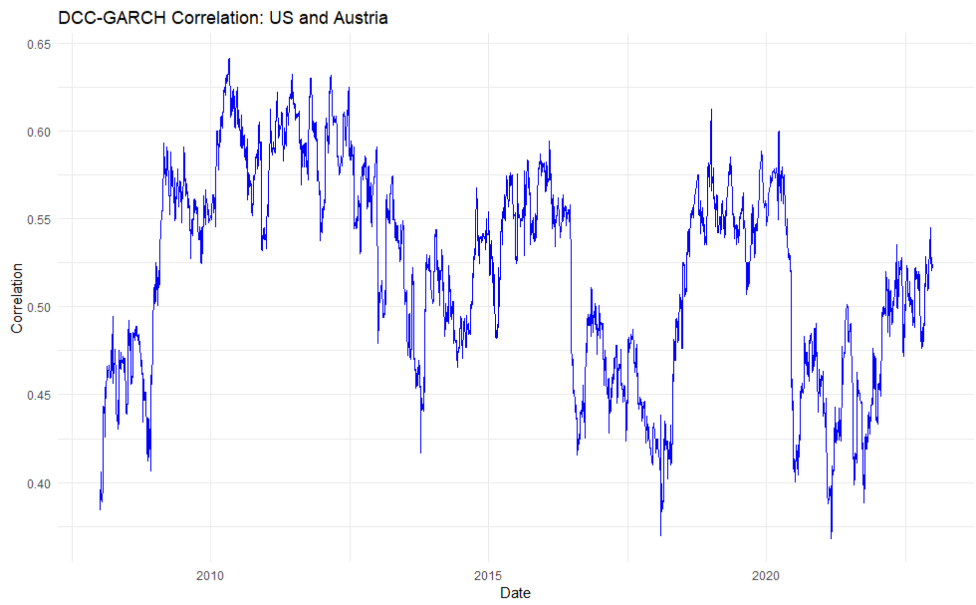



Fig. 27. Dynamic Conditional Correlation between US and Belgium.

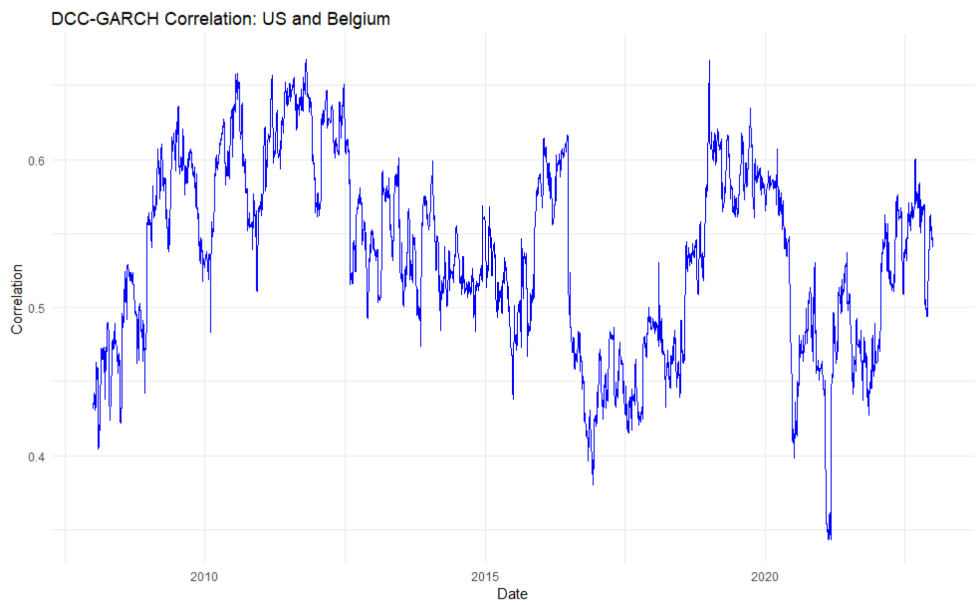



Fig. 28. Dynamic Conditional Correlation between US and Czech.

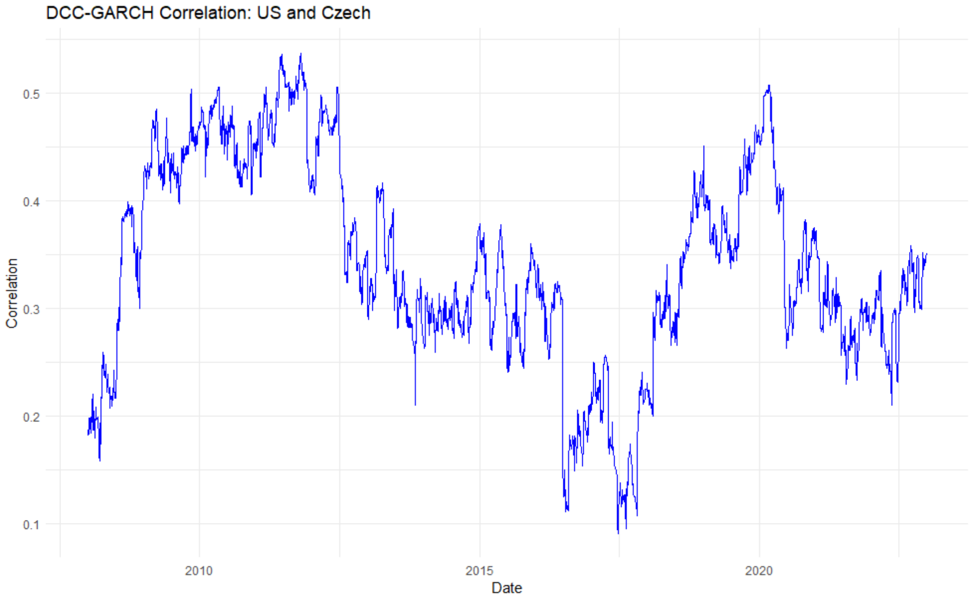



Fig. 29. Dynamic Conditional Correlation between US and Denmark.

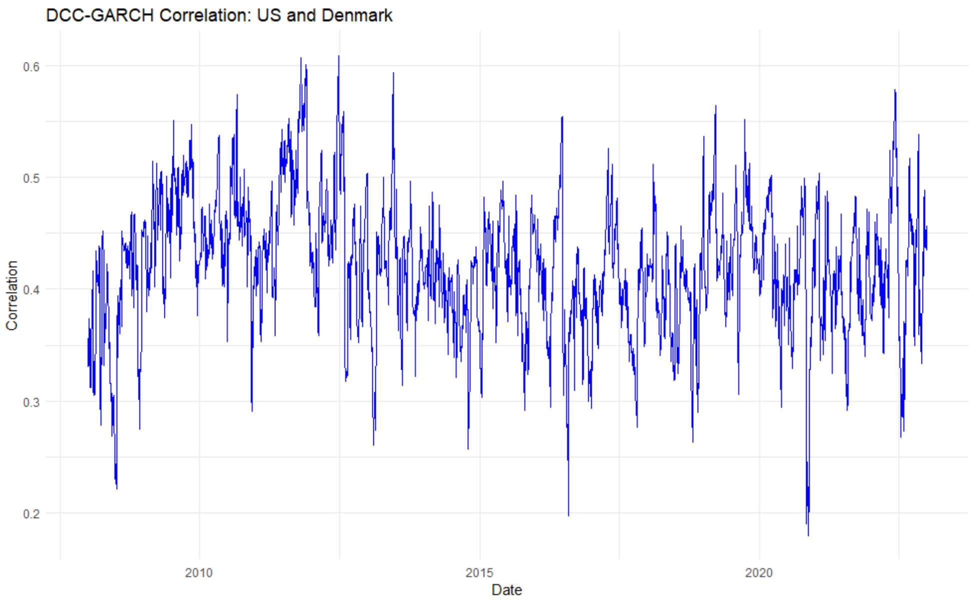



Fig. 30. Dynamic Conditional Correlation between US and Finland.

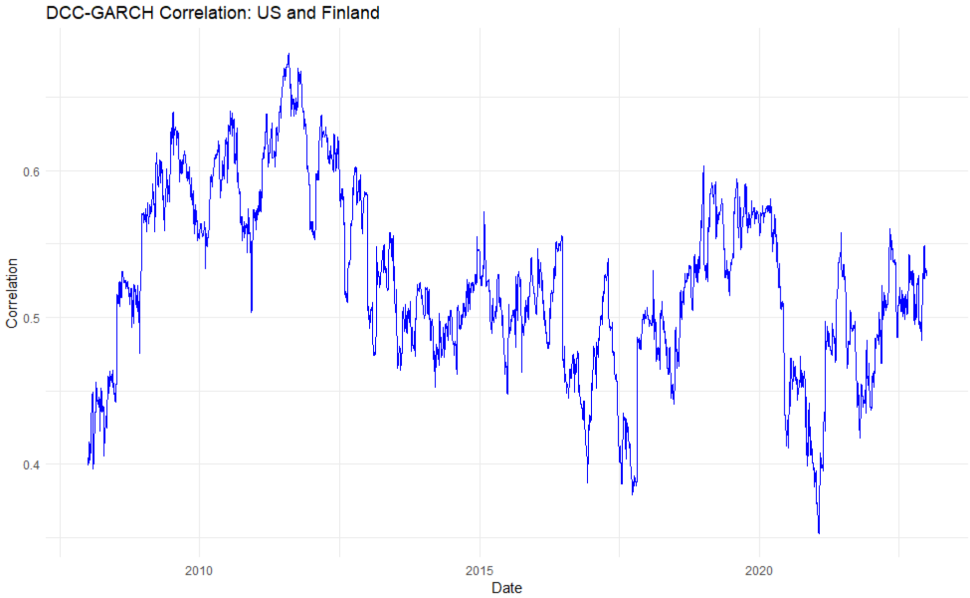



Fig. 31. Dynamic Conditional Correlation between US and France.

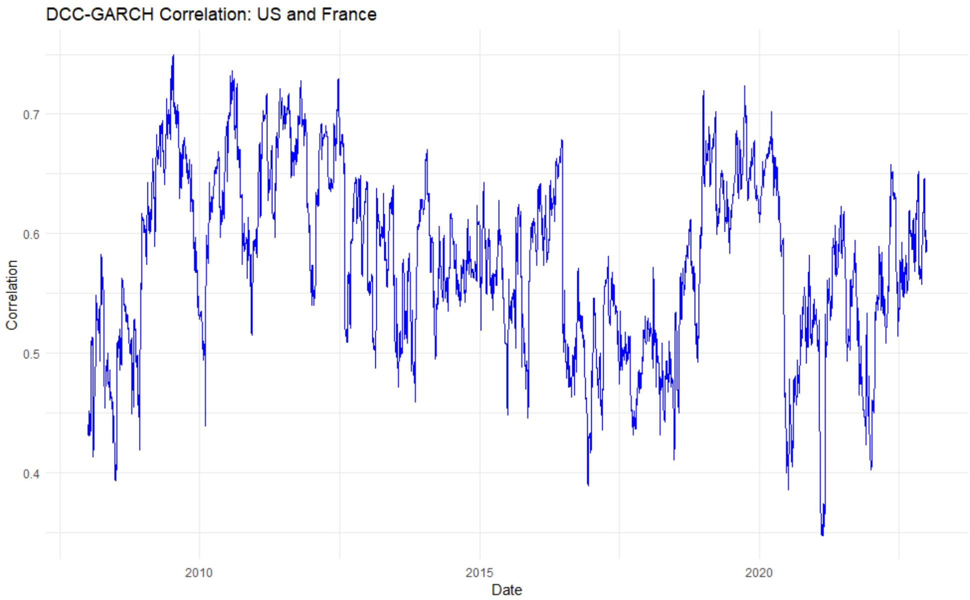



Fig. 32. Dynamic Conditional Correlation between US and Germany.

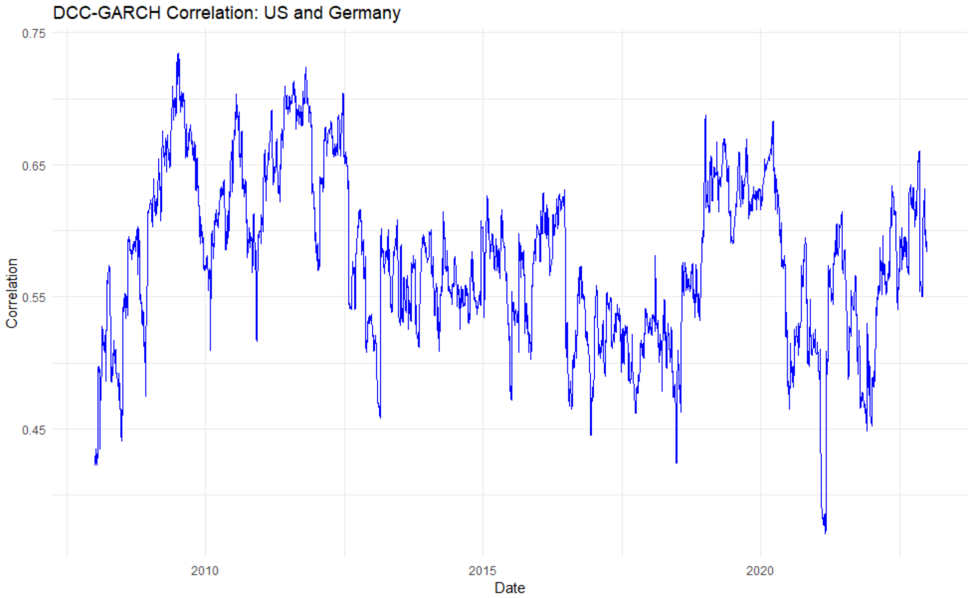



Fig. 33. Dynamic Conditional Correlation between US and Hungary.

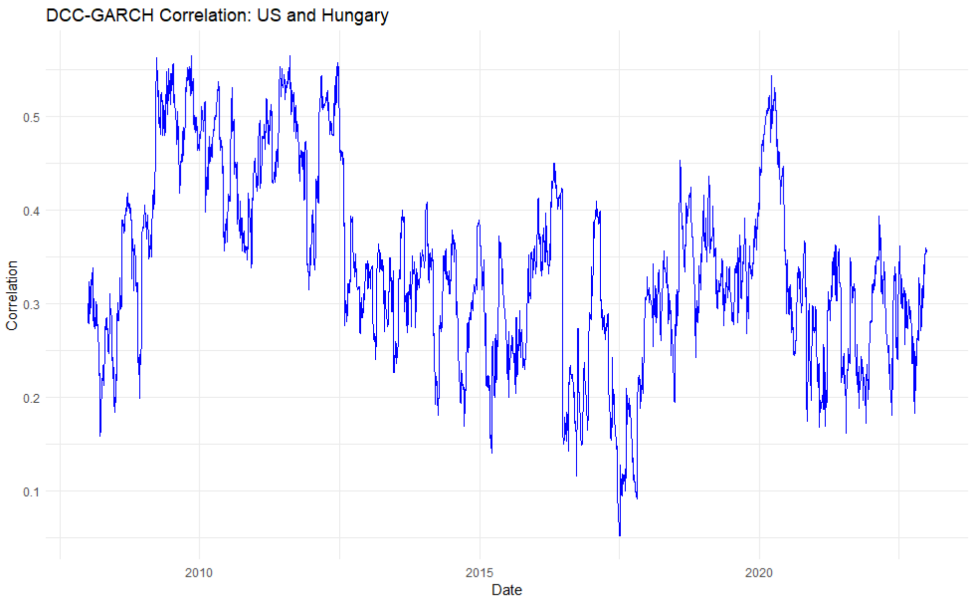



Fig. 34. Dynamic Conditional Correlation between US and Ireland.

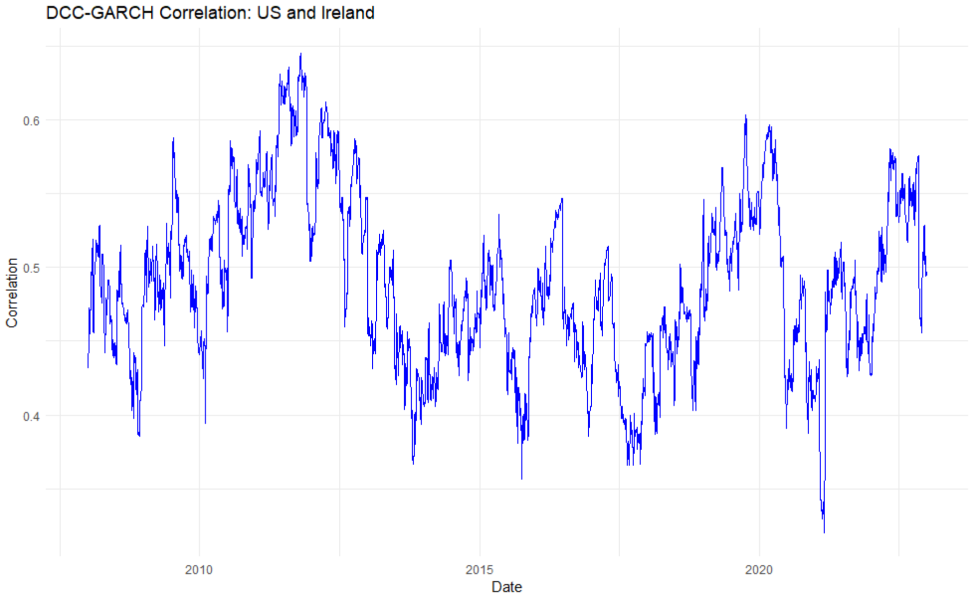



Fig. 35. Dynamic Conditional Correlation between US and Italy.

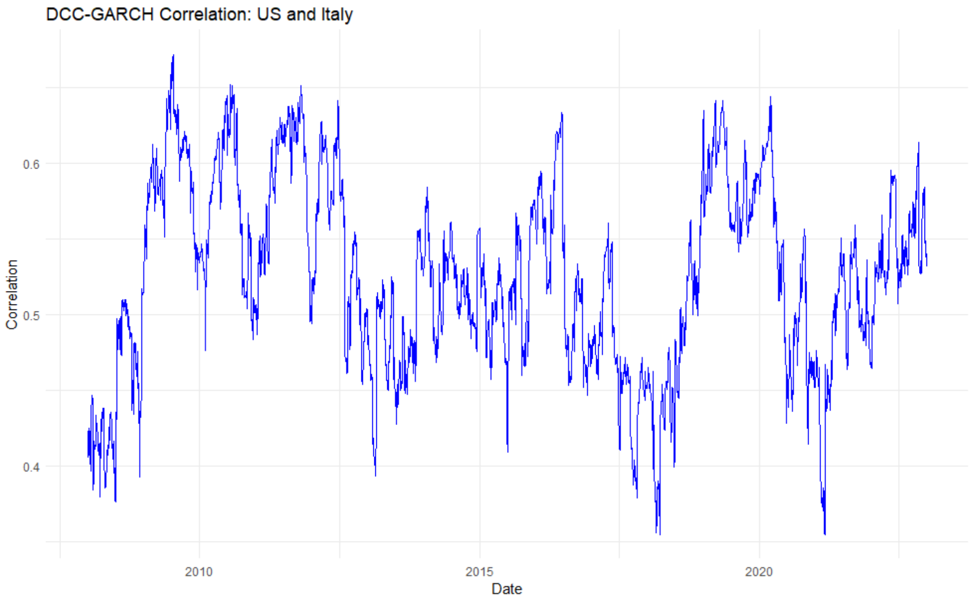



Fig. 36. Dynamic Conditional Correlation between US and Luxembourg.

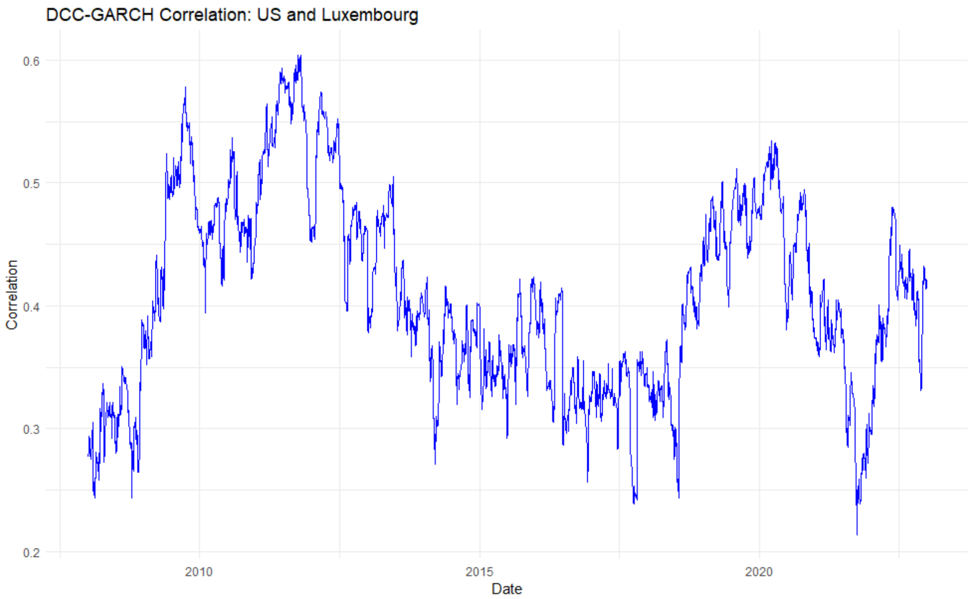



Fig. 37. Dynamic Conditional Correlation between US and Netherlands.

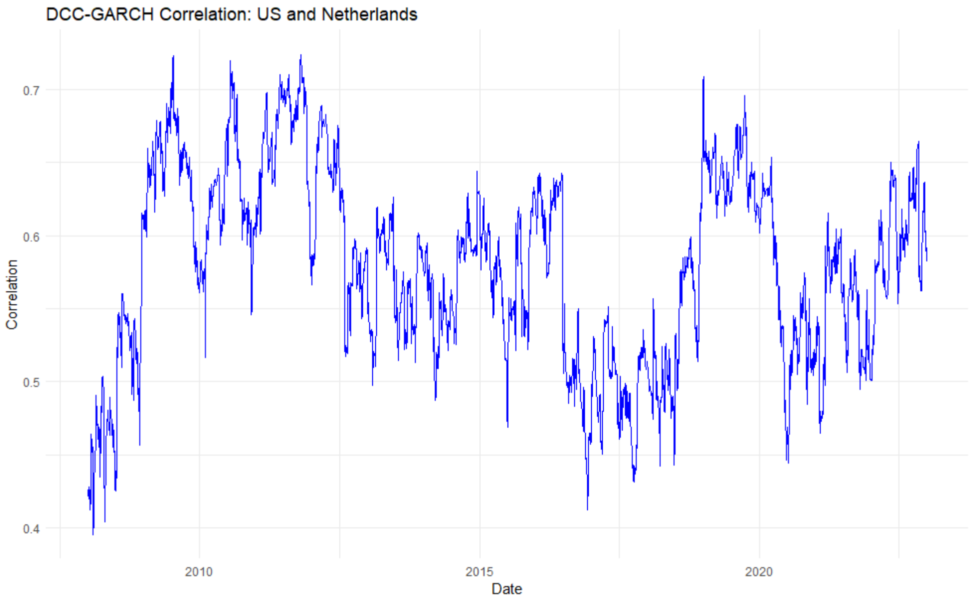



Fig. 38. Dynamic Conditional Correlation between US and Norway.

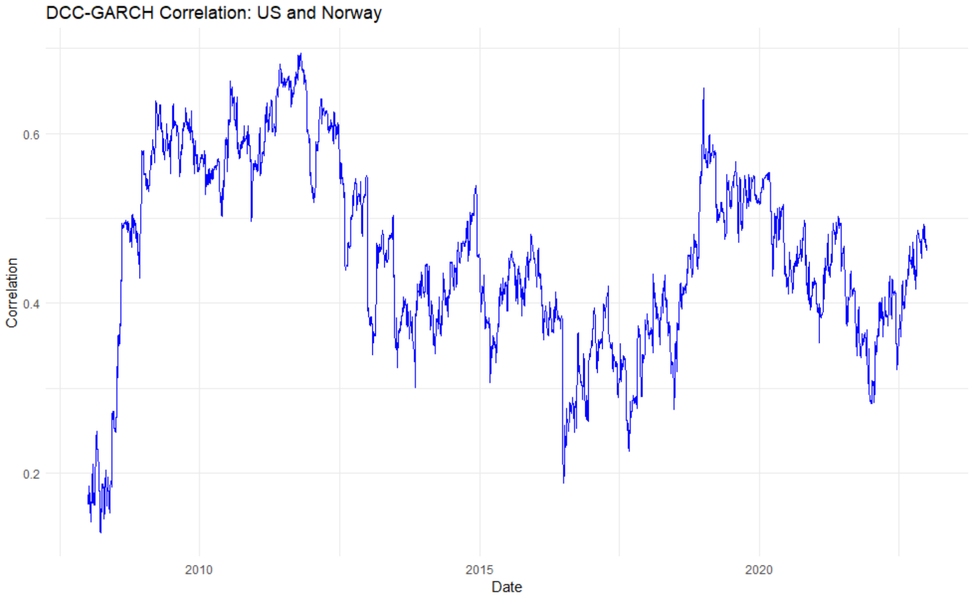



Fig. 39. Dynamic Conditional Correlation between US and Portugal.

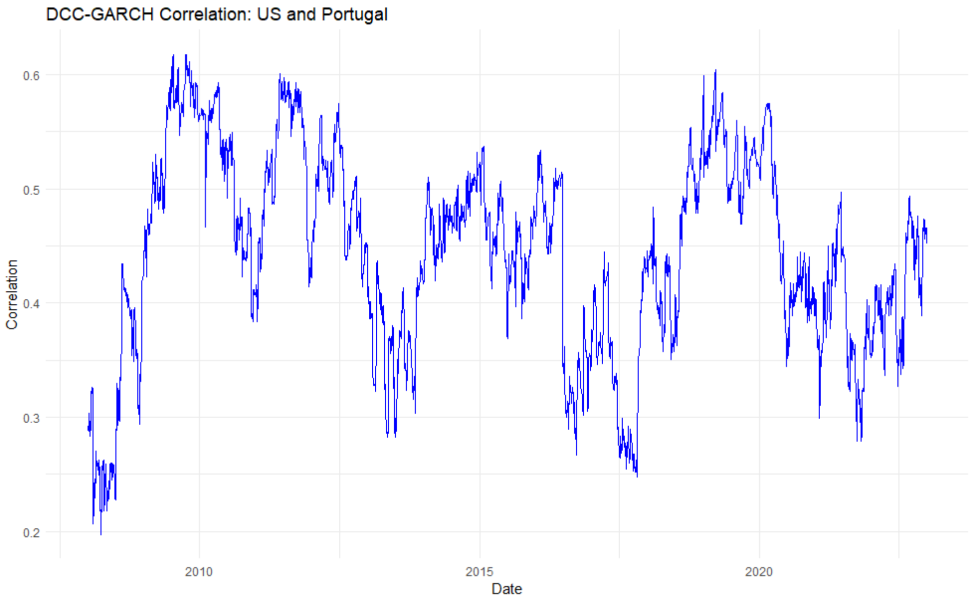



Fig. 40. Dynamic Conditional Correlation between US and Spain.

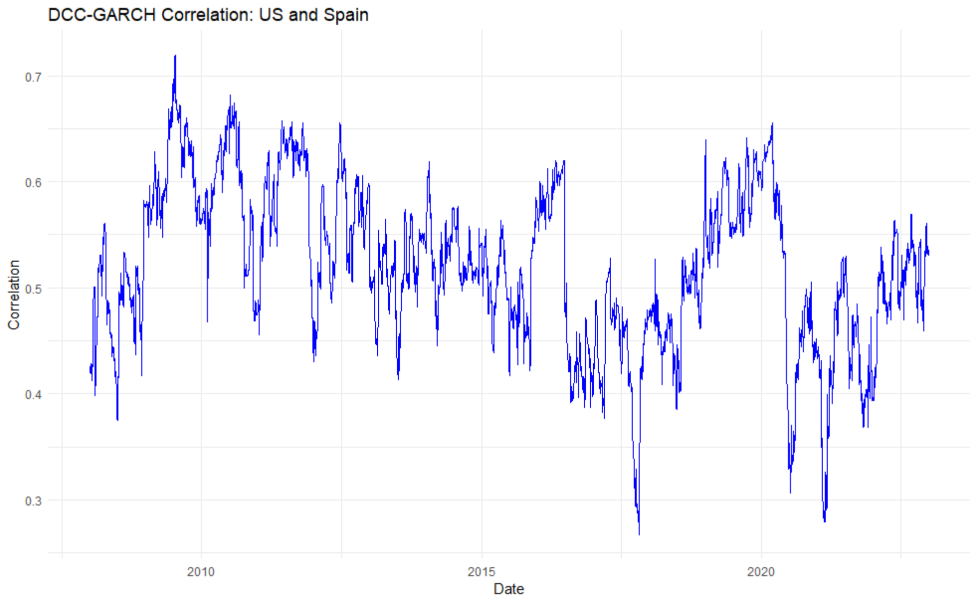



Fig. 41. Dynamic Conditional Correlation between US and Sweden.

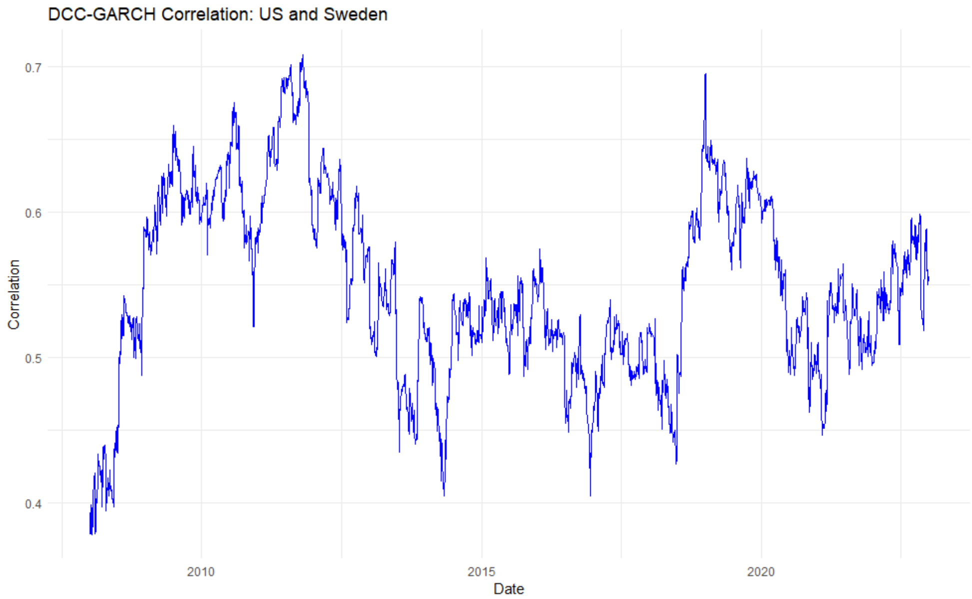



Fig. 42. Dynamic Conditional Correlation between US and Switzerland.

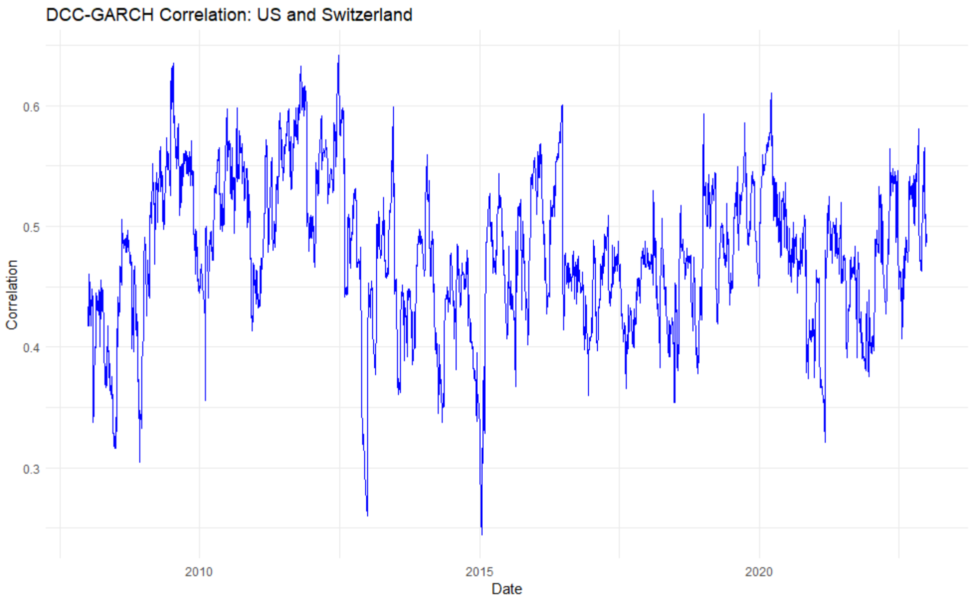



Fig. 44. Dynamic Conditional Correlation between US and UK.

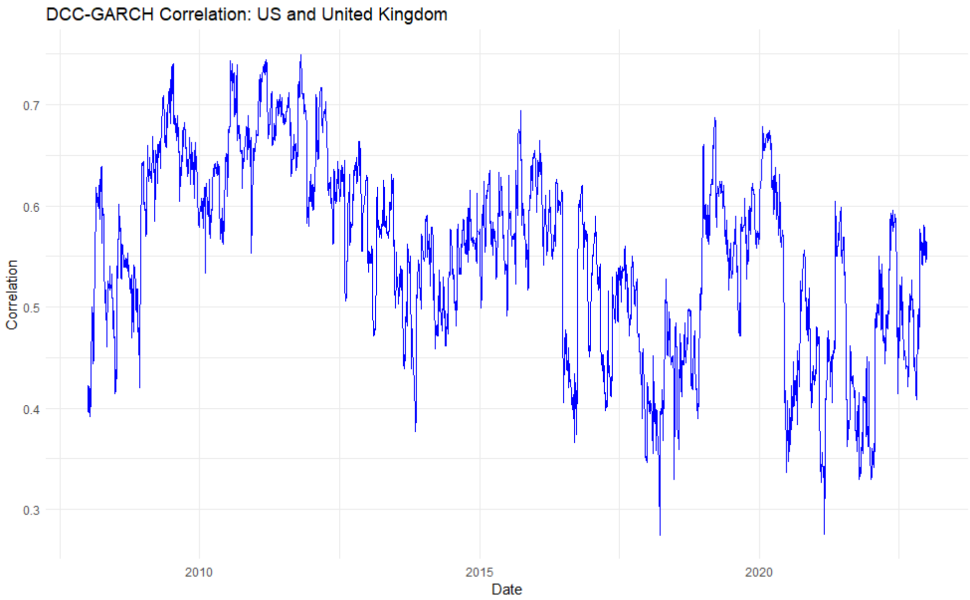
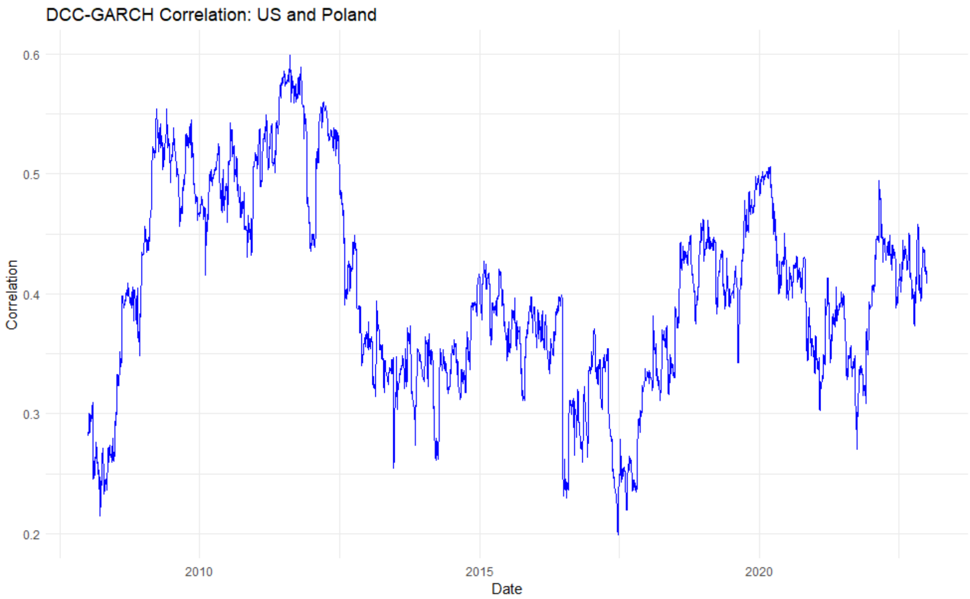



Fig. 45. Dynamic Conditional Correlation between US and Poland.


DCC-GARCH Correlation: US and Poland
0.6
0.5
0.4
0.3
0.2
Correlation
2010
2015
2020
Date