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Influence of stock market variables on correlations among S&P sectors

Master's thesis

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Declaration of Authorship

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Havlíčkův Brod, May 1, 2022

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Abstract

This thesis investigates the influence of the exogenous variables (S&P 500 Index, 10-year US Treasury Note, crude oil, and CBOE Volatility Index (VIX)) on the dynamics of correlations among S&P sectors. We concentrate on daily and weekly investment horizons, and employ the bivariate Dynamic Conditional Correlation (DCC) model. Changes in correlations implied by the DCC model are further modelled using the exogenous variables. The results indicate that VIX has the best ability to predict future changes in correlations. An increase in VIX on day (week) t is expected to cause a rise in correlations on day (week) $t + 1$. Next, correlations of the *Energy* sector tend to increase in weeks when crude oil prices are falling. Further, correlations of the *Information Technology* sector are likely to increase on days of rising yield on the 10-year US Treasury Note. Although we detect a certain power to predict future changes in correlations, very little of these changes is actually explained.

Keywords

correlation, DCC, S&P, bond yield, crude oil, VIX

Abstrakt

Tato práce zkoumá vliv exogenních proměnných (S&P 500 Index, 10letý americký státní dluhopis, ropa a CBOE Volatility Index (VIX)) na dynamiku korelací mezi sektory S&P. Zaměřujeme se na denní a týdenní investiční horizonty a aplikujeme bivariační Dynamic Conditional Correlation (DCC) model. Změny v korelacích implikované DCC modelem jsou dále modelovány pomocí exogenních regresorů. Výsledky ukazují, že VIX má nejlepší schopnost předpovidat budoucí změny v korelacích. Nárůst hodnoty indexu VIX v den (týden) t způsobuje nárůst v korelacích v den (týden) $t+1$. Dále, korelace sektoru *Energy* mají tendenci růst v týdny, kdy cena ropy padá. Co se týče sektoru *Information Technology*, jeho korelace většinou rostou v dny, kdy se výnos 10letého amerického státního dluhopisu zvyšuje. Ačkoliv jsme odhalili určitou schopnost predikovat budoucí změny v korelacích, jen velmi malá část těchto změn je ve skutečnosti vysvětlena.

Klíčová slova

korelace, DCC, S&P, výnos dluhopisu, ropa, VIX

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Master's Thesis Proposal

Author	Bc. Matěj Coufal
Supervisor	PhDr. František Čech, Ph.D.
Proposed topic	Influence of stock market variables on correlations among S&P sectors

Motivation

Determining the correlations between financial instruments has been the cornerstone of portfolio creation. Researchers over the past decades have focused on various ways of estimating the standard deviations (volatility) as well as correlations among different financial assets. Vast majority of studies analyzing the correlations investigated the co-movements of just aggregate stock indices from different countries. For example, Syllignakis, M.N. & Kouretas, G.P. (2011) examined the interconnection between stock markets in Germany, the US and Russia, and seven emerging countries from Central and Eastern Europe. Applying weekly data from 1997 to 2009 in the DCC-GARCH model, the authors show that returns on the US and German stock markets significantly influenced the returns on the CEE markets. On the other hand, the correlation between the Russian stock market and the CEE markets did not turn out to be statistically significant.

Next, Mensi, W. et al. (2016) examined the dynamic correlations between the stock markets in the US and BRICS countries (Brazil, Russia, India, China and South Africa). Using the data between September 1997 and October 2013, the results of the DCC-FIAPARCH model suggest that the US stock market returns were significant for forecasting returns on stock markets in all BRICS countries. Moreover, the correlations between the US and all BRICS countries except for Russia strengthened during and after the 2008 - 2009 financial crisis.

However, not much work has been devoted to the interrelation between individual sector or industry indices within one country. The main goal of this thesis is to examine the time-varying dependencies among S&P 500 sectors. All eleven sectors, represented by sector indices, will be considered in the analysis, whereas six sectors will be studied in more detail. These six sectors are selected such that both cyclical and non-cyclical sectors are represented. Further, although the precise distinction between value vs. growth sectors is not possible, some of the chosen sectors tend to be tilted to value, or growth, respectively. Hence, the dynamics of dependencies among cyclical, non-cyclical, rather-value, and rather-growth sectors will be observed and analyzed.

This research will aim to answer the question of how the analyzed sectors comove when the overall market, represented by the S&P 500 Index, goes up or down. The general notion is that stocks are correlated more in times of market corrections or crises (Ang, A. & Bekaert, G., 1999). However, this thesis is supposed to show the difference in reactions of individual correlation pairs to the returns of the S&P 500 Index. Next, a possible link between the US bond market (represented by the 10-year Treasury Note) and the dynamics of analyzed correlations will be examined. Arouri, M. et al. (2011) as well as Broadstock, D. C. & Filis, G. (2014) showed that sector stock indices might react to the oil market evolution differently. Hence, in my thesis I will also investigate how oil price changes affect the correlations among examined S&P 500 sectors.

Hypotheses

1. Hypothesis #1: Correlations among S&P 500 sectors increase in times of a market decline.
2. Hypothesis #2: US bond market significantly influences the dynamics of the correlations among S&P 500 sectors.
3. Hypothesis #3: There exists a significant relationship between oil price changes and correlations among analyzed S&P 500 sectors.

Methodology

I will work with the daily data on eleven S&P 500 sector indices, the 10-year Treasury Note, and oil prices. The data is available on the web page of S&P Global, The Wall Street Journal or Investing.com. To include two considerable market downtrends - the ones in 2007 - 2009 and 2020 - time period between January 2007 and February 2022 will be examined. Focusing on six sectors will lead to the detailed analysis of fifteen time-varying correlations.

The ultimate selection of sectors is *Consumer Staples*, *Energy*, *Financials*, *Health Care*, *Information Technology*, and *Utilities*. *Consumer Staples*, and *Utilities* represent non-cyclical sectors, whereas the remaining four sectors are considered cyclical. Concerning the distinction between value and growth sectors, *Financials* (value) and *Information Technology* (growth) are regarded as major counterparts. Next, *Health Care* is tilted toward the growth factor, while the other three are rather value sectors. (S&P Global web page)

For each sector index, the logarithmic daily returns will be calculated. An appropriate form of ARMA-GARCH model will be estimated, which will then become a basis for a multivariate GARCH model (e.g. Dynamic Conditional Correlation introduced by Engle, R. F., 2000). Time-varying correlations suggested by this model will be further analyzed. First, the descriptive statistics of dependencies between individual sectors will offer a general overview and comparison of the examined pairs.

Next, regression models will examine the relationship between the correlation pairs and the S&P 500 Index as well as the 10-year Treasury Note or the oil price changes. These regression models will be applied for three different lengths of returns: 1 day, 1 week, 1 month to see for which returns there are significant relationships between the independent variable (S&P 500 Index, 10-year U.S. Treasury Note, oil price changes) and the dependent variable (correlations among analyzed

S&P 500 sectors).

Expected contribution

This thesis should bring a deeper understanding of the dynamics of the interdependencies among S&P 500 sectors. Compared to studies that focused on correlations of aggregate stock indices, such as Gjika, D. & Horváth, R. (2013) or Mensi, W. et al. (2016), my thesis will offer the sectoral perspective on the US stock market. As both cyclical and non-cyclical sectors will be studied in more detail, this paper is supposed to explain how correlations between these two types of sectors evolve. Furthermore, it should explore the co-movement between sectors that are rather-value and rather-growth oriented.

Overall, the goal of this work is to deliver a better perception of the stock market - how the cyclical and noncyclical sectors are related, in which situations value and growth indices are less (more) correlated, how the U.S bond market or oil price changes influence individual correlation pairs, etc. Therefore, it should help investors with construction of a diversified portfolio based on the specific phase, in which the stock market currently stands.

Moreover, the year 2020 was a year full of records and extremes as far as the stock market and events related to it are concerned: oil price turned negative for the first time, the S&P 500 Index dropped by 34% between February and March (23 trading days), then a 68% increase in the index until the end of the year followed, and many other extremes. Maybe, this year has changed the style of investing. Therefore, it might be beneficial to show the results of the analysis covering the years 2020 as well as 2021. Perhaps, the correlations in and after 2020 will considerably differ from their values 10 years ago, for example. That all shall be shown by this thesis.

Outline

1. Introduction: I will introduce the topic and show why it is important to do further research in this area.
2. Literature review: An overview of previous studies and their conclusions will be provided in this part.
3. Data: In this section, I will describe the data I will work with. Also, the procedure of sectors selection will be discussed.
4. Methodology: This part will be devoted to the methodology I will follow in my research.
5. Results interpretation: In this section, I will present the results of my analysis, and show the differences among the examined correlation pairs.
6. Conclusion: In this part, I will summarize the main results and goals achieved by this thesis.

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Author	Supervisor

Acronyms

AIC	Akaike information criterion
ARMA	Autoregressive moving average
BIC	Bayes information criterion
DCC	Dynamic conditional correlation
GARCH	Generalized autoregressive conditional heteroskedasticity
IID	Independent and identically distributed
IT	Information technology sector
OLS	Ordinary least squares
S&P	S&P 500 Index
VIX	CBOE Volatility Index

Contents

1 Introduction

Correlations among financial instruments have since ever been a crucial factor for portfolio creation. Be it the minimum variance portfolio, the optimal risk-reward trade-off of a portfolio, or just a simple desire for diversification. At each point of time, investors need to know the correlations between the assets.

Financial markets react every day to the news. As a result of these news, expectations about the future of the businesses also change, leading to a drop or increase in their share prices. All this, in turn, has an impact on correlations between stocks. To efficiently manage their portfolios, investors, hedge funds, and alike should monitor these correlations, and adjust the holdings accordingly.

Correlations, transmission effects, and market contagion became a frequent research topic after the stock market crash in October 1987. For example, King & Wadhwani (1990) found out that the correlations among the stock markets in the US, the UK, and Japan had increased after October 19, 1987, the starting day of the crash. Moreover, they showed a positive statistically significant relationship between volatility and correlations.

Later, there appeared numerous papers aiming to determine which macroeconomic or geographical factors could have an impact on correlations among stock indices. King et al. (1990) concluded that macroeconomic variables explained very little of changes in covariances, and that these changes were driven rather by unobserved factors. Next, Syllignakis & Kouretas (2011) showed that the correlation between stock indices from two countries was positively related to the correlation between interest rates in these countries.

Last, there have been attempts to examine specifically the changes in correlations, and to determine what these changes are influenced by. Papers by Karanasos & Yfanti (2021) or McMillan (2022) showed different ways of expressing changes in correlations and regressing them on macroeconomic variables. While the first paper transformed time-varying correlations, ρ_t, as $\log\left(\frac{1+\rho_t}{1-\rho_t}\right)$, McMillan (2022) expressed the changes in correlations, $\Delta\rho_t$, as $\Delta\rho_t = \rho_t - \rho_{t-1}$.

Knowing which factors (macroeconomic or the ones related to the financial market) influence the movements in correlations can greatly facilitate our perception of the financial market dynamics. Moreover, with the knowledge of how each factor impacts the particular correlation pair, it becomes easier for investors to implement the right action to optimize the portfolio. Therefore, it is important to study the changes in correlations, and analyze factors that influence these changes.

A vast majority of papers on correlations studied merely the correlations among aggregate stock indices from different countries. Little attention has been paid to S&P sectors and correlations among them. This thesis focuses on the following six S&P sectors: *Consumer Staples*, *Energy*, *Financials*, *Health Care*, *Information Technology (IT)*, and *Utilities*.

It might be challenging to precisely determine whether the selected sectors are value or growth sectors. However, one may claim that *Financials* (value) and *Information Technology* (growth) can be considered the major counterparts in this distinction. Further, *Consumer Staples*, *Energy*, and *Utilities* are tilted toward the value factor, while *Health Care* is rather a growth sector. (S&P Global, 2022)

In this thesis, mutual correlations among the six S&P sectors are analyzed over the time period between 2007 and 2022. Therefore, in total 15 correlation pairs are examined. The main goal is to investigate how four variables related to the financial market (S&P 500 Index, 10-year US Treasury Note yield, crude oil, and CBOE Volatility Index (VIX)) influence the dynamics of the individual correlation pairs. Next, to show whether the COVID-19 pandemic and the corresponding market turbulence affected the results, the analysis is carried out for the periods 2007 - 2019 and 2007 - 2022 separately. Further, as different relationships might be valid for daily and weekly investment horizons, the analysis is performed for daily as well as weekly data. By conducting the analysis at the sectoral level, this thesis fills the gap of missing literature on correlations among S&P sectors.

The time-varying correlations are determined by bivariate DCC-GARCH models introduced by Engle (2002). Changes in correlations are expressed as a simple difference of consecutive correlation coefficient values. These changes in correlations are regressed on log-returns of the independent variables. In the first type of regressions, the regressors are from the same time period (day, week) as the regressand. Second, forecasting regressions, where the dependent variable is regressed on the first lag of independent variables, are also estimated.

The results show that among the four independent variables, VIX seems to be the most reliable one for predicting future changes in correlations. Its positive relationship with the dependent variable suggests that an increase in VIX in period t is expected to cause an increase in the correlation in period $t+1$. Next, for most of the correlation pairs, VIX achieved the highest adjusted R^2 in univariate regressions. This shows that among all four independent variables, VIX explains the most variability in the regressand.

Another interesting observation is that correlations of *Energy* tend to decrease during weeks of increasing crude oil price. The significance of crude oil, not only for the correlations of *Energy*, was detected more frequently for data until 2022 than for the time period 2007 - 2019. Therefore, one may conclude that this variable has gained importance for determining the changes in correlations since the start of 2020. For *IT*, it is observed that the correlation is likely to increase on days of rising yield on the 10-year US Treasury Note. Nevertheless, although some of the analyzed variables have some power to predict future changes in correlations, one needs to bear in mind that very little of these changes can be explained by S&P, 10-year US Treasury Note, crude oil, and VIX.

For all 15 correlation pairs, slightly different results are obtained for a different investment horizon (daily, weekly) and a different time period (2007 - 2019, 2007 - 2022). First, comparing these results brings a better understanding of the behavior of the analyzed correlation pairs. Second, and more importantly, the results offer an overview of specific independent variables that could be used for forecasting the correlations for each pair. When including these factors into models for forecasting covariance matrices, investors can better optimize a portfolio consisting of ETFs[1] tracking the sector indices analyzed in this thesis.

The remainder of this thesis is organized as follows. In Chapter 2, one can find an overview of literature regarding the topics on correlations. Next, Chapter 3 focuses on the description of data used in the analysis. Chapter 4 shows the methodology that is followed. Regression results are presented in Chapter 5. Main findings and conclusions are summarized in Chapter 6. Figures as well as tables summarizing the regression results can be found in Appendix.

[1]Exchange Traded Funds

2 Literature review

This chapter offers an overview of literature related to the topic of correlations among stock indices. Section 2.1 describes papers that investigate patterns and values of correlations, volatility transmissions, or structural breaks in these correlations and volatilities. In Section 2.2, the reader can find studies that deal with macroeconomic or geographical factors that could have an impact on levels of correlation coefficients. Section 2.3 contains papers that estimate regression models analyzing how the changes in correlations are affected by certain (not only macroeconomic) variables.

2.1 Correlations among stock indices

The stock market crash that started on October 19, 1987 stimulated research on market contagion, correlations, and transmission effects.

King & Wadhwani (1990) analyzed the interaction between the stock markets in the US, the UK, and Japan, using hourly data from July 1987 to February 1988. During the overlapping trading hours in the period of July 1 - October 16, the correlation coefficient between the markets in New York and London was 0.27. Between October 19 and November 30, the correlation was 0.48, and during the crash week (October 19 - October 23), it reached a value of 0.65. Considering also Japan, the authors showed that for all three markets, the contagion effects had increased as a consequence of the crash on October 19. Moreover, the volatility considerably increased from October 19. Further regressions showed that there was a statistically significant positive relationship between volatility and transmission effects, implying higher correlations between markets in periods of a higher volatility.

Kaltenhaeuser (2003) analyzed the degree of interrelation of 10 sectors among each other within a country or a currency area (CA) as well as how these sectors were correlated with the corresponding sectors in a different country or CA. Daily data on euro area countries, the United States, and Japan, ranging between 1986 and 2002, were used in a multivariate GARCH model. Rolling estimations were performed to examine the dynamics of the spillover effects. An interesting finding is that over the whole examined time period, the average correlations among sectors within one CA were considerably higher than average correlations between the same sectors from different CAs. Next, the results indicated that the sectors were more correlated with countries (or CAs) than with their counterparts in the corresponding country (or CA). The interdependence among the same sectors from the analyzed countries (or CAs) differed markedly. For *Cyclical Services*, *General Industrials*, and *Utilities*, there were rather small spillover effects from their foreign counterparts. On the other hand, *Information Technology*, *Resources*, and *Noncyclical Consumer Goods* experienced a higher degree of interconnection with the corresponding sectors in foreign CAs.

Berben & Jansen (2005) analyzed comovements between stock markets in the US, the UK, Japan, and Germany for the time period of 1980 - 2000. One of the main goals was to find out whether there had been structural changes in the correlations among the above mentioned markets. Besides the aggregate stock market indices, ten sectors were also considered. For the correlation pairs that had experienced a significant structural change, the authors applied the Smooth-Transition Correlation GARCH (STC-GARCH) model that enabled to determine when the change had started and ended as well as its pace. The results showed that correlations between the aggregate market indices exceeded the correlations between the same sectors from the corresponding two countries. The authors claimed that there had not been a significant change in correlation pairs including Japan. This was valid at both the aggregate and sectoral level. On the other hand, correlations among the aggregate US, UK, and German markets experienced a significant uptrend.

Regarding the pair of the US and the UK, a significant change was detected for 8 out of 10 sectors. The change in the correlation coefficient levels was significant for 4 out of 10 sectors for the pairs Germany - UK and Germany - US. There is a large variation in the dates when the changes in correlations began as well as in the lengths of these transition periods. The correlation between the US and the UK stock markets experienced a gradual increase from 0.3 in 1980 to 0.63 in 2000. For the correlation pair of Germany - UK, there was an increase from 0.21 to 0.66 over the examined period, whereas the transition phase occurred especially between 1986 and 1994. Last, the correlation between the US and Germany rose from 0.33 to 0.63, especially thanks to the time period of April 1995 - September 1997, when 80% of this change occurred.

Arouri et al. (2011) analyzed the volatility spillover effects between the oil market and stock markets in the US and Europe. The following seven sectors in Europe as well as the US were considered: *Automobile & Parts*, *Financials*, *Industrials*, *Basic Materials*, *Technology*, *Telecommunications*, and *Utilities*. Moreover, the Dow Jones Stoxx Europe 600 Index and the S&P 500 Index were also a part of the analysis to show the difference between the sectoral and aggregate market level. Weekly data between January 1998 and December 2009 were used in bivariate VAR(1)-GARCH(1,1) models (oil returns - particular stock index). The volatility of aggregate stock indices turned out to be significantly influenced by unexpected shocks to the oil prices. However, the past volatility of oil returns did not affect the stock market volatility significantly. Looking in the opposite direction, the oil market volatility was significantly affected by the unexpected shocks to the S&P 500 Index. Focusing on the sectoral level, the authors observed that there was a significant effect of past shocks to the stock returns on the oil market volatility for the following sectors: *Financials* and *Utilities* in Europe, and *Automobile & Parts*, *Financials*, *Industrials*, and *Utilities* in the US. Next, stock sector volatility was significantly driven by past oil shocks for all sectors, except for *Basic Materials* in Europe and *Industrials* as well as *Utilities* in the US. Further, the following three US sectors significantly responded to the past volatility on the oil market: *Automobile & Parts*, *Basic Materials*, and *Utilities*.

Another paper focusing on correlations between aggregate stock market indices was written by Mensi et al. (2016). They examined the dynamic correlations between the stock markets in the US and BRICS countries (Brazil, Russia, India, China, and South Africa). Daily data on representative indices between September 1997 and October 2013 became a basis for the Dynamic Conditional Correlation Fractionally Integrated Asymmetric Power ARCH model (DCC-FIAPARCH). First, the results indicated that the conditional volatilities experienced asymmetry and long memory. The application of the Granger causality test revealed that the US stock market returns were significant for determining returns on stock markets in all the BRICS countries. Next, volatility spillover effects between the US and the above mentioned five countries were also detected. For all analyzed countries, September 15, 2008 was identified as a common structural break that had changed the dynamics of unconditional variances. Hence, the authors divided the analyzed period into two subperiods: pre-crisis and post-crisis period. They showed that the dependence between the US and four BRICS countries (Brazil, India, China, and South Africa) strengthened after September 15, 2008. On the contrary, the correlation between the US and Russia in the post-crisis era was found to be lower than in the pre-crisis times, pointing out to a certain degree of decoupling between the Russian and US stock markets.

2.2 Macroeconomic and geographical factors

King et al. (1990) attempted to determine how both observed and unobserved factors influenced the covariances between world stock markets. For the time period of 1970 - 1988, monthly data on stock indices from 16 countries became a basis for the analysis. Observed factors were represented by 10 macroeconomic variables that might influence the stock market evolution. Among others, these were the yield on US Treasury Bills, oil price, exchange rates between the US dollar and some other world currencies. The results revealed a striking observation. The observable factors explained a very small portion of changes in the covariances between the analyzed markets. Moreover, the influence of these factors on variances on the markets was lower than expected. Hence, the authors concluded that changes in the examined covariances were driven mainly by unobserved factors, such as investor sentiment.

Similar results were delivered by Karolyi & Stulz (1996). They investigated the influence of various fundamental factors on the correlations between portfolios of US stocks and Japanese ADRs[1] traded on the American and New York Stock Exchanges. Using data between May 1988 and May 1992, the authors showed that the correlations varied across weekdays (higher values on Monday). Nevertheless, the correlations did not turn out to be significantly influenced by US macroeconomic announcements, shocks to the Yen/US Dollar exchange rate, or the US Treasury Bill returns. Instead, large shocks to aggregate market indices (Nikkei Stock Average and S&P 500 Stock Index) did have a positive impact on values and persistence of examined correlations.

Flavin et al. (2002) applied the Gravity model to analyze which geographical factors influence the correlations among stock markets. Data on 27 stock markets (country level) from the year of 1999 were used for the analysis. The model included the following independent variables: great circular distance (GCD) between the main financial centers of the two countries, product of market capitalizations of both markets, and dummy variables on language, common border, common currency, and past colonial links. The correlation between the two countries was the dependent variable. The authors showed that all independent variables were statistically significant at 5% level, the exceptions were the dummies on language and past colonial links. GCD, negatively related to the correlation, seemed to be the key factor for determining the correlations between stock markets in different

[1] American Depository Receipts

countries as it was associated with the lowest p-value. This should not be surprising as the difficulties in gathering information from a country that is far away stimulate investors to focus on markets that are nearby. Although the paper by Flavin et al. (2002) presents rather a simple model that captures the correlations merely from the year of 1999, it offers an interesting insight into variables that could explain the correlations between financial markets.

Baele et al. (2010) examined how the correlation and covariance between stocks and bonds were influenced by macroeconomic and liquidity factors. Stocks were represented by value-weighted indices of NYSE, AMEX, and NASDAQ, while the 10-year US Treasury Note was used as a bond variable. Quarterly data between 1968 and 2007 were analyzed by the dynamic factor model. The results showed that macroeconomic variables (output gap, inflation, short-term interest rate) explained very little of changes in correlations between stocks and bonds. Similarly, the model failed to explain a satisfactory portion of variation in the corresponding covariances. The authors concluded that liquidity factors were better at explaining changes in correlations (covariances) between stocks and bonds.

Syllignakis & Kouretas (2011) examined the interconnection between stock markets in Germany, the US, Russia, and the following seven emerging countries from Central and Eastern Europe (CEE): Czech Republic, Estonia, Hungary, Poland, Romania, Slovakia, and Slovenia. Weekly data from 1997 to 2009 on representative stock indices (S&P 500 for the US) became a basis for the DCC-GARCH model. The results showed that returns on the US and German stock markets significantly influenced the returns on the CEE markets, whereas the Russian stock market did not play an important role in this respect. Regarding the dynamic correlation coefficients, the contagion effects were present especially during the crisis in 2007 - 2009. Next, the authors applied a rolling stepwise regression to examine how the correlation coefficient between a CEE country and Germany depended on the volatility of returns on the German and the corresponding CEE market. The results indicated that the volatility on the German market had been positively related to the correlation coefficients at the beginning of the analyzed time period. Between the years 2002 and 2003, the estimated effect was negative for most CEE countries, though. During the crash in October 2008, the volatility of the German stock market again significantly positively influenced the individual correlation pairs. Last, the authors claimed that the correlation between interest rates in two countries had a positive relationship with the correlation of the corresponding two stock markets. The results concerning proxies for inflation, exchange rate, or credit rating did not provide a clear conclusion on significance or sign.

Broadstock & Filis (2014) examined how three different oil price shocks influenced the returns on aggregate stock markets in the US and China. The types of oil price shocks were as follows: supply, aggregate demand, and oil-market specific demand-based shocks. Monthly data from January 1995 to July 2013 on stock indices and from January 1990 to July 2013 on world oil production, oil prices, and global economic activity were collected. Dynamic conditional correlations between the corresponding stock indices and oil price shocks were determined by the Scalar-BEKK model. The results showed that correlations between oil price shocks and aggregate stock indices (NYSE and Shanghai Composite Index) had varied over time, with fluctuations around both positive and negative values. Next, as opposed to the Shanghai Composite index, the NYSE index experienced mostly a higher correlation with the oil price shocks. For the NYSE index, the aggregate demand shocks to oil prices turned out to exhibit the highest (and always positive) correlation. On the other hand, the supply-side shock was the one with the lowest (mostly negative, apart from 2000 - 2003 and 2012 - 2013) correlation with the NYSE index. For the Chinese aggregate stock index, there was a higher degree of correlation with the supply-side shock than in the case of the US. The other two oil price shocks were less correlated with the Shanghai Composite index than with the NYSE index.

2.3 Changes in correlations

Wang & Moore (2008) analyzed how stock markets in Poland, Hungary, and the Czech Republic were correlated with the eurozone market. The second point of interest was to find out which factors from economic and monetary integration as well as currency risk drove the dynamics of individual correlations. The DCC model based on the bivariate exponential GARCH for daily data from April 1994 to December 2006 was applied. The eurozone market was represented by the value-weighted average of stock indices of the 12 EU countries that had already adopted the euro. The results showed that higher levels of correlation as well as fluctuation were present mainly in times of external shocks and crises. Next, the integration towards the eurozone market increased after May 2004, when the analyzed countries joined the European Union. The authors regressed the DCC values on dummy variables (one dummy in each regression) representing the currency crisis in the Czech Republic (May 27, 1997), the Asian crisis (October 14, 1997), the Russian crisis (August 17, 1998), and the entry to the EU (May 5, 2004). The results indicated that all the above-mentioned events had had a significant positive effect on the values of conditional correlations. The only exception was the EU entry for Hungary, which had been insignificant for the correlation between the Hungarian and eurozone market. These results thus confirmed that correlations between financial markets tended to increase in times of crises, and that the integration was supported by entering a common union.

Andersson et al. (2008) analyzed how volatility and expectations about inflation and GDP influenced the correlation between stocks and government bonds in the US, Germany, and the UK. The data covered the time frame between 1991 and 2006. The following two methods of measuring the stocks - bonds correlation were used: (i) a simple rolling window correlation and (ii) the DCC model. These correlations were regressed on expected inflation, expected GDP, and volatility implied by the stock index options. To deal with the fact that correlations range between -1 and 1, while the right hand side of the regression equation can reach out of this interval, the Fisher z-transformation[2] was applied. The results indicated that the expected inflation had had a positive impact on the stocks - bonds correlations, statistically significant in 4 out of 6 cases.[3] Next, the implied volatility was significant in all cases and negatively related to the dependent variable. Last, the GDP expectations did not turn out to be statistically significant for determining the levels of the stocks - bonds correlation.

Karanasos & Yfanti (2021) aimed to find out which macroeconomic factors have an impact on the dynamic correlations between equities, real estate, and commodities markets. Daily data between January 2000 and March 2019 were analyzed by the GJR-GARCH-DECO model. The Fisher z-transformation was applied to daily correlations implied by the model. These transformed values were regressed on their first lags and proxies for the following macroeconomic factors: economic policy uncertainty (EPU), financial uncertainty (FU), volatility on US Treasury Bonds (VTB), and economic activity (EA). The results suggested that there was a positive and mostly significant effect of EPU, FU, and VTB on the examined correlation pairs. On the other hand, EA had a negative impact on correlations. The authors estimated the regressions also on a monthly basis. The monthly correlations were determined as the average of daily correlations in the corresponding month. In these monthly regressions, the proxy for FU was not considered. Instead, proxies for business/consumer sentiment (B/C-S) and global geopolitical risk (GGR) were included. B/C-S showed a negative and mostly significant effect on correlations. GGR also turned out to be negatively related to correlations. This relationship was significant for correlation pairs commodities - equities, and commodities - real estate. Such results were rather unexpected as they implied lower correlations in times of a higher geopolitical risk.

Zhao & Wang (2021) analyzed how the US and Chinese economic policy uncer-

[2]Correlations in time t, ρ_t, were transformed as $\log\left(\frac{1+\rho_t}{1-\rho_t}\right)$.

[3]6 cases: 2 methods (simple rolling window correlation, DCC) times 3 countries

tainty (EPU) and monetary policy uncertainty (MPU) influenced the following two correlation pairs: oil - stocks and gold - stocks. Data used for the analysis ranged between January 2000 and November 2020. The authors applied the DCC-GARCH t-Copula model on daily log-returns of stock indices (S&P 500 and Shanghai Composite Index), NYMEX WTI crude oil futures, and COMEX gold futures. Monthly correlations were then calculated as the average of daily correlations implied by the DCC-GARCH t-Copula model within the month. Next, Fisher's z-transformation was applied to the correlations, and these values were regressed on their lags and the Chinese as well as US EPU and MPU. Both the OLS and the quantile regression were estimated. The results indicated that the independent variables from the US played a more important role for determining the analyzed correlations than the Chinese ones did.

McMillan (2022) examined the correlations between S&P 500 log-returns and the following three variables: 10-year US Treasury yield, inflation, and money supply growth. The goal was to investigate how changes in these correlations were influenced by the real interest rate, industrial production growth rate, inflation, change in the dividend/price ratio, and a macroeconomic uncertainty measure (NCFI[4]). Monthly data between 1959 and 2020 were used in the analysis. The dynamics of correlations was determined by 5-year rolling estimates of correlations. For the regression equation, changes in correlations, $\Delta\rho_t$, were expressed as a simple difference between the current (ρ_t) and previous (ρ_{t-1}) value of correlation. The results showed that the change in the interest rate had turned out to be statistically significant for determining changes in all three correlation pairs. The relationship was positive for correlations of S&P 500 returns with bond yields as well as inflation. A negative relationship was detected for the correlation pair S&P 500 returns - money supply growth. Other independent variables were significant for maximum of two out of three correlation pairs.

[4]National Financial Conditions Index

3 Data

Daily data covering the time period between January 03, 2007 and February 25, 2022 were downloaded from the following sources. Data on closing prices of the S&P 500 Index were downloaded from the Yahoo Finance web page. Data on closing prices of all 11 S&P sector indices were downloaded from web pages of S&P Global[1] and Investing.com.[2] Data on the 10-year US Treasury Note yield, crude oil,[3] and VIX were downloaded from the Yahoo Finance web page.

The six analyzed sectors were selected for the following reasons. *Consumer Staples* and *Utilities* can be considered clearly non-cyclical sectors, whereas the others are rather cyclical (although the distinction might sometimes be indeterminate). *Financials* and *IT* are among all the sectors the ones most markedly tilted to value (*Financials*) or growth (*IT*) factor (S&P Global, 2022). *Energy* was added due to the fact that this sector could very likely respond to changes in the crude oil price. Last, *Health Care* was selected as this sector might have become more attractive as an aftermath of the COVID-19 pandemic, during which pharmaceutical companies played an important role.

For all time series, logarithmic returns were calculated as

$$LR_{it} = \log\left(\frac{P_t}{P_{t-1}}\right),$$

where LR_{it} represents the log-return of series i in period t, P_t and P_{t-1} are closing prices[4] of series i in periods t and $t-1$, respectively.

[1] Data between February 28, 2011 and February 25, 2022 were downloaded from the S&P Global web page.

[2] Data before February 28, 2011 were downloaded from the Investing.com web page.

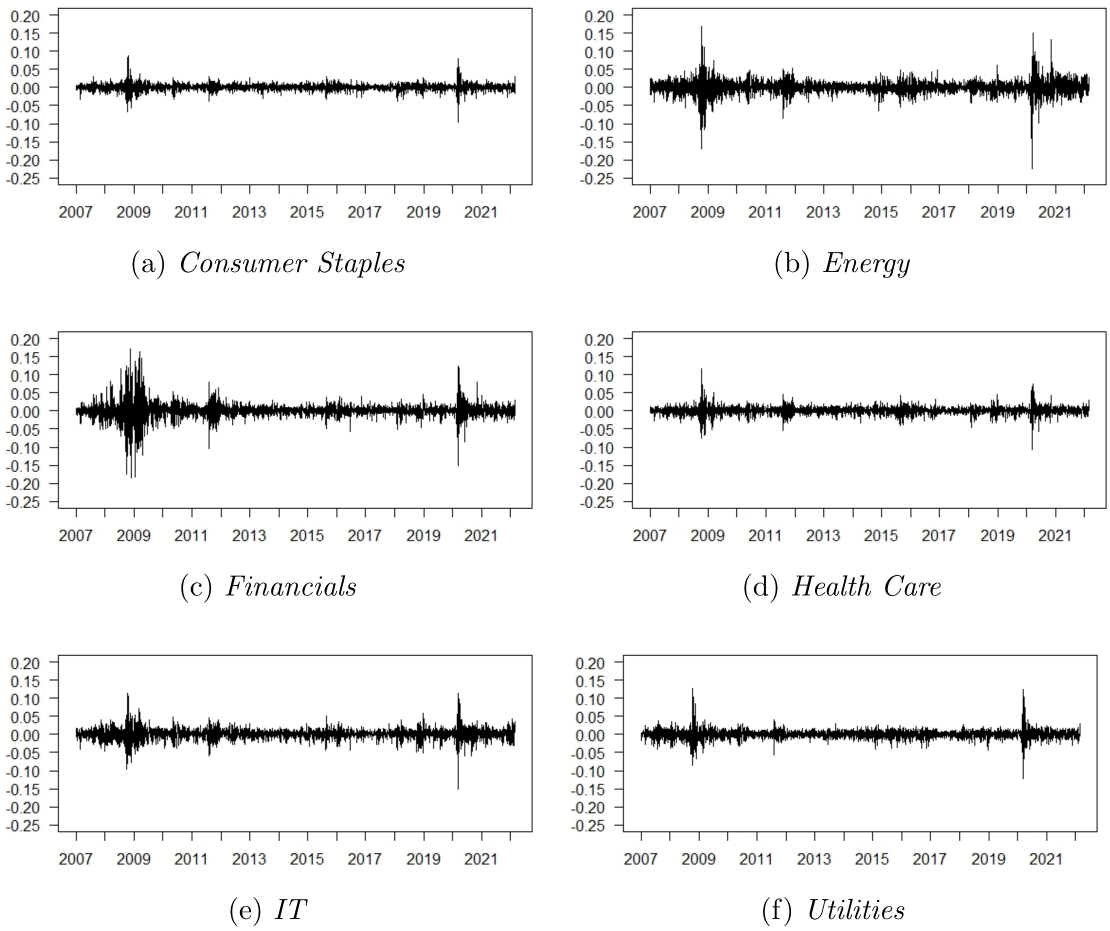
[3] represented by the closing prices of the Crude Oil WTI futures contract expiring in April 2022

[4] or values of yields on the 10-year US Treasury Note

Daily log-returns of six sectors that are part of the empirical analysis are presented in Figure 1.

Figure 1: Daily log-returns of six analyzed sectors

This figure shows the daily log-returns of the following six S&P sectors: (a) *Consumer Staples*, (b) *Energy*, (c) *Financials*, (d) *Health Care*, (e) *IT*, and (f) *Utilities*.



(a) *Consumer Staples*

(b) *Energy*

(c) *Financials*

(d) *Health Care*

(e) *IT*

(f) *Utilities*

From this graphical comparison of the analyzed indices, one can see that over the examined period, there were two periods with a significantly higher volatility. First, the Global financial crisis caused an increased volatility between 2007 and 2009. Second, the markets became much more turbulent in February 2020, when the global COVID-19 pandemic started. It is visible that both events considerably changed the behavior of all log-returns. The impact was different on each sector index, though. Further, Figure A1 shows the daily price (value) evolution and log-returns of the S&P 500 Index, bond yield, crude oil, and VIX.

Table A1 shows the summary statistics of daily as well as weekly log-returns of the aggregate S&P 500 Index and eleven sector indices. Among all sectors, *Consumer Staples* experienced the highest minimum daily log-return (−9.7%), the lowest maximum daily log-return (8.8%), and had the lowest volatility (1.0%) of daily log-returns. On the other hand, *Energy* suffered the lowest minimum daily log-return (−22.4%), whereas *Real Estate* recorded the highest maximum daily log-return (18.9%) and also the highest volatility (2.2%). All sectors had a positive average daily log-return, with 0.05% for *IT* being the highest value.

Daily log-returns of all sectors but one (*Utilities* with skewness of 0.06) were negatively skewed. The minimum value of skewness was −0.66 (*Energy*). It is worth noticing that only this sector was more negatively skewed than the aggregate index S&P 500 (skewness of −0.55).[5] All sector indices had values of the kurtosis coefficient larger than 10.[6] 11.5 (*Materials*) and 19.4 (*Real Estate*) were the smallest and largest values of kurtosis coefficient, respectively.

Weekly log-returns are summarized in Panel B of Table A1. *Energy* experienced the lowest weekly log-return (−28.8%). On the other hand, *Financials* recorded the highest weekly log-return (29.2%), being also the most volatile sector (4.2% volatility of weekly log-returns). Similarly as for daily log-returns, *Consumer Staples* was the least volatile sector (1.9% volatility of weekly log-returns). Distributions of weekly log-returns for all sectors were negatively skewed and leptokurtic.

Unconditional correlations (daily and weekly) among all sectors and the S&P 500 Index over the examined time period are presented in Table 1.

[5]Skewness coefficient was calculated as $Skew = \frac{\mu_3}{\mu_2^{3/2}}$, where μ_2 and μ_3 are the second and the third central moments, respectively.

[6]Kurtosis coefficient was calculated as $Kurt = \frac{\mu_4}{\mu_2^2}$, where μ_2 and μ_4 are the second and the fourth central moments, respectively.

Table 1: Unconditional correlations - stock indices

This table presents the unconditional correlations among eleven sector indices and the aggregate S&P 500 Index over the time period January 03, 2007 - February 25, 2022. Panel A depicts correlations of daily log-returns. Panel B shows the correlations of weekly log-returns. The abbreviations as the names of rows and columns are as follows: S&P (S&P 500 Index), CD (*Consumer Discretionary*), CS (*Consumer Staples*), Ener. (*Energy*), Fin. (*Financials*), HC (*Health Care*), Ind. (*Industrials*), IT (*Information Technology*), Mat. (*Materials*), RE (*Real Estate*), TS (*Telecommunication Services*), Util. (*Utilities*). The last rows ('average') show average correlations of the particular sector index if correlations with itself and with the S&P 500 Index are omitted.

Panel A

	S&P	CD	CS	Ener.	Fin.	HC	Ind.	IT	Mat.	RE	TS	Util.
S&P	1.00											
CD	0.93	1.00										
CS	0.82	0.74	1.00									
Ener.	0.79	0.66	0.60	1.00								
Fin.	0.87	0.79	0.65	0.67	1.00							
HC	0.86	0.77	0.79	0.63	0.68	1.00						
Ind.	0.93	0.86	0.75	0.77	0.83	0.77	1.00					
IT	0.92	0.87	0.71	0.65	0.72	0.77	0.82	1.00				
Mat.	0.89	0.80	0.70	0.80	0.76	0.72	0.88	0.78	1.00			
RE	0.77	0.74	0.64	0.54	0.81	0.60	0.73	0.66	0.68	1.00		
TS	0.79	0.74	0.70	0.58	0.64	0.67	0.69	0.72	0.65	0.59	1.00	
Util.	0.70	0.59	0.76	0.56	0.54	0.66	0.64	0.58	0.62	0.60	0.61	1.00
average	–	0.76	0.70	0.65	0.71	0.71	0.77	0.73	0.74	0.66	0.66	0.62

Panel B

	S&P	CD	CS	Ener.	Fin.	HC	Ind.	IT	Mat.	RE	TS	Util.
S&P	1.00											
CD	0.93	1.00										
CS	0.81	0.72	1.00									
Ener.	0.77	0.63	0.58	1.00								
Fin.	0.86	0.80	0.62	0.66	1.00							
HC	0.84	0.73	0.77	0.58	0.65	1.00						
Ind.	0.93	0.85	0.72	0.75	0.84	0.72	1.00					
IT	0.91	0.86	0.69	0.62	0.68	0.72	0.81	1.00				
Mat.	0.88	0.80	0.65	0.77	0.76	0.67	0.88	0.77	1.00			
RE	0.75	0.74	0.61	0.48	0.73	0.57	0.73	0.63	0.68	1.00		
TS	0.76	0.71	0.69	0.56	0.62	0.64	0.65	0.66	0.60	0.53	1.00	
Util.	0.68	0.57	0.71	0.53	0.51	0.63	0.60	0.55	0.57	0.59	0.58	1.00
average	–	0.74	0.68	0.62	0.69	0.67	0.76	0.70	0.71	0.63	0.62	0.58

The lowest daily (weekly) unconditional correlation of 0.54 (0.48) was for the pair of *Financials* - *Utilities* (*Real Estate* - *Energy*). Not considering the correlations with the S&P 500 Index, the highest daily as well as weekly unconditional correlation of 0.88 was found for the pair *Industrials* - *Materials*. Omitting the correlation with the S&P 500 Index and with itself, *Industrials* experienced the highest average correlation (daily: 0.77, weekly: 0.76), whereas *Utilities* was, on average, the least correlated (daily: 0.62, weekly: 0.58) with other sectors.

For oil prices, on October 10, 2016 and November 11, 2016, the dataset contained missing values. For the 10-year US Treasury Note yield, there were missing values for October 11, 2010, October 10, 2016, and November 11, 2016. All missing values were replaced by values from the previous trading day, implying no change in the variable on these days with missing values.

On April 20, 2020, the crude oil futures closed at $-\$37.63$. For such a case, the log-return is not defined. Therefore, for the purposes of summary statistics, the simple rate of return was calculated instead.[7] April 20, 2020[8] was the only day when the crude oil price closed below zero. For April 21, 2020, the simple rate of return was used again instead of the log-return.[9] In the empirical analysis of daily data, observations of crude oil on April 20 and April 21, 2020 were omitted. This seems to be a better way than using simple returns for these days (unproportionally large numbers) that could markedly shift the coefficients estimates.

Data on bond yield are in percentages - implied annual yield on the 10-year US Treasury Note. It might be logical to express changes in these yields as simple dif-

[7] The closing price on the previous trading day was \$18.27. Hence, the simple rate of return on April 20, 2020 was equal to -305.97%.

[8] April 20, 2020 was Monday, so the negative price on this day did not influence weekly log-returns that were calculated Friday-Friday (if Friday was the last trading day of the week).

[9] On April 21, 2020, the closing price was \$10.01. Although by definition the simple rate of return would be -126.6%, the return on this day was set equal to $+126.6\%$ to reflect the fact that the price of crude oil increased on that day.

ferences between yields on consecutive days. However, this measure would become inconsistent as the values of yields vary from 0.499% to 5.248% over the examined time period. Therefore, to better reflect the relative changes, log-returns were applied to bond yield too.

Table A2 presents the summary statistics of daily and weekly log-returns of crude oil, VIX, bond yield as well as the S&P 500 Index. Considering the adjusted dataset on crude oil daily changes,[10] the maximum daily (weekly) log-return of crude oil was 32.0% (27.6%), whereas the minimum value was −28.2% (−34.7%). With the daily (weekly) coefficient of kurtosis being equal to 23.5 (9.5), the distributions can be characterized as leptokurtic. The coefficient of skewness was 0.16 for daily log-returns and −0.8 for weekly log-returns. Volatility of daily (weekly) log-returns turned out of be 2.7% (5.5%).

Regarding the log-returns of bond yield, the minimum and maximum daily (weekly) values were −34.7% (−46.8%) and 40.5% (33.3%), respectively. The standard deviations of 2.9% (daily) and 5.9% (weekly) make bond yield slightly more volatile than the crude oil in case the two extreme daily changes from April 2020 are replaced by median values. Next, daily (weekly) log-returns of bond yield had the coefficient of skewness of 0.2 (−0.2) and the coefficient of kurtosis of 31.3 (11.7).

VIX experienced the maximum daily (weekly) log-return of 76.8% (85.4%) and the minimum daily (weekly) log-return of −35.1% (−55.6%). With the volatility of 7.8% (daily) and 15.6% (weekly), VIX was the most volatile independent variable included in the analysis. Skewness of 1.1 (0.7) and kurtosis of 9.0 (5.9) were observed for daily (weekly) log-returns of VIX.

Table 2 shows daily as well as weekly unconditional correlations among the S&P 500 Index, bond yield, crude oil,[10] and VIX.

[10] Extreme values from April 20 and April 21, 2020 are replaced by median values (0.1%).

Table 2: Unconditional correlations - independent variables

This table presents the unconditional correlations between the S&P 500 Index (S&P), 10-year US Treasury Note yield (BY), crude oil (CO), and VIX over the time period January 03, 2007 - February 25, 2022. Panel A presents the unconditional correlations of daily log-returns after replacing the extreme values of log-returns on crude oil from April 20 and April 21, 2020 by median values (0.1%). Panel B shows the unconditional correlations of weekly log-returns.

Panel A

	S&P	BY	CO	VIX
S&P	1.00			
BY	0.38	1.00		
CO	0.32	0.24	1.00	
VIX	-0.73	-0.29	-0.24	1.00

Panel B

	S&P	BY	CO	VIX
S&P	1.00			
BY	0.31	1.00		
CO	0.37	0.23	1.00	
VIX	-0.72	-0.29	-0.29	1.00

There was a strong negative correlation between S&P and VIX. Next, S&P was positively correlated with bond yield as well as with crude oil. The correlation between crude oil and bond yield was also positive. Last, VIX was negatively correlated with bond yield as well as with crude oil.

The empirical analysis is performed separately for two time periods, 2007 - 2019 and 2007 - 2022. For each variable, the daily dataset contains 3271 log-returns for the time period of 2007 - 2019 and 3814 log-returns for 2007 - 2022. Regarding the weekly data, the time period of 2007 - 2019 is represented by 677 observations, while 790 observations form the time frame between 2007 and 2022.

4 Methodology

This chapter describes the logic behind the models that are applied in the analysis. Section 4.1 is devoted to the ARMA and GARCH processes. Section 4.2 shows how the Dynamic Conditional Correlation (DCC) model works. Next, the estimation of the DCC model is presented in Section 4.3. Last, Section 4.4 describes the steps that are followed in the empirical analysis of this study.

4.1 ARMA & GARCH processes

Log-returns of asset i at time t, r_{it}, follow an autoregressive process of order p, AR(p),

$$r_{it} = a_{i0} + \sum_{j=1}^{p} a_{ij} r_{i(t-j)} + \eta_{it}, \tag{1}$$

where $a_{i0}, \dots, a_{ip}$ are parameters to be estimated, and $\eta_{it} \sim \mathrm{IID}(0, \sigma_i^2)$ is the error term.

Similarly, log-returns of asset i follow a moving average process of order q, MA(q),

$$r_{it} = b_{i0} + \sum_{j=1}^{q} b_{ij} \varepsilon_{i(t-j)} + \varepsilon_{it}, \tag{2}$$

where $b_{i0}, \dots, b_{iq}$ are parameters to be estimated, and $\varepsilon_{it} \sim \mathrm{IID}(0, \sigma_i^2)$ is the error term.

Combining (1) and (2), log-returns of asset i follow the ARMA(p,q) process

$$r_{it} = a_{i0} + \sum_{j=1}^{p} a_{ij} r_{i(t-j)} + \sum_{j=1}^{q} b_{ij} u_{i(t-j)} + u_{it}, \tag{3}$$

where $a_{i0}, \dots, a_{ip}$, $b_{i1}, \dots, b_{iq}$ are parameters to be estimated, and $u_{it} \sim \mathrm{IID}(0, \sigma_i^2)$ is the error term.

According to the autoregressive conditional heteroskedasticity process of order k, ARCH(k), the expected value of residuals u_{it} from (3) can be modelled as

$$\mathbb{E}(u_{it})^2 = c_{i0} + \sum_{j=1}^{k} c_{ij} u_{i(t-j)}^2 \tag{4}$$

Adding m lags of $\mathbb{E}(u_{it})^2$ to the right hand side of (4) leads to the standard GARCH(k,m) model (Bollerslev, 1986)

$$\mathbb{E}(u_{it})^2 = c_{i0} + \sum_{j=1}^{k} c_{ij} u_{i(t-j)}^2 + \sum_{j=1}^{m} d_{ij} \mathbb{E}(u_{i(t-j)})^2, \tag{5}$$

where $c_{i0}, \ldots, c_{ik}$, $d_{i1}, \ldots, d_{im}$ are parameters to be estimated.

Denoting $h_{it} \coloneqq \mathbb{E}(u_{it})^2$, (5) can be rewritten as

$$h_{it} = c_{i0} + \sum_{j=1}^{k} c_{ij} u_{i(t-j)}^2 + \sum_{j=1}^{m} d_{ij} h_{i(t-j)} \tag{6}$$

4.2 Dynamic Conditional Correlation model (DCC)

In this section, the Dynamic Conditional Correlation model (DCC), introduced by Engle (2002), is presented.

Considering n assets, (3) can be expressed as

$$\boldsymbol{r}_t = \boldsymbol{x}_t + \boldsymbol{u}_t, \tag{7}$$

where
$\boldsymbol{r}_t$ is an $(n \times 1)$ vector of log-returns at time t,
$\boldsymbol{x}_t$ is an $(n \times 1)$ vector of conditional expectations of $\boldsymbol{r}_t$ at time t,
$\boldsymbol{u}_t$ is an $(n \times 1)$ vector of conditional errors, whereas $\mathbb{E}(\boldsymbol{u}_t)$ is equal to an $(n \times 1)$ vector of zeros, and $\mathrm{Cov}(\boldsymbol{u}_t) = \boldsymbol{H}_t$.

Next,

$$\boldsymbol{u}_t = \boldsymbol{H}_t^{\frac{1}{2}} \boldsymbol{z}_t, \tag{8}$$

where $\boldsymbol{z}_t$, with $\mathbb{E}(\boldsymbol{z}_t) = 0$ and $\mathbb{E}(\boldsymbol{z}_t \boldsymbol{z}_t') = \boldsymbol{I}$ (identity matrix), is an $(n \times 1)$ vector of IID errors.

The $(n \times n)$ covariance matrix, $\boldsymbol{H}_t$, can be expressed as

$$\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t, \tag{9}$$

where $\boldsymbol{D}_t$ is an $(n \times n)$ diagonal matrix of conditional standard deviations from univariate GARCH models represented by (6),

$$\boldsymbol{D}_t = \begin{bmatrix} \sqrt{h_{1t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{h_{nt}} \end{bmatrix} \tag{10}$$

and $\boldsymbol{R}_t$ is a symmetric $(n \times n)$ matrix with conditional correlations of standardized disturbances $\boldsymbol{\epsilon}_t = \boldsymbol{D}_t^{-1} \boldsymbol{u}_t$,

$$\boldsymbol{R}_t = \begin{bmatrix} 1 & \rho_{12t} & \rho_{13t} & \cdots & \rho_{1nt} \\ \rho_{21t} & 1 & \rho_{23t} & \cdots & \rho_{2nt} \\ \rho_{31t} & \rho_{32t} & 1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \rho_{(n-1)nt} \\ \rho_{n1t} & \rho_{n2t} & \cdots & \rho_{n(n-1)t} & 1 \end{bmatrix} \tag{11}$$

By definition of correlation, all elements in $\boldsymbol{R}_t$ lie in the interval $[-1, 1]$. Matrix $\boldsymbol{R}_t$ is determined as

$$\boldsymbol{R}_t = \boldsymbol{Q}_t^{*-1} \boldsymbol{Q}_t \boldsymbol{Q}_t^{*-1} \tag{12}$$

For the DCC(p,q) model,

$$\boldsymbol{Q}_t = \left(1 - \sum_{i=1}^{p} \alpha_i - \sum_{j=1}^{q} \beta_j\right) \overline{\boldsymbol{Q}} + \sum_{i=1}^{p} \alpha_i \boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t' + \sum_{j=1}^{q} \beta_j \boldsymbol{Q}_{t-1}, \tag{13}$$

where $\overline{\boldsymbol{Q}} = \mathrm{Cov}(\boldsymbol{\epsilon}_t \boldsymbol{\epsilon}_t')$ and

$$\boldsymbol{Q}_t^* = \begin{bmatrix} \sqrt{q_{11t}} & 0 & \cdots & 0 \\ 0 & \sqrt{q_{22t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{q_{nnt}} \end{bmatrix} \tag{14}$$

with q_{iit}, $i \in \{1, \ldots, n\}$, being the elements of $\boldsymbol{Q}_t$.

Since $\boldsymbol{H}_t$ is a covariance matrix and none of its rows is a linear combination of any other rows, this matrix is positive-definite. Next, $\boldsymbol{D}_t$ is also positive-definite as all its diagonal elements are positive. Hence, for $\boldsymbol{H}_t$ in (9) to be positive-definite, $\boldsymbol{R}_t$ also needs to be positive-definite. To ensure this, $\boldsymbol{Q}_t$ in (12) has to be positive-definite. Therefore, the following conditions regarding parameters from (13) must hold

$$\begin{aligned}
&\alpha_i \geq 0, \quad i = 1, \ldots, p \\
&\beta_j \geq 0, \quad j = 1, \ldots, q \\
&\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1
\end{aligned}$$

4.3 DCC Estimation

A two-step maximum likelihood method is applied for the estimation of the parameters of the DCC-GARCH model (Engle, 2002, Orskaug, 2009). Assuming the standard normal distribution of $\boldsymbol{z}_t$, the likelihood function for $\boldsymbol{u}_t = \boldsymbol{H}_t^{\frac{1}{2}} \boldsymbol{z}_t$ is of the following form

$$L(\boldsymbol{\theta}) = \prod_{t=1}^{T} \frac{1}{(2\pi)^{\frac{n}{2}} \left| \boldsymbol{H}_t^{\frac{1}{2}} \right|} \exp\left\{ -\frac{1}{2} \boldsymbol{u}_t' \boldsymbol{H}_t^{-1} \boldsymbol{u}_t \right\}, \tag{15}$$

where $\boldsymbol{\theta}$, representing the parameters of the model, can be further defined as $\boldsymbol{\theta} = (\boldsymbol{\gamma}, \boldsymbol{\omega}) = (\boldsymbol{\gamma_1}, \ldots, \boldsymbol{\gamma_n}, \boldsymbol{\omega})$, where $\boldsymbol{\gamma_i} = (c_{i0}, \ldots, c_{ik}, d_{i1}, \ldots, d_{im})$ is a vector of parameters from (6), $i = 1, \ldots, n$, and $\boldsymbol{\omega} = (\alpha_1, \ldots, \alpha_p, \beta_1, \ldots, \beta_q)$ are parameters from (13).

Taking the logarithm of (15) gives

$$\begin{aligned}
\log(L(\boldsymbol{\theta})) &= \log\left(\prod_{t=1}^{T} \frac{1}{(2\pi)^{\frac{n}{2}} \left|\boldsymbol{H}_t^{\frac{1}{2}}\right|} \exp\left\{-\frac{1}{2}\boldsymbol{u}_t'\boldsymbol{H}_t^{-1}\boldsymbol{u}_t\right\}\right) = \\
&= \sum_{t=1}^{T} \log\left(\frac{1}{(2\pi)^{\frac{n}{2}} \left|\boldsymbol{H}_t^{\frac{1}{2}}\right|} \exp\left\{-\frac{1}{2}\boldsymbol{u}_t'\boldsymbol{H}_t^{-1}\boldsymbol{u}_t\right\}\right) = \\
&= \sum_{t=1}^{T} \left(-\frac{1}{2} n\log(2\pi) - \frac{1}{2}\log|\boldsymbol{H}_t| - \frac{1}{2}\boldsymbol{u}_t'\boldsymbol{H}_t^{-1}\boldsymbol{u}_t\right) = \\
&= -\frac{1}{2}\sum_{t=1}^{T} \left(n\log(2\pi) + \log|\boldsymbol{H}_t| + \boldsymbol{u}_t'\boldsymbol{H}_t^{-1}\boldsymbol{u}_t\right) \qquad (16)
\end{aligned}$$

Substituting $\boldsymbol{H}_t = \boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t$ into (16) yields

$$\begin{aligned}
\log(L(\boldsymbol{\theta})) &= -\frac{1}{2}\sum_{t=1}^{T} \left(n\log(2\pi) + \log|\boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t| + \boldsymbol{u}_t'\boldsymbol{D}_t^{-1}\boldsymbol{R}_t^{-1}\boldsymbol{D}_t^{-1}\boldsymbol{u}_t\right) = \\
&= -\frac{1}{2}\sum_{t=1}^{T} \left(n\log(2\pi) + 2\log|\boldsymbol{D}_t| + \log|\boldsymbol{R}_t| + \boldsymbol{u}_t'\boldsymbol{D}_t^{-1}\boldsymbol{R}_t^{-1}\boldsymbol{D}_t^{-1}\boldsymbol{u}_t\right) \quad (17)
\end{aligned}$$

In the first step, quasi-likelihood function, $\log(L_1(\boldsymbol{\gamma}))$, is obtained by replacing $\boldsymbol{R}_t$ with an identity matrix $\boldsymbol{I}$

$$\begin{aligned}
\log(L_1(\boldsymbol{\gamma})) &= -\frac{1}{2}\sum_{t=1}^{T} \left(n\log(2\pi) + 2\log|\boldsymbol{D}_t| + \log|\boldsymbol{I}| + \boldsymbol{u}_t'\boldsymbol{D}_t^{-1}\boldsymbol{I}\boldsymbol{D}_t^{-1}\boldsymbol{u}_t\right) = \\
&= -\frac{1}{2}\sum_{t=1}^{T} \left(n\log(2\pi) + 2\log|\boldsymbol{D}_t| + \boldsymbol{u}_t'\boldsymbol{D}_t^{-1}\boldsymbol{I}\boldsymbol{D}_t^{-1}\boldsymbol{u}_t\right) = \\
&= -\frac{1}{2}\sum_{t=1}^{T} \left(n\log(2\pi) + \sum_{i=1}^{n}\left[\log(h_{it}) + \frac{u_{it}^2}{h_{it}}\right]\right) = \\
&= -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{n} \left(\log(2\pi) + \log(h_{it}) + \frac{u_{it}^2}{h_{it}}\right) \qquad (18)
\end{aligned}$$

Maximizing (18) yields the estimates of $\boldsymbol{\gamma} = (\boldsymbol{\gamma_1}, \ldots, \boldsymbol{\gamma_n})$. Knowing the estimates of $\boldsymbol{\gamma}$ enables the estimation of h_{it}, $\boldsymbol{\epsilon}_t = \boldsymbol{D}_t^{-1}\boldsymbol{u}_t$, and $\overline{\boldsymbol{Q}} = \mathrm{Cov}(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t')$.

The second step of the estimation starts by substituting the estimates of $\boldsymbol{\gamma}$ obtained in step one into (17). Then, parameters $\boldsymbol{\omega} = (\alpha_1, \ldots, \alpha_p, \beta_1, \ldots, \beta_q)$ are to be estimated. The corresponding quasi-likelihood function has the following form

$$\log(L_2(\boldsymbol{\omega})) = -\frac{1}{2}\sum_{t=1}^{T}\left(n\log(2\pi) + 2\log|\boldsymbol{D}_t| + \log|\boldsymbol{R}_t| + \boldsymbol{u}_t'\boldsymbol{D}_t^{-1}\boldsymbol{R}_t^{-1}\boldsymbol{D}_t^{-1}\boldsymbol{u}_t\right) =$$
$$= -\frac{1}{2}\sum_{t=1}^{T}\left(n\log(2\pi) + 2\log|\boldsymbol{D}_t| + \log|\boldsymbol{R}_t| + \boldsymbol{\epsilon}_t'\boldsymbol{R}_t^{-1}\boldsymbol{\epsilon}_t\right) \tag{19}$$

It can be noted that $\boldsymbol{D}_t$ now contains only constant terms. Therefore, for the purposes of maximization, $\boldsymbol{D}_t$ as well as $n\log(2\pi)$ (constant) can be omitted, and (19) thus simplifies into

$$\log(L_2^*(\boldsymbol{\omega})) = -\frac{1}{2}\sum_{t=1}^{T}\left(\log|\boldsymbol{R}_t| + \boldsymbol{\epsilon}_t'\boldsymbol{R}_t^{-1}\boldsymbol{\epsilon}_t\right) \tag{20}$$

Maximizing (20) results in estimates of parameters $\boldsymbol{\omega}$.

4.4 Empirical analysis

4.4.1 Estimation of ARMA-GARCH-DCC models

To uncover potential differences between daily and weekly investment horizons, the empirical analysis in this thesis focused on daily as well as weekly log-returns. Two time periods, 2007 - 2019 and 2007 - 2022, were considered separately to show how the COVID-19 pandemic and the corresponding market turbulence (starting in February 2020) had affected the regression results. For each sector index, daily and weekly log-returns were calculated.

First, the Augmented Dickey-Fuller test and the Kwiatkowski-Phillips-Schmidt-Shin test were applied to determine whether the daily (weekly) log-returns were stationary or not. In all cases, these tests showed that the underlying data were stationary.[1]

[1]The Kwiatkowski-Phillips-Schmidt-Shin tests failed to reject the null hypothesis of stationarity.

Next, the optimal order of an ARMA(p,q) model was selected. Considering maximum order equal to 5, all possible ARMA(p,q) models (for p, $q \in \{0, \ldots, 5\}$) were estimated. Akaike information criterion (AIC) as well as Bayes information criterion (BIC) became two main criteria for the determination of the (p,q) order as lower values of AIC (BIC) point to a better fit. Second, the goal was not to overfit the model and thus keep the number of parameters as low as possible.[2] Last, the Ljung-Box test[3] was applied to residuals of the ARMA model. In this test, 20 lags were considered for daily data and 4 lags for weekly data. Thus, for both the daily and weekly data, it tested the no-autocorrelation null hypothesis at lags corresponding to 4 trading weeks. Further, $p + q$ degrees of freedom were deducted in the Ljung-Box tests in order to better approximate the null hypothesis distribution (Box & Pierce, 1970, Ljung & Box, 1978).

The optimal model was not determined strictly by selecting the one with the lowest value of AIC and/or BIC. Instead, all criteria mentioned in the paragraph above were taken into account simultaneously. Therefore, the optimal model was chosen such that it had the lowest possible value of AIC or BIC, parameters of the model were significant, and the Ljung-Box test suggested that there was no autocorrelation among the residuals.

For *Financials*, the optimal order would be (2,4) for daily log-returns between 2007 and 2019, (5,4) for daily log-returns between 2007 and 2022, and (3,2) for weekly log-returns between 2007 and 2019. Similarly, for *Health Care*, the order of (3,2) resulted as optimal for weekly log-returns between 2007 and 2019. However, the estimated coefficients in these cases were in absolute values uncommonly high (even higher than 1), and AR(i) coefficients were almost eliminated by MA(i) coefficients. Hence, a different ARMA order was selected for *Financials* and *Helath Care*, although these models were not *the best* based on the selecting algorithm.

[2]If some parameters were insignificant, a model with a different order was considered.

[3]Under the null hypothesis, the data are independently distributed.

For all sectors, ARMA models of daily log-returns experienced autocorrelation in residuals. For weekly log-returns, autocorrelation in residuals of ARMA models was detected for *Energy* (2007 - 2019 as well as 2007 - 2022[4]) and *Utilities* (2007 - 2022). It might be due to the very long time period as a different ARMA order would fit better for specific intervals of the whole period of 2007 - 2022. Nevertheless, given the data, the best possible models were selected.

After finding the optimal ARMA models, the Engle (1982) ARCH test was conducted to test the null hypothesis of homoscedastic residuals of the ARMA models. In all cases, the null hypothesis was rejected, pointing to a (G)ARCH structure in the residuals. Hence, a similar approach as for finding the optimal ARMA model was followed to find the optimal GARCH model. The model was selected such that it had the lowest possible value of AIC and/or BIC, the corresponding parameters were significant, and there was no autocorrelation among its residuals and no autocorrelation among its squared residuals.

The maximum order was set at 3, and the following types of GARCH models were included into the algorithm for searching *the best* model: standard GARCH (Bollerslev, 1986), exponential GARCH (Nelson, 1991), GJR GARCH (Glosten et al., 1993). Two types of errors distribution were considered - normal and Student's t distribution. Further, the Ljung-Box test was applied to standardized residuals as well as to squared standardized residuals of the GARCH model to see if there was any unexplained structure remaining. The number of lags at which the no-autocorrelation null hypothesis was tested was set to 20 for daily log-returns and to 4 for weekly log-returns.

The overview of optimal ARMA-GARCH models is shown in Table A3. Mostly, (1,1) was the optimal GARCH order, and the exponential GARCH (eGARCH)

[4]For weekly log-returns of *Energy* between 2007 and 2022, the Ljung Box test could not be carried out at 4 lags as the optimal model was ARMA(2,2). Applying this test at 5 lags rejected the null hypothesis of no autocorrelation.

was selected as the best type. For *Financials*, though, GJR GARCH resulted as the optimal type for both daily and weekly log-returns in both time periods. Next, for all models, the optimal errors distribution in the GARCH model was the Student's t distribution.

With the use of optimal ARMA-GARCH models, the bivariate DCC(p,q) model was estimated for each correlation pair. All combinations of $p \in \{0, 1, 2, 3\}$ and $q \in \{0, 1, 2, 3\}$ were considered (except for $p = 0$, $q = 0$), and the optimal order was selected such that the model had the lowest possible value of AIC and/or BIC, and the number of parameters was kept as low as possible. Mostly, the optimal DCC order was (1,1). The exceptions are

- *Energy* - *IT* for daily log-returns between 2007 and 2022
- *Energy* - *IT* for weekly log-returns between 2007 and 2022
- *Financials* - *IT* for daily log-returns between 2007 and 2019
- *Financials* - *IT* for daily log-returns between 2007 and 2022

In all these four cases, (1,2) resulted as the optimal DCC order.

4.4.2 Regression analysis

For each correlation pair, each length of log-returns (daily, weekly) and each time period (2007 - 2019 and 2007 - 2022), the time-varying correlation implied by the DCC model was extracted. Daily correlations for the time period of 2007 - 2022 are shown in Figure 2 and Figure A2 - Figure A5. In these figures, the range of the vertical axis is always the same (from -0.5 to 1) which allows for an easy graphical comparison of individual correlation pairs.

In the regressions, the goal was to show how independent variables influence the correlations. One possibility was to follow the approach of Andersson et al. (2008) or Karanasos & Yfanti (2021), and apply the Fisher z-transformation to the correlations, ρ_t, to deal with the fact that $\rho_t \in [-1, 1]$, while the right hand side of the regression could be outside of this interval. However, the aim of this analysis was to show how *changes* in correlations are affected by the external regressors. These changes could have been expressed for example as log-returns, simple returns, or simple differences. Since the correlations might be negative, some issues could arise when using log-returns or simple returns. Therefore, $\Delta\rho_t = \rho_t - \rho_{t-1}$, the simple difference between the correlation level in time t and the correlation level in time $t-1$, was used to express the change in the correlation. Also, the interpretation is quite straightforward as this dependent variable is in basis points.

As already stated, these $\Delta\rho_t$ were regressed on log-returns of the independent variables: S&P 500 Index (S&P), 10-year US Treasury Note yield (BY), crude oil (CO), and CBOE Volatility index (VIX). It might have helped to include lags of $\Delta\rho_t$ as another independent variable into the regressions. However, since the DCC model estimates the conditional correlation such that it depends on its previous values, the inclusion of lags of $\Delta\rho_t$ into the regression might have driven the R^2 in the OLS model to values close to 1, which would make the inference more difficult. Instead, $\Delta\rho_t$ were regressed purely on the external regressors. As a result, the R^2 was sometimes very low (adjusted R^2 even negative), but for the purposes of this analysis, it seems to be the most appropriate way. Therefore, for each time period (2007 - 2019, 2007 - 2022) and each length of log-returns (daily, weekly), the following two multivariate regressions were estimated

$$\Delta\rho_t = \beta_0 + \beta_1 \text{S\&P}_t + \beta_2 \text{BY}_t + \beta_3 \text{CO}_t + \beta_4 \text{VIX}_t + \epsilon_t \tag{21}$$

$$\Delta\rho_t = \beta_0 + \beta_1 \text{S\&P}_{t-1} + \beta_2 \text{BY}_{t-1} + \beta_3 \text{CO}_{t-1} + \beta_4 \text{VIX}_{t-1} + \epsilon_t \tag{22}$$

Next, the following simple regression models were also estimated

$$\Delta\rho_t = \beta_0 + \beta_1 \text{Variable}_t + \epsilon_t \tag{23}$$

$$\Delta\rho_t = \beta_0 + \beta_1 \text{Variable}_{t-1} + \epsilon_t, \tag{24}$$

where Variable $\in$ {S&P, BY, CO, VIX}, and t is the time index. The regressions[5] represented by (21) and (23) serve for answering the question *"What is happen-*

[5]In the results description, often referred to as "first-type regressions".

ing to the correlation if this is happening to the independent variable(s)?". Hence, these regressions enable to test the hypothesis of whether the correlations between sector indices increase or decrease in times of a decline of the aggregate S&P 500 Index. Similar hypotheses can be tested for the other three independent variables. The results of these regressions can help investors understand how shocks to independent variables are accompanied by changes in the analyzed correlations.

The second type of regressions,[6] represented by (22) and (24), serves for answering the question *"What is expected to happen to the correlation in the next period if this is happening to the independent variable(s) in this period?"*. In other words, these regressions investigate whether the external regressors have some power for predicting the changes in the correlations. The results of these regressions might be even more interesting and practical as they can indicate how the individual correlations could move conditional on what happens now.

While the univariate regressions, (23) and (24), are rather indicative in terms of the relationship between the independent variable and the regressand, it is the multivariate regressions, (21) and (22), that the most attention should be paid to. As it is controlled for other variables, more accurate partial effects of the regressors on the explained variable are likely to be uncovered. Hence, even if some regressors turn out to be statistically significant in univariate models, it would be incorrect to present it as a significant relationship if it is not confirmed by the results of the multivariate regression.

Regressions (21) - (24) were estimated using the OLS model. For the time series, the following assumptions for the OLS model apply. First, the model is linear in parameters. Second, the independent variables are not perfectly correlated.[7] Third, the expected value of the error term ϵ_t conditional on independent variables is equal to zero for all time periods t. The fourth assumption requires homoscedas-

[6] In the results description, often referred to as "forecasting regressions".

[7] Evidence can be seen in Table 2.

tic error terms. The fifth assumption states that given the independent variables, errors ϵ_t and ϵ_s are uncorrelated for all $t \neq s$ (there is no serial correlation). If these five assumptions hold, the OLS is the best linear unbiased estimator. The sixth assumption restricts the errors to be independently and identically distributed, $\epsilon_t \sim \mathrm{N}(0, \sigma^2)$. If all six assumptions are met, then t-tests, F-tests, p-values, and corresponding confidence intervals are reliable. (Wooldridge, 2013)

As it is often the case in the financial time series analysis, the errors in the regressions (21) - (24) were not normally distributed. Nevertheless, the statistical inference can still be carried out if the sample is *large enough*, and the time series process (dependent variable) is stationary and weakly dependent.[8] Under these adjusted assumptions, the OLS is an asymptotically normally distributed estimator, and t-tests, F-tests, and p-values are asymptotically valid. By *sample large enough* it is generally assumed a minimum size of 30. (Wooldridge, 2013)

Since the regressions (21) - (24) were based on a dataset with 676 - 3813 observations, the criterion of a *large sample* was met. The assumption of weak dependence was checked graphically with the use of the autocorrelation function plots. In most cases,[9] the correlation at the first lag was typically high and statistically significant. At the second lag, the correlation rapidly dropped and was not statistically different from zero. Similarly for autocorrelations at higher lags.

Next, after estimating the OLS for regressions (21) - (24), the Ljung-Box test[10] was applied to check whether the residuals suffered from serial correlation, and the Breusch-Pagan test (Breusch & Pagan, 1979) was applied to figure out whether

[8] A simplified definition of weak dependence states that for a stationary process $\{x_t\}$ with a finite variance, correlation between x_t and x_{t+h} approaches zero fast enough as $h \longrightarrow \infty$.

[9] For the following pairs, the insignificance of autocorrelation started at a lag higher than 2: *Consumer Staples - Health Care*, *Consumer Staples - Utilities*, *Energy - IT*, *Financials - IT*, *Health Care - IT*.

[10] For daily-frequency regressions, the no-autocorrelation null hypothesis was tested at 20 lags. For weekly-frequency regressions, the number of lags was set to 4.

heteroskedasticity was present. If necessary, heteroskedasticity (White, 1980) or heteroskedasticity and autocorrelation (Andrews, 1991) robust standard errors were calculated which allowed for a valid inference. Last, adjusted R^2 was calculated for each regression.

P-values presented in Table 3 and Table A5 - Table A19 are based on the two-sided test. Hence, these p-values correspond to the null hypothesis of no significance. If we were to test the null hypothesis of a regressor positively or negatively affecting the dependent variable, the one-sided test would be appropriate. Specifically for S&P, the null hypothesis of $H_0 : \beta_1 \geq 0$ could be tested against the alternative $H_1 : \beta_1 < 0$. In case of rejecting this null hypothesis, one would then conclude that the correlation increases in times of falling S&P.

Although the p-values presented in the tables correspond to the two-sided test, when looking at the sign of the estimated coefficient and the p-value for the two-sided test, it is not difficult to infer whether the variable would be statistically significant and positively/negatively impacting the regressand if the one-sided test was used.

5 Results

In this chapter, results of the regression models are discussed. Table 3 and Table A5 - Table A18 present these results for the individual correlation pairs. Next, Table A4 shows the summary statistics of daily and weekly changes in correlations for the time period 2007 - 2022. Table A4 is supposed to bring an easier perception and interpretation of the estimated coefficients from the regressions as one can see how volatile the individual correlation pairs are. Comparing this volatility with the strength of partial effects of the regressors among the 15 correlation pairs should enhance the overall understanding of the regression results.

5.1 Correlations of Consumer Staples

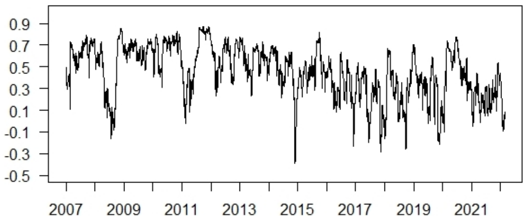
This section describes the regression results concerning the correlation pairs between *Consumer Staples* and: *Energy*, *Financials*, *Health Care*, *IT*, and *Utilities*. Corresponding graphs of the daily correlations implied by the DCC models are shown in Figure 2.

5.1.1 Energy

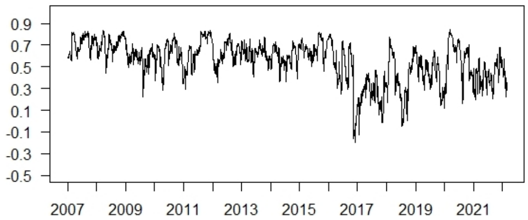
The regression results for the pair *Consumer Staples* - *Energy* are presented in Table 3. In the first-type regressions, not many variables played an important role in determining the changes in the correlation. For daily changes, VIX turned out to be statistically significant (always at 1% level) in both simple and multiple regressions. In all these cases, the relationship was negative, with the coefficient estimates ranging between -0.049 and -0.033. Further, VIX achieved the highest adjusted R^2 in simple regressions for daily frequency data. In the weekly data analysis, crude oil appeared as a significant regressor with a negative impact on the dependent variable.

Figure 2: DCC of *Consumer Staples*

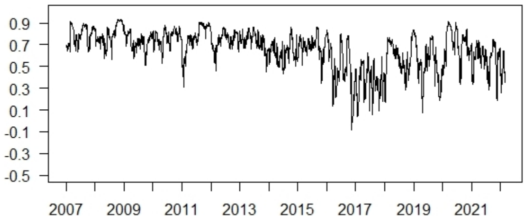
This figure presents the daily DCC values for correlation pairs between *Consumer Staples* and (a) *Energy*, (b) *Financials*, (c) *Health Care*, (d) *IT*, (e) *Utilities.*



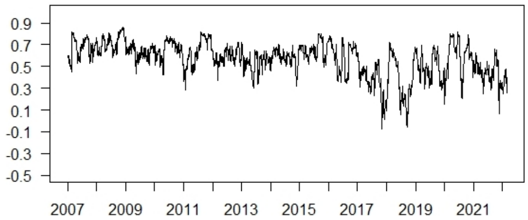
(a) *Energy*



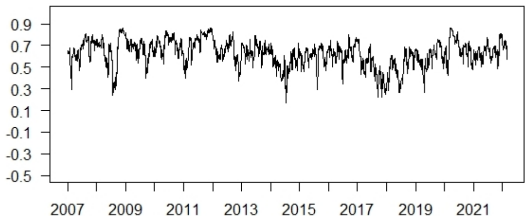
(b) *Financials*



(c) *Health Care*



(d) *IT*



(e) *Utilities*

More can be said about the results of forecasting regressions. In the simple regressions, S&P always resulted as a significant variable negatively related to the change in the correlation. Comparing the magnitude of the effect between the datasets until 2019 and until 2022, one can say that S&P influenced the dependent variable less negatively as the sample contained data until 2022. However, in multivariate regressions, the significance of S&P was not confirmed, except for daily data between 2007 and 2022, where the relationship was even positive.

Further, the significance was detected in the daily simple regressions for bond

Table 3: Regression results for the correlation pair *Consumer Staples - Energy*

This table presents the results of regression models (21) - (24) for the correlation pair *Consumer Staples - Energy*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.8885)	(0.9105)	(0.9093)	(0.9106)	(0.9287)
S&P	0.0951				-0.1002
	(0.2050)				(0.3890)
BY		0.0056			-0.0220
		(0.8934)			(0.6363)
CO			-0.0063		-0.0225
			(0.8694)		(0.5887)
VIX				**-0.0330**	**-0.0486**
				(0.0059)	(0.0064)
Adj. R^2	0.00019	-0.00030	-0.00030	0.00201	0.00168

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0002	-0.0001	-0.0001	-0.0002
	(0.9636)	(0.8682)	(0.9213)	(0.9073)	(0.8253)
S&P	**-0.5410**				0.2758
	(0.0000)				(0.0516)
BY		**-0.2116**			-0.0799
		(0.0000)			(0.1232)
CO			-0.1088		-0.0026
			(0.0790)		(0.9685)
VIX				**0.1392**	**0.1640**
				(0.0000)	(0.0000)
Adj. R^2	0.01562	0.00744	0.00213	0.04101	0.04237

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.8592)	(0.8943)	(0.8884)	(0.8981)	(0.9339)
S&P	0.1023				-0.0908
	(0.0881)				(0.3252)
BY		0.0184			0.0054
		(0.4952)			(0.8545)
CO			-0.0190		-0.0408
			(0.5019)		(0.1734)
VIX				**-0.0348**	**-0.0488**
				(0.0004)	(0.0007)
Adj. R^2	0.00050	-0.00014	-0.00014	0.00301	0.00317

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0001	-0.0001	-0.0001	-0.0002
	(0.9572)	(0.8642)	(0.9257)	(0.8607)	(0.7814)
S&P	**-0.4899**				**0.2330**
	(0.0000)				(0.0299)
BY		**-0.1395**			-0.0590
		(0.0000)			(0.0777)
CO			**-0.1001**		-0.0162
			(0.0157)		(0.6972)
VIX				**0.1286**	**0.1491**
				(0.0000)	(0.0000)
Adj. R^2	0.01722	0.00673	0.00304	0.04436	0.04589

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0001	0.0000	0.0000	-0.0001	0.0008
	(0.9793)	(0.9972)	(0.9956)	(0.9884)	(0.8785)
S&P	-0.1769				-0.4806
	(0.4916)				(0.1295)
BY		0.0464			0.1211
		(0.6603)			(0.2968)
CO			-0.2269		**-0.2397**
			(0.0747)		(0.0323)
VIX				-0.0244	-0.0867
				(0.4670)	(0.0767)
Adj. R^2	-0.00040	-0.00119	0.00578	-0.00070	0.00826

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0011	-0.0001	0.0001	0.0000	0.0003
	(0.7966)	(0.9900)	(0.9868)	(0.9953)	(0.9448)
S&P	**-0.8755**				-0.1269
	(0.0047)				(0.7579)
BY		-0.0812			0.1478
		(0.4425)			(0.2713)
CO			-0.1557		-0.0434
			(0.2434)		(0.7412)
VIX				**0.1858**	**0.1831**
				(0.0003)	(0.0122)
Adj. R^2	0.02499	-0.00061	0.00194	0.04420	0.04246

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0003	-0.0005	-0.0003	-0.0004	-0.0004
	(0.9037)	(0.8582)	(0.9138)	(0.8933)	(0.8931)
S&P	-0.0324				0.0020
	(0.7695)				(0.9900)
BY		-0.1026			-0.0997
		(0.2302)			(0.0538)
CO			**-0.1210**		**-0.1210**
			(0.0192)		(0.0307)
VIX				-0.0071	-0.0301
				(0.6996)	(0.2520)
Adj. R^2	-0.00116	0.00440	0.00569	-0.00108	0.00822

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0006	-0.0005	-0.0002	-0.0005	-0.0001
	(0.8321)	(0.8729)	(0.9315)	(0.8562)	(0.9657)
S&P	**-0.6361**				-0.2174
	(0.0027)				(0.4168)
BY		**-0.0988**			0.0094
		(0.0421)			(0.8752)
CO			-0.1414		-0.0311
			(0.0598)		(0.6097)
VIX				**0.1202**	**0.0923**
				(0.0003)	(0.0264)
Adj. R^2	0.04078	0.00398	0.00823	0.05378	0.05336

yield and crude oil. Both variables were negatively related to future changes in the correlation. The most convincing results concerned VIX. In all regressions, this variable was statistically significant and positively related to future changes in the correlation. Moreover, comparing simple and multiple regressions, the estimate of the coefficient did not change substantially, leading to the conclusion that the effect of VIX was robust as we controlled for other variables. The magnitude of the effect decreased as the dataset was extended until 2022. VIX also experienced the highest adjusted R^2 in simple regressions.

5.1.2 Financials

The results of the regressions for the correlation pair *Consumer Staples - Financials* are summarized in Table A5. Regressions of type (21) and (23) showed that in the daily-frequency analysis, VIX had been statistically significant at 1% level and negatively related to the dependent variable. The relationship was not as strong as for the previous correlation pair, which might be due to the fact that the correlation between *Consumer Staples* and *Energy* was more volatile than the correlation between *Consumer Staples* and *Financials*.[1]

In the forecasting regressions, S&P and bond yield were always significant in the simple regressions; crude oil in three out of four cases. All coefficients were negative, and a stronger relationship was detected for datasets until 2019. Moreover, for daily regressions, bond yield resulted as a significant variable in multivariate models as well. The impact on future changes in the correlation was again negative. It is worth noting that S&P showed a positive significant relationship in the multiple regressions for daily data.

The forecasting regressions revealed a positive and statistically significant impact of VIX on future changes in the correlation between *Consumer Staples* and *Financials*. For daily-frequency models, the estimated coefficients of ca. 0.1 imply

[1] See Table A4

a 0.01 (1 basis point) increase in the correlation on day t if, ceteris paribus,[2] VIX experienced a log-return of 10% on day $t-1$. Among all four variables, VIX seems to have the best forecasting power as its adjusted R^2 was always the highest. To conclude, based on the significant variables from the multivariate daily regressions, the partial effects on the future change in the correlation were positive for S&P and VIX, and negative for bond yield.

5.1.3 Health Care

Table A6 summarizes the results of regressions for the correlation between *Consumer Staples* and *Health Care*. In the first-type regressions, the significance of the variables occurred mainly in the multivariate models. In the daily-frequency multivariate model for the time period 2007 - 2022, S&P, crude oil, and VIX turned out to be statistically significant at 5% level. The relationship with the dependent variable was always negative. Regarding the weekly-frequency regressions, VIX was the only significant variable in the multivariate model. Its negative relationship with the change in the correlation was stronger for the time period 2007 - 2019 than for the dataset until 2022.

In the forecasting regressions, S&P turned out to be significant at 1% level in all univariate models, negatively affecting the regressand. In the multivariate models, S&P was significant only for daily data between 2007 and 2022. As the corresponding coefficient was positive, it can be concluded that the effect of S&P on the future change in the correlation was positive, not negative as suggested by the simple regressions. Further, bond yield as well as crude oil resulted as significant regressors negatively related to the dependent variable. This was the case in univariate regressions only.

VIX was the only explanatory variable that turned out to be significant in both

[2]A ceteris paribus situation is unlikely, though, as it never happens that the remaining three regressors stay unchanged, while VIX increases.

univariate and multivariate forecasting regressions. Its positive impact on the regressand implies that a rise in the correlation is expected in the next period if VIX increases in this period. In the simple regressions, VIX reached the highest adjusted R^2 among all four variables.

5.1.4 IT

For the correlation pair *Consumer Staples - IT*, the regression results are presented in Table A7. The first-type regressions for daily changes revealed a negative statistically significant relationship between VIX and the dependent variable. This was the case in both univariate and multivariate models, with p-values always lower than 1%. For daily data until 2022, S&P as well as crude oil, both negatively related to the regressand, turned out to be statistically significant at 5% in the multiple regression. Next, bond yield showed a significant positive relationship with the change in the correlation in both the simple and multiple model.

Moving on to the forecasting regressions, one can observe that S&P was statistically significant in all four univariate models, negatively influencing the explained variable. However, in the daily multivariate regressions, S&P was significant and positively affecting the regressand. Hence, in these cases, a more accurate conclusion is that the relationship between S&P and the future change in the correlation was positive.

Next, bond yield as well as crude oil turned out to be significant and negatively related to the change in the correlation; in the simple regressions for daily data only, though. Last, VIX resulted as a significant variable in both univariate and multivariate models in all cases. Its explanatory power seems to be the best among the four analyzed variables as VIX reached always the highest adjusted R^2 in simple regressions.

5.1.5 Utilities

The results of the regressions for the pair *Consumer Staples* - *Utilities* are presented in Table A8. Among all correlation pairs, this pair has the lowest number of variables with a statistically significant effect on the change in the correlation. In the regressions represented by (21) and (23), only bond yield was statistically significant in the daily-frequency univariate model for the time period of 2007 - 2019.

The forecasting regressions revealed significant variables only for daily changes. In univariate models for both time periods, S&P turned out to be statistically significant at 0.1% level and negatively related to the future change in the correlation. Next, crude oil was significant (in the simple regression model) for the dataset until 2022, but not until 2019. The same was detected for the correlation pairs of *Consumer Staples* with *Energy* and *Health Care*. Hence, this may offer some evidence that crude oil has become a more significant variable for determining changes in the correlation since the start of the year 2020.

Last, VIX resulted as a significant variable in both univariate and multivariate regressions of daily changes. Its positive impact on the dependent variable slightly strengthened as the whole time period was considered. The adjusted R^2 corresponding to VIX from simple forecasting regressions was the highest among all four variables (except for weekly changes for 2007 - 2019). However, it was still lower than any VIX-related adjusted R^2 from the previous four correlation pairs,[3] suggesting that for *Consumer Staples*, the correlation with *Utilities* might be the most difficult one to be explained.

[3]In all forecasting regressions for the previous four correlation pairs, VIX was the variable with the highest adjusted R^2 in the univariate models.

5.2 Correlations of Energy

This section describes the regression results concerning the correlation pairs between *Energy* and: *Financials*, *Health Care*, *IT*, and *Utilities*. Corresponding graphs of the daily correlations implied by the DCC models are shown in Figure A2.

5.2.1 Financials

Table A9 shows the results of regressions for the correlation between *Energy* and *Financials*. In the first-type regressions, significance was detected only for the datasets until 2019. For daily changes, VIX was statistically significant at 5% in both single and multiple models. With the estimated coefficients of -0.016 (single regression) and -0.024 (multiple), it showed a mild negative, but significant relationship with the change in the correlation. In the weekly-frequency analysis, VIX turned out to be significant in the multivariate regression only, while crude oil was significant in the simple regression only. Both variables appeared as negatively correlated with the regressand.

In the forecasting regressions, all four variables were statistically significant at 1% in univariate models for daily changes. In these simple regressions, S&P, bond yield, and crude oil were negatively related to future changes in the correlation, whereas VIX had a positive impact on the regressand. However, since only VIX proved to be significant in daily multivariate regressions as well, the only conclusion that can be drawn is that an increase in VIX on day t is expected to cause an increase in the correlation between *Energy* and *Financials* on day $t + 1$.

5.2.2 Health Care

Regression results for the pair *Energy* - *Health Care* are summarized in Table A10. In the regressions of type (21) and (23), VIX resulted as a significant variable (always at 1%) in both univariate and multivariate regressions for daily changes and both time periods. Another regressor that significantly negatively impacted the dependent variable was crude oil. For daily changes, it was only in the multivariate regression for the time period of 2007 - 2022. However, in the weekly-frequency analysis, crude oil turned out to be significant in all cases. Since the coefficients in the simple regressions were quite similar to the ones in the multiple regression, one can say that the estimates are relatively robust to including further variables into the regression. Going in line with the detection of significant variables, VIX (crude oil) reached the highest adjusted R^2 in the simple regressions for daily (weekly) changes.

Forecasting regressions revealed the significance of S&P in all four univariate regressions, but never in the multivariate model. Next, bond yield as well as crude oil were significant in simple regressions for daily returns for both time periods. As it was the case in some of the previous correlation pairs, VIX resulted as a significant variable positively influencing the regressand in all eight regressions. Moreover, adjusted R^2 in the simple regression models was always the highest for VIX. Last, one may notice that the magnitude of the effect of significant variables diminished as the analyzed time period was extended until 2022.

5.2.3 IT

Table A11 summarizes the results of the regression models for the correlation between *Energy* and *IT*. In the first-type regressions, VIX was significant in both the univariate and multivariate model for daily changes between 2007 and 2019. In the weekly-frequency analysis, crude oil turned out to be significant in both simple and multiple regressions, supporting the expectation that crude oil is a factor influencing correlations of *Energy*. Moreover, the adjusted R^2 in the univariate regressions was the highest for crude oil. The negative relationship between crude oil and the dependent variable indicates that the correlation between *Energy* and *IT* tends to decrease during weeks of rising crude oil price.

In the forecasting regressions, all four variables turned out to be statistically significant at 1% in the univariate models for daily data. The effect of VIX on the change in the correlation was positive, whereas for the other three regressors, it was negative. In the multivariate models, significance was detected for VIX as well as S&P. Both variables influenced the regressand positively. Moving on to the weekly forecasting models, one may notice that S&P and VIX were the only two significant variables in the simple regression models. The estimated coefficients were negative for S&P and positive for VIX.

Further, VIX appeared to be the variable with the best predictive power as the corresponding adjusted R^2 was the highest among the four simple regressions. Next, comparing the magnitudes of effects of significant regressors on the dependent variable between the two time periods, we can conclude that there was a stronger effect if the whole time period (2007 - 2022) was considered. This observation contradicts the results of the previous correlation pairs, where in most cases, the magnitude of the effects was higher for the time period of 2007 - 2019.

5.2.4 Utilities

The regression results for the pair *Energy* - *Utilities* are summarized in Table A12. The regressions of type (21) and (23) revealed two main significant variables. First, it is crude oil that turned out to be significant in the multivariate models for daily changes. In the weekly-frequency analysis for the time period of 2007 - 2022, the significance of crude oil was detected in both simple and multiple regressions. The estimated coefficients were approximately -0.06, suggesting that the correlation between *Energy* and *Utilities* tends to decrease in times of a rising price of crude oil. The next significant variable appeared to be VIX - in the daily regressions only, though. Its relationship with the dependent variable was also negative.

Forecasting regressions traditionally showed more significant variables. First, it was S&P in the simple regression models in all four cases and in the multivariate regression for weekly data between 2007 and 2022. The estimated coefficient was always negative, suggesting that for this correlation pair, an increase in S&P in week t is likely to cause a drop in the correlation in week $t+1$. Next, bond yield turned out to be significant in simple regressions of daily data at 0.1% level. In univariate models, crude oil appeared as a significant regressor in three out of four cases. The estimated coefficient was always negative.

In the daily-frequency analysis, VIX resulted as a significant variable in both univariate and multivariate models. Moreover, as VIX recorded the highest adjusted R^2 among the simple regressions for daily data, it can be considered a variable with the best predictive power. Regarding the weekly regressions, it was S&P that had the highest adjusted R^2.

5.3 Correlations of Financials

This section presents the regression results concerning the correlation pairs between *Financials* and: *Health Care*, *IT*, and *Utilities*. Corresponding graphs of the daily correlations implied by the DCC models are shown in Figure A3.

5.3.1 Health Care

For the correlation pair *Financials - Health Care*, the regression results can be seen in Table A13. In the first-type regressions, VIX turned out to be statistically significant, always at 5% level, in all multiple regressions. For weekly changes, it resulted as a significant variable also in the univariate models. In all these cases, the estimated coefficient corresponding to VIX was negative. Moreover, VIX recorded the highest adjusted R^2 among the simple regressions. Besides that, crude oil, negatively related to the dependent variable, appeared as a significant regressor in the multivariate regression of weekly data for 2007 - 2022.

In the forecasting regressions, S&P resulted as a statistically significant variable at 0.1% level in all univariate models, and at 5% level in the multiple regressions of daily data. While its influence on the dependent variable was negative in the simple regressions, it appeared to be positive in the multivariate models. Next, bond yield and crude oil turned out to be significant in univariate regressions, except for weekly data between 2007 and 2019.

Further, VIX was statistically significant in both univariate and multivariate regressions in all cases. Its positive relationship with the dependent variable suggests that an increase in VIX in period t is expected to cause an increase in the correlation in period $t+1$. Similarly as in the first-type regressions for this correlation pair, VIX showed the best predictive power as measured by the adjusted R^2.

5.3.2 IT

Table A14 summarizes the results of regressions for the correlation between *Financials* and *IT*. The only significant variable in the regressions of type (21) or (23) was bond yield for daily data between 2007 and 2022. The significance at 5% level was detected in both the univariate and multivariate model. The positive relationship between bond yield and the change in the correlation suggests that an increase in the yield on the 10-year US Treasury Note is accompanied by an increase in the correlation between *Financials* and *IT*.

In the forecasting regressions, S&P turned out to be statistically significant at 0.1% in all four univariate models with a negative estimated coefficient. Next, bond yield also resulted as a significant regressor in all four simple regressions. For crude oil, however, the significance was detected only for the datasets until 2022.

Further, VIX appeared to be statistically significant at 0.1% level for daily-frequency data in both simple and multiple regressions. The estimated coefficients were positive and the highest among all correlation pairs. For weekly data, VIX was statistically significant in univariate models only.

5.3.3 Utilities

The results of the regressions for the pair *Financials* - *Utilities* are presented in Table A15. In the first-type regressions, S&P resulted as a significant variable with a positive impact on the regressand for daily-frequency data in univariate models. Next, VIX turned out to be significant in both simple and multiple regressions for both analyzed time periods of daily data. Its influence on the dependent variable was negative. Further, the statistical significance and a negative estimated coefficient were detected for crude oil in the univariate and VIX in the multivariate model of weekly data between 2007 and 2022.

The forecasting regressions revealed that all variables were significant in the univariate models for both time periods of daily data and the time frame between 2007 and 2019 of weekly data. S&P, bond yield as well as crude oil were negatively related to the change in the correlation, whereas VIX had a positive relationship with the dependent variable. Next, bond yield and VIX appeared to be significant in the multivariate models for daily data too, with the estimated coefficients of the same sign as in the simple regressions. From this, one could say that an increase in VIX (bond yield) on day t will lead to a rise (decrease) in the correlation on day $t + 1$.

5.4 Correlations of Health Care

This section discusses the regression results concerning the correlation pairs between *Health Care* and: *IT* and *Utilities*. Corresponding graphs of the daily correlations implied by the DCC models are shown in Figure A4.

5.4.1 IT

The regression results for the correlation between *Health Care* and *IT* are summarized in Table A16. The regressions represented by (21) and (23) revealed significant variables especially for daily-frequency datasets. For both time periods, the significance was detected for S&P in the multivariate and for VIX in the univariate as well as multivariate model. Both regressors influenced the dependent variable negatively, and their effect strengthened as the analyzed time period was extended until 2022. Bond yield was the next significant variable for the time period 2007 - 2022. Its positive relationship with the regressand suggests that the correlation between *Health Care* and *IT* tends to increase on days when the yield on the 10-year US Treasury Note rises.

In the forecasting regressions, all four variables turned out to be statistically significant in the univariate models of daily data. S&P, bond yield, and crude oil were negatively related to the future change in the correlation, while VIX showed a positive effect. However, in the multivariate regressions, S&P appeared to be significant and positively influencing the regressand. As the partial effect of S&P on the regressand is more accurate in the multivariate models, one may claim that the correlation between *Health Care* and *IT* tends to increase on day t if S&P increased on day $t-1$.

In the weekly analysis, simple regressions pointed to the significance of S&P, crude oil, and VIX. However, only VIX resulted as significant in the multiple regressions, leading to the conclusion that this variable can be considered important for determining the future weekly changes in the correlation of *Health Care* - *IT*.

5.4.2 Utilities

For the correlation pair *Health Care* - *Utilities*, the regression results are presented in Table A17. The first-type regressions did not reveal many significant variables.

The only one was bond yield in the univariate model for daily data between 2007 and 2019.

More significant variables occurred in the forecasting regressions. For daily data between 2007 and 2019, it was S&P and bond yield in the univariate models. Both regressors showed a negative relationship with the dependent variable. On the other hand, VIX, significant in both the simple and multiple regression, influenced the future change in the correlation positively. If daily data for the whole time period were considered, all four regressors turned out to be significant in the univariate models, while VIX was significant in the multivariate regression too.

In this daily-frequency forecasting analysis, measured at the adjusted R^2 of the univariate models, VIX tends to have the best predictive power. For weekly data, S&P recorded the highest adjusted R^2 in the simple regressions.

5.5 Correlations of IT

This section describes the regression results, summarized in Table A18, for the correlation pair *IT - Utilities.* The time-varying conditional correlation implied by the DCC model is depicted in Figure A5.

5.5.1 Utilities

In the regressions of type (21) and (23), VIX appeared as a significant variable in both simple and multiple models of daily data. It influenced the regressand negatively, and also recorded the highest adjusted R^2 in univariate models. Next, for daily changes between 2007 and 2022, bond yield was significant in simple as well as multivariate regressions, and showed a positive influence on the dependent variable. This observation can be seen for all correlation pairs of *IT* with the exception of *IT - Energy.* In the multivariate regression for daily data and the time period extended until 2022, also S&P and crude oil turned out to be statistically significant. Their impact on the change in the correlation was negative.

Forecasting regressions revealed the statistical significance of VIX for daily data in both univariate and multivariate models. Similarly as for all previous correlation pairs, the effect of VIX on the dependent variable was positive. Further, in the daily simple regressions, the significant variables appeared to be S&P and bond yield, both influencing the future correlation negatively. Moving on to the weekly forecasting models, the significance was detected for S&P only, in both univariate and multivariate models, though. An increase in S&P in week t translates to an expected fall in the correlation in week $t + 1$. The effect of S&P strengthened as the time period was extended until 2022.

5.6 Discussion and comparison of results

Looking at the regression results for all the correlation pairs, one can see certain similarities and patterns. In the first-type regressions, for twelve[4] correlation pairs, VIX recorded the highest adjusted R^2 in the daily-frequency analysis for both examined periods. Also, VIX was the most frequent significant variable in these daily regressions. In all models of type (21) and (23), where VIX resulted as significant, the impact of this regressor on the change in the correlation was negative. This would imply an increase in correlations on days of a falling VIX, which could go against the expectations and economic intuition. However, this feature might be caused by the dependence of VIX on its past values and the fact that in the forecasting models, VIX turned out to be significant and positively related to future changes in correlations. Indeed, when running a regression of VIX log-returns on their first lag, a significant negative relationship was obtained.

Hence, it might not be accurate to draw such a conclusion that negative returns on VIX in period t are accompanied by positive increases in the correlations in the

[4]The exceptions are *Consumer Staples - Health Care*, *Consumer Staples - Utilities*, *Health Care - Utilities*.

same period. Rather, one should say that an increasing VIX in period t implies an increased correlation in period $t+1$. This is confirmed by the fact that VIX was also the most frequent significant variable in the forecasting regressions. For six correlation pairs, it appeared to be significant in all eight forecasting regressions containing VIX. For the remaining pairs, VIX was significant in all daily forecasting regressions. Its effect on the regressand was always positive. As the significance and magnitude of the effect from the univariate models were often confirmed in the multivariate models, VIX seems to be the most reliable variable in this aspect. Moreover, in all daily univariate forecasting regressions, VIX achieved the highest adjusted R^2.

As far as the S&P 500 Index is concerned, its significance was detected for a very low number of cases in regressions of type (21) and (23). A negative significant influence in daily-frequency multivariate models appeared for four[5] pairs. In daily simple regressions, S&P resulted as a significant regressor positively affecting the regressand for the correlation pairs of *Utilities* with *Energy*, *Financials*, and *IT*, pointing to the fact that correlation pairs of *Utilities* might behave slightly differently than the others. Nevertheless, a more accurate relationship between S&P and the correlations can be seen in the multivariate regressions. For daily data, all the S&P-related coefficients from the multiple regressions were negative. However, as already stated, significance occurred for four correlation pairs only.

In the forecasting regressions, S&P turned out to be significant in all univariate models, except for correlation pairs of *Utilities* with *Consumer Staples* and *Health Care*. The estimated coefficients were always negative. Nonetheless, in the multivariate daily forecasting models, the S&P-related coefficient was always positive, and for eight[6] correlation pairs, S&P resulted as significant for at least

[5] *Consumer Staples - Health Care*, *Consumer Staples - IT*, *Health Care - IT*, *IT - Utilities*

[6] *Consumer Staples - Energy*, *Consumer Staples - Financials*, *Consumer Staples - Health Care*, *Consumer Staples - IT*, *Energy - IT*, *Financials - Health Care*, *Financials - IT*, *Health Care - IT*

one analyzed time period. Hence, controlling for other variables, the effect of S&P was suddenly positive. And since the multivariate regressions are expected to show more accurate partial effects of individual regressors, one may conclude that for these eight correlation pairs, an increase in S&P on day t has a positive effect on the correlation on day $t + 1$.

In the weekly forecasting models, though, S&P never turned out to be positive and significant in multivariate models. Instead, significance and a negative relationship between S&P and the future change in the correlation was detected in the multivariate weekly regressions for the correlation pairs *Energy* - *Utilities* and *IT* - *Utilities*. Hence, for these two pairs, it can be inferred that a negative weekly return on S&P will lead to an increase in the correlation in the next week.

In the first-type regressions, crude oil appeared as a significant regressor at least once for 10 correlation pairs, more for weekly than daily data. In these cases of significance, the influence on the dependent variable was always negative. For correlation pairs of *Energy*, with the exception of *Energy* - *Financials*, crude oil was significant in the multivariate weekly regressions. As the corresponding coefficients were negative, one can conclude that correlations of *Energy* fall in weeks of rising crude oil price.

In the forecasting regressions, crude oil turned out to be significant in at least one univariate model for all correlation pairs, but never in the multiple regression. It can be seen that the significance of crude oil in these univariate models was detected for the period 2007 - 2022 more frequently, suggesting that this variable became more important for predicting changes in correlations from the start of 2020. As crude oil did not appear to be significant in multivariate forecasting regressions, it is difficult to determine its effect on future changes in correlations.

Last, for all correlation pairs of *IT* with the exception of *IT* - *Energy*, bond yield resulted as a significant variable in univariate as well as multivariate first-type regressions of daily data between 2007 and 2022. A possible explanation of why bond yield resulted as a significant variable for the correlation pairs of *IT* could be the following. The yield on the 10-year US Treasury Note is related to the interest rate, and returns of *IT* stocks (mostly growth stocks) depend on the interest rate stronger than returns of stocks from other sectors. A positive coefficient corresponding to bond yield suggests that the correlations of *IT* increase on days of rising yield on the 10-year US Treasury Note.

As bond yield was never significant in multivariate forecasting daily regressions for correlations of *IT*, the positive relationship in the first-type regressions does not seem to be caused by possible dependence of bond yield on its past values. Indeed, a regression of bond yield log-returns on their first lag showed an insignificant relationship.

In the forecasting models, bond yield turned out to be significant in the univariate daily regressions for 14 correlation pairs.[7] In all these cases, the coefficient was negative, mostly[8] higher in absolute values for the period 2007 - 2019 than for 2007 - 2022. The significance in the multivariate daily regressions was detected for two[9] correlation pairs only. As these estimated coefficients were always negative, for these two correlation pairs it holds that a decrease in bond yield on day t is expected to raise the correlation on day $t + 1$.

The correlation pair *Consumer Staples* - *Utilities* can be considered a pair of two non-cyclical sectors. As can be seen in Panel (e) of Figure 2, this pair moved within the narrowest range among all correlation pairs, and deviations and spikes in this correlation were not that marked. Moreover, the lowest number of significant variables was detected for this correlation pair, whereas no variable turned

[7] The only exception was *Consumer Staples* - *Utilities*.

[8] The exceptions are *Energy* - *IT*, *Financials* - *IT*.

[9] *Consumer Staples* - *Financials*, *Financials* - *Utilities*

out to be significant in weekly regressions.

To sum up, the key findings of this thesis are as follows. First, VIX turned out to be a variable with the best predictive power for the moves in the correlations. Its positive effect implies that correlations tend to increase on day (week) t if VIX increased on day (week) $t-1$. Second, correlations of *Energy* are likely to decrease in weeks of rising crude oil price. Third, daily increases in the yield on the 10-year US Treasury Note are accompanied by daily increases in correlations of *IT*.

Last, the adjusted R^2 from all regressions were very low, suggesting that the analyzed variables explain very little of the moves in correlations. To investigate whether the low adjusted R^2 are caused by the fact that a very long time period is analyzed, regressions for the time period 2007 - 2011 for *Energy* - *IT*[10] were estimated. As Table A19 shows, although only a 5-year time period was considered, the adjusted R^2 did not increase considerably. This leads to the conclusion that indeed, very little of the dynamics of correlations among S&P sectors can be explained by S&P, bond yield, crude oil, or VIX. Since the adjusted R^2 were very low, any testing of the out-of-sample forecasting performance based on the estimated models would not make much sense.

[10] This correlation pair was randomly selected.

6 Conclusion

The main goal of this thesis was to examine how S&P 500 Index, 10-year US Treasury Note yield (bond yield), crude oil price, and CBOE Volatility index (VIX) impact the correlations among the following six S&P sectors: *Consumer Staples*, *Energy*, *Financials*, *Health Care*, *Information Technology*, and *Utilities*. Therefore, in total 15 correlation pairs were examined. The analysis was carried out for the time period of January 03, 2007 - February 25, 2022. To uncover potential differences between daily and weekly investment horizons, daily as well as weekly data were considered. Next, as the year 2020 and the corresponding market turbulence caused by the COVID-19 pandemic might be a significant breakpoint in the financial markets history, the analysis was performed for two time periods, 2007 - 2019 and 2007 - 2022, and certain differences were observed.

For log-returns of each sector index, each investment horizon and each time period, the optimal ARMA-GARCH model was selected. Daily as well as weekly time-varying correlations, ρ_t, among the examined sectors were estimated by bivariate DCC-GARCH models. Changes in correlations in time t, $\Delta\rho_t$, were expressed as $\Delta\rho_t = \rho_t - \rho_{t-1}$. These $\Delta\rho_t$ were regressed on log-returns of S&P, bond yield, crude oil, and VIX. In the first type of regressions, the independent variables were from the same time period as the regressand. Next, forecasting models regressed $\Delta\rho_t$ on independent variables from the time period $t-1$. For both types of regressions, univariate and multivariate (including all four variables) models were estimated.

The results indicate that VIX turned out to be the most reliable regressor in the forecasting models. Not only recorded VIX the highest adjusted R^2 in most of the simple regressions, it was also the most frequent significant variable in both univariate and multivariate forecasting regressions. Its positive impact on the dependent variable suggests that analyzed correlations tend to increase on day (week) t if VIX increased on day (week) $t-1$. Connecting this observation with the definition[1] of VIX, one may claim that a higher volatility leads to increases in correlations on the next day (week).

S&P did not turn out to be significant as frequently as VIX did. However, in the first-type multivariate regressions, a negative significant relationship was detected for daily data between 2007 and 2022 for the following four correlation pairs: *Consumer Staples - Health Care*, *Consumer Staples - IT*, *Health Care - IT*, *IT - Utilities*. Hence, for these pairs, there exists some evidence that correlations are likely to increase on days when the overall market declines. In the multivariate forecasting daily-data regressions, S&P turned out to influence the future change in the correlation positively for eight[2] pairs. In the weekly forecasting models, if significant, the relationship was negative, though. It concerns the following two pairs: *Energy - Utilities*, *IT - Utilities*. In these two cases, a decrease in S&P in week t is expected to cause a rise in the correlation in week $t+1$.

Crude oil never appeared to be statistically significant in multivariate forecasting regressions, leading to the conclusion that it is impossible to determine the effect of crude oil on future changes in correlations. In the first-type regressions, the significance of crude oil and its negative impact on the regressand were detected in the weekly models for four correlation pairs of *Energy*.[3] This points to the fact that correlations of *Energy* tend to fall during weeks of a rising crude oil price. For *Consumer Staples - Health Care*, *Consumer Staples - IT*, *Energy - Health Care*, and *IT - Utilities*, crude oil was significant in daily multivariate regressions for the time period of 2007 - 2022 only. This indicates that from the start of 2020,

[1] VIX is a measurement of the 30-day expected volatility of the S&P 500 Index implied by options on the S&P 500 Index (CBOE, 2022).

[2] *Consumer Staples - Energy*, *Consumer Staples - Financials*, *Consumer Staples - Health Care*, *Consumer Staples - IT*, *Energy - IT*, *Financials - Health Care*, *Financials - IT*, *Health Care - IT*

[3] The exception was *Energy - Financials*.

this variable might have gained importance for determining the parallel changes in correlations.

Bond yield resulted as a significant variable in both univariate and multivariate first-type regressions of daily data between 2007 and 2022 for four correlation pairs of *IT*.[4] This suggests that, from a daily perspective, an increasing bond yield is accompanied by increases in the correlations of *IT*. Next, as bond yield was significant for time period 2007 - 2022 only, one may say that this regressor became more important in this respect from the start of 2020.

Although the results show that some variables can be used for forecasting the future changes in correlations, there is one striking observation common for all regressions and all correlation pairs. The adjusted R^2 were very low - the highest value of 0.093 was recorded in the weekly multivariate forecasting regression (2007 - 2022) for *Consumer Staples* - *Financials*. The fact of low adjusted R^2 does not seem to be due to the very long examined time period. The regressions for *Energy* - *IT* based on data between 2007 and 2011 yielded similarly low adjusted R^2. Hence, the same way as King et al. (1990) or Baele et al. (2010) claimed that macroeconomic variables explained very little of changes in correlations or covariances, this thesis shows that factors related to the financial market do not explain much of changes in correlations either.

The analyzed variables (S&P, bond yield, crude oil, VIX) are common financial market factors. They are not specifically related to any of the analyzed sectors. Presumably, more explanatory power would be found in factors that are directly related to the S&P sector indices. Such variables could be the volatility or past returns of these time series. Alternatively, an ideal factor for determining the future correlation changes might be an interaction of technical analysis indicators of the corresponding two sectors indices. For example, a dummy variable

[4] The only exception was *IT* - *Energy*.

on MACD difference[5] of one sector index interacted with a dummy variable on MACD difference of the other sector index could be a more appropriate regressor for explaining the future change in the correlation between these two sector indices.

To conclude, this thesis conducts an analysis of the correlations among six S&P sectors that was up until now rather missing. It is shown how S&P 500 Index, 10-year US Treasury Note, crude oil, and VIX influence the changes in the examined correlations. The results indicate that, among these four variables, VIX seems to have the best ability to forecast future changes in correlations. However, one needs to bear in mind that very little of these changes can be explained by the analyzed variables. Hence, it might become a goal for further research to investigate which factors, possibly some technical analysis indicators, can explain more of changes in correlations among financial assets.

[5] Difference between MACD (Moving Average Convergence/Divergence) and its 9-day moving average. Their intersection is often considered a buy/sell signal (Achelis, 2011).

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Appendix

Table A1: Log-returns - stock indices

This table shows the summary statistics of daily (Panel A) and weekly (Panel B) logarithmic returns of eleven S&P sectors and the aggregate S&P 500 Index. Minimum (Min), first quartile (Q1), median (Med), mean (Mean), third quartile (Q3), maximum (Max), and standard deviation (Std) are presented in percentages. Last two columns contain coefficients of skewness (Skew) and kurtosis (Kurt).

Panel A

	Min	Q1	Med	Mean	Q3	Max	Std	Skew	Kurt
S&P 500	-12.77	-0.40	0.072	0.030	0.58	10.96	1.29	-0.55	16.02
Consumer Discretionary	-12.88	-0.52	0.116	0.040	0.69	12.31	1.41	-0.38	12.18
Consumer Staples	-9.69	-0.38	0.048	0.028	0.48	8.84	0.95	-0.17	16.95
Energy	-22.42	-0.81	0.036	0.005	0.88	16.96	1.93	-0.66	18.32
Financials	-18.64	-0.72	0.055	0.007	0.81	17.20	2.10	-0.23	18.21
Health Care	-10.53	-0.44	0.076	0.036	0.60	11.71	1.13	-0.23	13.80
Industrials	-12.16	-0.53	0.081	0.025	0.67	12.00	1.43	-0.52	11.91
IT	-14.98	-0.54	0.111	0.053	0.74	11.46	1.47	-0.32	12.60
Materials	-12.93	-0.66	0.080	0.024	0.82	12.47	1.60	-0.49	11.47
Real Estate	-20.42	-0.67	0.086	0.012	0.74	18.85	2.15	-0.18	19.43
Telecommunication Services	-11.03	-0.58	0.062	0.011	0.67	12.93	1.34	-0.07	13.44
Utilities	-12.27	-0.54	0.086	0.016	0.62	12.68	1.25	0.06	19.26

Panel B

	Min	Q1	Med	Mean	Q3	Max	Std	Skew	Kurt
S&P 500	-20.08	-0.90	0.310	0.144	1.49	11.42	2.58	-1.08	12.02
Consumer Discretionary	-20.19	-1.15	0.327	0.193	1.88	15.75	3.03	-0.45	8.97
Consumer Staples	-17.36	-0.86	0.268	0.137	1.21	8.00	1.94	-1.59	14.79
Energy	-28.81	-1.69	0.202	0.023	2.10	15.23	3.89	-1.24	12.11
Financials	-27.05	-1.58	0.287	0.035	1.89	29.16	4.18	-0.24	14.78
Health.Care	-20.37	-0.97	0.329	0.172	1.54	9.08	2.41	-1.32	12.71
Industrials	-20.31	-1.24	0.284	0.121	1.76	14.35	3.06	-0.64	8.58
IT	-16.55	-1.10	0.431	0.255	1.89	10.07	2.88	-0.72	6.94
Materials	-16.64	-1.38	0.336	0.115	1.74	18.78	3.31	-0.43	7.86
Real Estate	-26.12	-1.49	0.284	0.062	1.74	19.41	3.89	-0.63	12.25
Telecommunication Services	-21.81	-1.30	0.031	0.054	1.56	14.88	2.67	-0.65	10.88
Utilities	-22.61	-1.03	0.235	0.079	1.43	16.28	2.63	-1.25	18.16

Table A2: Log-returns - independent variables

This table shows the summary statistics of daily (Panel A) and weekly (Panel B) logarithmic returns of the S&P 500 Index, 10-year US Treasury Note yield (BY), crude oil (CO), and VIX. Minimum (Min), first quartile (Q1), median (Med), mean (Mean), third quartile (Q3), maximum (Max), and standard deviation (Std) are presented in percentages. Last two columns contain coefficients of skewness (Skew) and kurtosis (Kurt). The row named 'CO*' in Panel A presents the summary statistics of daily log-returns of crude oil in case the returns on April 20, 2020 (-305.97%) and April, 21, 2020 (126.6%) are replaced by median values (0.1%).

Panel A

	Min	Q1	Med	Mean	Q3	Max	Std	Skew	Kurt
S&P 500	-12.77	-0.40	0.07	0.030	0.58	10.96	1.29	-0.55	16.02
BY	-34.70	-1.35	-0.06	-0.022	1.27	40.48	2.86	0.21	31.29
CO	-305.97	-1.18	0.10	-0.019	1.25	126.60	6.02	-31.96	1801.29
CO*	-28.22	-1.17	0.10	0.028	1.24	31.96	2.74	0.16	23.49
VIX	-35.06	-4.38	-0.64	0.022	3.58	76.82	7.83	1.07	9.01

Panel B

	Min	Q1	Med	Mean	Q3	Max	Std	Skew	Kurt
S&P 500	-20.08	-0.90	0.31	0.144	1.49	11.42	2.58	-1.08	12.02
BY	-46.77	-3.27	-0.42	-0.108	2.67	33.29	5.87	-0.23	11.67
CO	-34.69	-2.40	0.46	0.062	2.90	27.58	5.52	-0.80	9.51
VIX	-55.62	-9.24	-1.10	0.104	8.00	85.37	15.63	0.70	5.89

Table A3: ARMA-GARCH models details

This table presents the details on ARMA-GARCH models. Columns named 'ARMA' ('GARCH') show the optimal ARMA (GARCH) order. In the column named 'type', the optimal type of the GARCH model is stated. The column named 'GARCH errors' shows the optimal errors distribution in the GARCH model. Columns named 'p.v.(u^2)' and 'p.v.(u)' show the p-values corresponding to the Ljung-Box test applied to squared standardized residuals and to standardized residuals of the GARCH model, respectively.

Panel A: daily log-returns 2007 - 2019

	ARMA	GARCH	type	GARCH errors	p.v.(u^2)	p.v.(u)
Consumer Staples	2,0	1,1	eGARCH	Student's t	0.9179	0.8838
Energy	2,0	1,1	eGARCH	Student's t	0.2199	0.4776
Financials	1,0	1,1	gjrGARCH	Student's t	0.2192	0.0301[a]
Health Care	3,0	2,1	eGARCH	Student's t	0.2445	0.4766
IT	0,1	1,1	eGARCH	Student's t	0.0164[a]	0.0914
Utilities	2,0	1,1	gjrGARCH	Student's t	0.1061	0.9389

Panel B: daily log-returns 2007 - 2022

	ARMA	GARCH	type	GARCH errors	p.v.(u^2)	p.v.(u)
Consumer Staples	0,1	1,1	eGARCH	Student's t	0.2906	0.8537
Energy	0,1	1,1	eGARCH	Student's t	0.0141[a]	0.4469
Financials	1,0	1,1	gjrGARCH	Student's t	0.2447	0.0524
Health Care	1,0	1,1	eGARCH	Student's t	0.2963	0.6167
IT	1,0	1,1	eGARCH	Student's t	0.5834	0.2105
Utilities	0,1	1,1	gjrGARCH	Student's t	0.0684	0.9632

Panel C: weekly log-returns 2007 - 2019

	ARMA	GARCH	type	GARCH errors	p.v.(u^2)	p.v.(u)
Consumer Staples	1,0	1,1	eGARCH	Student's t	0.9775	0.9527
Energy	1,1	1,1	gjrGARCH	Student's t	0.5014	0.6762
Financials	1,1	1,1	gjrGARCH	Student's t	0.7967	0.9467
Health Care	0,1	1,1	eGARCH	Student's t	0.3536	0.7272
IT	1,1	2,1	eGARCH	Student's t	0.8461	0.6254
Utilities	1,1	1,1	eGARCH	Student's t	0.4498	0.3563

Panel D: weekly log-returns 2007 - 2022

	ARMA	GARCH	type	GARCH errors	p.v.(u^2)	p.v.(u)
Consumer Staples	0,1	1,1	eGARCH	Student's t	0.8377	0.8021
Energy	2,2	1,1	eGARCH	Student's t	0.0682	0.8716
Financials	1,1	1,1	gjrGARCH	Student's t	0.9122	0.9163
Health Care	0,1	1,1	eGARCH	Student's t	0.4641	0.7814
IT	1,0	1,1	eGARCH	Student's t	0.4464	0.9634
Utilities	0,1	1,1	eGARCH	Student's t	0.5464	0.2747

[a]Although the p-value was lower than 0.05, this model was selected since it was *the best* model given the available data.

Table A4: Changes in correlations - summary statistics

This table presents the summary statistics of daily (Panel A) and weekly (Panel B) changes in correlations for the time period 2007 - 2022. These changes are calculated as a simple difference of consecutive correlation values implied by the DCC model. The column names are as follows: Min (minimum), Q1 (first quartile), Med (median), Mean (mean), Q3 (third quartile), Max (maximum), AAV (average absolute value of change in the correlation), and Std (standard deviation). The abbreviations in the row names are as follows: CS (*Consumer Staples*), Ener. (*Energy*), Fin. (*Financials*), HC (*Health Care*), IT (*Information Technology*), Util. (*Utilities*).

Panel A

	Min	Q1	Med	Mean	Q3	Max	AAV	Std
CS - Ener.	-0.5267	-0.0127	-0.00050	-0.000107	0.0128	0.6073	0.0263	0.0477
CS - Fin.	-0.4702	-0.0093	-0.00080	-0.000060	0.0093	0.3339	0.0199	0.0367
CS - HC	-0.3818	-0.0090	-0.00072	-0.000087	0.0096	0.3109	0.0210	0.0388
CS - IT	-0.4287	-0.0084	-0.00053	-0.000088	0.0086	0.3645	0.0176	0.0323
CS - Util.	-0.1955	-0.0082	-0.00055	-0.000021	0.0085	0.3082	0.0172	0.0294
Ener. - Fin.	-0.2208	-0.0075	-0.00049	-0.000092	0.0068	0.3882	0.0156	0.0288
Ener. - HC	-0.3914	-0.0132	-0.00078	-0.000133	0.0125	0.4888	0.0269	0.0467
Ener. - IT	-0.5578	-0.0343	-0.00060	-0.000156	0.0339	0.6778	0.0506	0.0757
Ener. - Util.	-0.2972	-0.0103	0.00009	-0.000135	0.0104	0.2655	0.0212	0.0365
Fin. - HC	-0.3972	-0.0142	-0.00186	0.000004	0.0157	0.6184	0.0311	0.0543
Fin. - IT	-0.8849	-0.0313	-0.00148	-0.000030	0.0313	0.6172	0.0491	0.0772
Fin. - Util.	-0.5998	-0.0100	-0.00004	-0.000032	0.0103	0.4380	0.0215	0.0391
HC - IT	-0.6624	-0.0129	-0.00143	0.000023	0.0148	0.4896	0.0288	0.0523
HC - Util.	-0.4902	-0.0102	-0.00053	0.000009	0.0112	0.3370	0.0228	0.0399
IT - Util.	-0.3766	-0.0092	-0.00014	0.000008	0.0085	0.3865	0.0182	0.0325

Panel B

	Min	Q1	Med	Mean	Q3	Max	AAV	Std
CS - Ener.	-0.4717	-0.0286	-0.00326	-0.000392	0.0297	0.4956	0.0505	0.0801
CS - Fin.	-0.3267	-0.0068	-0.00009	-0.000082	0.0076	0.3019	0.0147	0.0286
CS - HC	-0.3975	-0.0329	-0.00012	-0.000238	0.0386	0.2866	0.0508	0.0745
CS - IT	-0.1670	-0.0154	-0.00091	-0.000084	0.0166	0.2281	0.0251	0.0382
CS - Util.	-0.1831	-0.0179	-0.00089	-0.000075	0.0179	0.3106	0.0269	0.0396
Ener. - Fin.	-0.1287	-0.0061	-0.00034	-0.000002	0.0052	0.1991	0.0112	0.0207
Ener. - HC	-0.3748	-0.0135	-0.00154	-0.000635	0.0119	0.3030	0.0247	0.0437
Ener. - IT	-0.5543	-0.0453	0.00181	-0.000463	0.0440	0.4710	0.0698	0.1012
Ener. - Util.	-0.3229	-0.0110	-0.00070	-0.000535	0.0099	0.6706	0.0215	0.0429
Fin. - HC	-0.4621	-0.0105	-0.00100	-0.000331	0.0126	0.2277	0.0210	0.0377
Fin. - IT	-0.4707	-0.0148	-0.00020	-0.000264	0.0196	0.4231	0.0354	0.0637
Fin. - UT	-0.2153	-0.0051	-0.00040	-0.000123	0.0047	0.4370	0.0099	0.0231
HC - IT	-0.1718	-0.0148	0.00018	0.000014	0.0142	0.1915	0.0212	0.0318
HC - Util.	-0.0545	-0.0027	-0.00002	0.000052	0.0025	0.2461	0.0059	0.0135
IT - Util.	-0.1255	-0.0110	-0.00042	0.000006	0.0093	0.3143	0.0168	0.0273

Table A5: Regression results for the correlation pair *Consumer Staples - Financials*

This table presents the results of regression models (21) - (24) for the correlation pair *Consumer Staples - Financials*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.8719)	(0.8873)	(0.8950)	(0.8957)	(0.8918)
S&P	0.0754				-0.0289
	(0.1688)				(0.7340)
BY		-0.0222			-0.0452
		(0.4705)			(0.1844)
CO			-0.0216		-0.0318
			(0.4432)		(0.2954)
VIX				**-0.0236**	**-0.0338**
				(0.0070)	(0.0096)
Adj. R^2	0.00027	-0.00015	-0.00013	0.00192	0.00233

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0002	-0.0001	-0.0001	-0.0002
	(0.9919)	(0.8204)	(0.8986)	(0.8860)	(0.7736)
S&P	**-0.3799**				**0.2212**
	(0.0000)				(0.0429)
BY		**-0.2288**			**-0.1499**
		(0.0000)			(0.0090)
CO			**-0.1014**		-0.0145
			(0.0003)		(0.6207)
VIX				**0.0944**	**0.1053**
				(0.0000)	(0.0000)
Adj. R^2	0.01439	0.01666	0.00366	0.03529	0.04160

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0001	-0.0001	-0.0001	0.0000
	(0.8909)	(0.9206)	(0.9247)	(0.9291)	(0.9673)
S&P	0.0729				-0.0694
	(0.1146)				(0.2677)
BY		0.0031			-0.0078
		(0.8817)			(0.7199)
CO			-0.0181		-0.0327
			(0.4048)		(0.0677)
VIX				**-0.0264**	**-0.0384**
				(0.0028)	(0.0053)
Adj. R^2	0.00039	-0.00026	-0.00008	0.00292	0.00328

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0001	0.0000	-0.0001	-0.0002
	(0.9408)	(0.8776)	(0.9536)	(0.8863)	(0.7752)
S&P	**-0.3591**				**0.2454**
	(0.0000)				(0.0040)
BY		**-0.1406**			**-0.0853**
		(0.0000)			(0.0167)
CO			**-0.0938**		-0.0287
			(0.0000)		(0.1648)
VIX				**0.0973**	**0.1155**
				(0.0000)	(0.0000)
Adj. R^2	0.01558	0.01171	0.00463	0.04283	0.04809

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0002	-0.0001	-0.0001	-0.0002	0.0000
	(0.9140)	(0.9375)	(0.9180)	(0.9193)	(0.9985)
S&P	0.0007				-0.0694
	(0.9881)				(0.3754)
BY		0.0270			0.0387
		(0.4199)			(0.3313)
CO			-0.0458		-0.0584
			(0.2304)		(0.1442)
VIX				-0.0102	-0.0188
				(0.2816)	(0.1578)
Adj. R^2	-0.00148	-0.00034	0.00201	0.00013	0.00313

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0003	-0.0003	-0.0001	-0.0002	-0.0001
	(0.8510)	(0.8204)	(0.9219)	(0.8987)	(0.9361)
S&P	**-0.3601**				-0.1081
	(0.0124)				(0.6635)
BY		**-0.1308**			-0.0608
		(0.0191)			(0.3595)
CO			-0.0786		-0.0089
			(0.0846)		(0.7537)
VIX				**0.0645**	0.0447
				(0.0019)	(0.1432)
Adj. R^2	0.05123	0.02529	0.00878	0.06327	0.06869

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.9151)	(0.8914)	(0.9523)	(0.9424)	(0.8861)
S&P	0.0187				0.0262
	(0.6356)				(0.7482)
BY		-0.0490			-0.0557
		(0.3330)			(0.3115)
CO			-0.0307		-0.0319
			(0.0961)		(0.0918)
VIX				-0.0068	-0.0131
				(0.2982)	(0.1725)
Adj. R^2	-0.00098	0.00889	0.00225	0.00011	0.01324

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0003	-0.0002	0.0000	-0.0001	0.0000
	(0.7530)	(0.8556)	(0.9716)	(0.8776)	(0.9660)
S&P	**-0.2873**				-0.0907
	(0.0034)				(0.4539)
BY		**-0.0875**			-0.0448
		(0.0000)			(0.1541)
CO			**-0.0667**		-0.0105
			(0.0277)		(0.5216)
VIX				**0.0529**	**0.0361**
				(0.0012)	(0.0469)
Adj. R^2	0.06619	0.03118	0.01536	0.08254	0.09307

Table A6: Regression results for the correlation pair *Consumer Staples - Health Care*

This table presents the results of regression models (21) - (24) for the correlation pair *Consumer Staples - Health Care*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0001	-0.0001	-0.0001	0.0000
	(0.9295)	(0.9367)	(0.9349)	(0.9348)	(0.9621)
S&P	0.0192				-0.0869
	(0.6596)				(0.1842)
BY		0.0062			0.0014
		(0.8376)			(0.9673)
CO			-0.0114		-0.0171
			(0.6290)		(0.5125)
VIX				-0.0136	-0.0251
				(0.1266)	(0.0696)
Adj. R^2	-0.00027	-0.00029	-0.00026	0.00038	-0.00005

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0001	-0.0001	-0.0001	-0.0001
	(0.9627)	(0.8956)	(0.9391)	(0.9287)	(0.8688)
S&P	**-0.3493**				0.1374
	(0.0000)				(0.1143)
BY		**-0.1359**			-0.0592
		(0.0020)			(0.2099)
CO			-0.0387		0.0349
			(0.1727)		(0.2492)
VIX				**0.0877**	**0.1011**
				(0.0000)	(0.0000)
Adj. R^2	0.01115	0.00521	0.00023	0.02802	0.02885

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0001	-0.0001	-0.0001	0.0000
	(0.9012)	(0.8928)	(0.9066)	(0.8941)	(0.9726)
S&P	-0.0251				**-0.1400**
	(0.5554)				(0.0256)
BY		0.0062			0.0160
		(0.7364)			(0.4309)
CO			**-0.0361**		**-0.0392**
			(0.0367)		(0.0364)
VIX				-0.0101	**-0.0286**
				(0.2649)	(0.0278)
Adj. R^2	-0.00019	-0.00024	0.00039	0.00015	0.00128

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0001	-0.0001	-0.0001	-0.0002
	(0.9806)	(0.8714)	(0.9170)	(0.8600)	(0.7851)
S&P	**-0.3465**				**0.1897**
	(0.0000)				(0.0121)
BY		**-0.0800**			-0.0202
		(0.0073)			(0.4708)
CO			**-0.0630**		-0.0053
			(0.0044)		(0.7948)
VIX				**0.0956**	**0.1160**
				(0.0000)	(0.0000)
Adj. R^2	0.01293	0.00321	0.00171	0.03697	0.03799

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	0.0001	0.0000	0.0000	0.0004
	(0.9773)	(0.9851)	(0.9938)	(0.9967)	(0.8810)
S&P	0.0403				-0.2281
	(0.7013)				(0.0953)
BY		0.0534			0.0460
		(0.3933)			(0.5016)
CO			-0.0144		-0.0284
			(0.7967)		(0.6226)
VIX				-0.0326	**-0.0568**
				(0.1161)	(0.0451)
Adj. R^2	-0.00129	-0.00020	-0.00138	0.00327	0.00260

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0004	-0.0002	0.0000	-0.0001	-0.0003
	(0.8593)	(0.9355)	(0.9975)	(0.9781)	(0.9023)
S&P	**-0.3652**				0.1665
	(0.0052)				(0.4517)
BY		-0.1219			-0.0306
		(0.0827)			(0.6831)
CO			-0.0891		-0.0312
			(0.1482)		(0.5970)
VIX				**0.0941**	**0.1081**
				(0.0000)	(0.0009)
Adj. R^2	0.01410	0.00521	0.00230	0.03820	0.03568

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0004	-0.0002	-0.0002	-0.0002	-0.0001
	(0.8825)	(0.9182)	(0.9312)	(0.9333)	(0.9803)
S&P	0.0947				-0.0845
	(0.3059)				(0.4743)
BY		0.0020			-0.0188
		(0.9730)			(0.7705)
CO			-0.0071		-0.0282
			(0.8715)		(0.5361)
VIX				-0.0345	**-0.0494**
				(0.0606)	(0.0416)
Adj. R^2	-0.00020	-0.00127	-0.00124	0.00396	0.00155

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0003	-0.0004	-0.0002	-0.0004	-0.0006
	(0.8785)	(0.8568)	(0.9488)	(0.8806)	(0.8039)
S&P	**-0.3980**				0.1312
	(0.0011)				(0.4307)
BY		**-0.1348**			-0.0638
		(0.0173)			(0.2629)
CO			**-0.1044**		-0.0237
			(0.0453)		(0.6032)
VIX				**0.1012**	**0.1073**
				(0.0000)	(0.0001)
Adj. R^2	0.01775	0.01004	0.00472	0.04381	0.04332

Table A7: Regression results for the correlation pair *Consumer Staples - IT*

This table presents the results of regression models (21) - (24) for the correlation pair *Consumer Staples - IT*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9243)	(0.9524)	(0.9441)	(0.9448)	(0.9892)
S&P	0.0460				-0.0858
	(0.2527)				(0.1683)
BY		0.0214			0.0151
		(0.3426)			(0.5435)
CO			-0.0212		-0.0356
			(0.3047)		(0.1091)
VIX				**-0.0197**	**-0.0311**
				(0.0022)	(0.0011)
Adj. R^2	0.00009	-0.00003	0.00002	0.00257	0.00332

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0001	0.0000	0.0000	-0.0001
	(0.9510)	(0.9026)	(0.9503)	(0.9380)	(0.8335)
S&P	**-0.2476**				**0.1976**
	(0.0000)				(0.0080)
BY		**-0.1025**			-0.0425
		(0.0000)			(0.1464)
CO			**-0.0421**		0.0087
			(0.0413)		(0.6740)
VIX				**0.0710**	**0.0910**
				(0.0000)	(0.0000)
Adj. R^2	0.01131	0.00604	0.00097	0.03712	0.03987

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0001	-0.0001	-0.0001	0.0000
	(0.8494)	(0.8788)	(0.8805)	(0.8749)	(0.9859)
S&P	0.0385				**-0.1575**
	(0.3438)				(0.0117)
BY		**0.0372**			**0.0412**
		(0.0423)			(0.0385)
CO			-0.0345		**-0.0521**
			(0.0710)		(0.0102)
VIX				**-0.0252**	**-0.0442**
				(0.0002)	(0.0000)
Adj. R^2	-0.00003	0.00082	0.00059	0.00346	0.00702

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0001	-0.0001	-0.0001	-0.0002
	(0.9980)	(0.8468)	(0.8952)	(0.8321)	(0.7231)
S&P	**-0.2995**				**0.2315**
	(0.0000)				(0.0016)
BY		**-0.0678**			-0.0129
		(0.0045)			(0.5453)
CO			**-0.0703**		-0.0224
			(0.0013)		(0.2305)
VIX				**0.0889**	**0.1134**
				(0.0000)	(0.0000)
Adj. R^2	0.01395	0.00333	0.00328	0.04611	0.04901

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	-0.0001	0.0001
	(0.9989)	(0.9886)	(0.9785)	(0.9707)	(0.9574)
S&P	-0.0554				-0.0502
	(0.4537)				(0.6580)
BY		0.0266			0.0567
		(0.4804)			(0.1726)
CO			-0.0610		-0.0694
			(0.0948)		(0.0832)
VIX				0.0044	-0.0009
				(0.7132)	(0.9580)
Adj. R^2	-0.00065	-0.00074	0.00265	-0.00128	0.00107

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0002	-0.0001	-0.0001	-0.0001	-0.0002
	(0.9188)	(0.9441)	(0.9681)	(0.9512)	(0.9231)
S&P	**-0.2216**				0.0919
	(0.0240)				(0.4488)
BY		-0.0307			0.0347
		(0.4154)			(0.4159)
CO			-0.0532		-0.0285
			(0.1455)		(0.4153)
VIX				**0.0584**	**0.0706**
				(0.0015)	(0.0054)
Adj. R^2	0.01186	-0.00050	0.00166	0.03398	0.03214

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.9570)	(0.9317)	(0.9621)	(0.9522)	(0.9666)
S&P	-0.0077				-0.0158
	(0.8785)				(0.8310)
BY		-0.0250			-0.0252
		(0.5392)			(0.5856)
CO			-0.0293		-0.0295
			(0.2810)		(0.2885)
VIX				-0.0036	-0.0113
				(0.7233)	(0.4306)
Adj. R^2	-0.00124	0.00021	0.00052	-0.00105	-0.00105

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0002	-0.0001	-0.0001	-0.0002	-0.0002
	(0.8811)	(0.9296)	(0.9662)	(0.8989)	(0.8906)
S&P	**-0.2057**				0.0389
	(0.0144)				(0.6358)
BY		-0.0145			0.0296
		(0.6103)			(0.2079)
CO			-0.0540		-0.0215
			(0.0568)		(0.3669)
VIX				**0.0515**	**0.0572**
				(0.0009)	(0.0022)
Adj. R^2	0.01804	-0.00078	0.00483	0.04321	0.04221

Table A8: Regression results for the correlation pair *Consumer Staples - Utilities*

This table presents the results of regression models (21) - (24) for the correlation pair *Consumer Staples - Utilities*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9339)	(0.9753)	(0.9532)	(0.9543)	(0.9949)
S&P	0.0482				-0.0451
	(0.2493)				(0.5283)
BY		**0.0524**			0.0514
		(0.0167)			(0.0562)
CO			-0.0042		-0.0227
			(0.8096)		(0.2565)
VIX				-0.0134	-0.0156
				(0.1309)	(0.2719)
Adj. R^2	0.00011	0.00127	-0.00029	0.00095	0.00146

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9579)	(0.9368)	(0.9568)	(0.9490)	(0.9445)
S&P	**-0.2219**				0.0249
	(0.0005)				(0.7449)
BY		-0.0433			0.0148
		(0.1534)			(0.6342)
CO			-0.0295		0.0078
			(0.2138)		(0.7620)
VIX				**0.0517**	**0.0566**
				(0.0002)	(0.0033)
Adj. R^2	0.00853	0.00076	0.00029	0.01848	0.01786

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9542)	(0.9742)	(0.9638)	(0.9697)	(0.9736)
S&P	0.0217				-0.0851
	(0.5579)				(0.1633)
BY		0.0252			0.0265
		(0.1097)			(0.1341)
CO			-0.0057		-0.0145
			(0.6683)		(0.3490)
VIX				-0.0126	-0.0213
				(0.1350)	(0.0970)
Adj. R^2	-0.00017	0.00034	-0.00023	0.00086	0.00121

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9200)	(0.9548)	(0.9899)	(0.9413)	(0.9242)
S&P	**-0.2342**				0.0566
	(0.0000)				(0.3833)
BY		-0.0328			0.0112
		(0.0711)			(0.5360)
CO			**-0.0440**		-0.0089
			(0.0184)		(0.6242)
VIX				**0.0590**	**0.0662**
				(0.0000)	(0.0000)
Adj. R^2	0.01023	0.00075	0.00141	0.02442	0.02412

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0001
	(0.9881)	(0.9878)	(0.9899)	(0.9827)	(0.9397)
S&P	-0.0587				-0.0962
	(0.4652)				(0.4608)
BY		0.0090			0.0343
		(0.7892)			(0.3652)
CO			-0.0677		-0.0710
			(0.0813)		(0.1152)
VIX				-0.0011	-0.0143
				(0.9349)	(0.4634)
Adj. R^2	-0.00075	-0.00142	0.00248	-0.00147	-0.00020

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0003	0.0001	0.0000	0.0000	0.0005
	(0.8531)	(0.9556)	(0.9858)	(0.9896)	(0.7822)
S&P	-0.2486				-0.3083
	(0.1192)				(0.1730)
BY		0.0536			0.1099
		(0.2790)			(0.0749)
CO			0.0155		0.0470
			(0.7819)		(0.2937)
VIX				0.0332	0.0121
				(0.0846)	(0.6362)
Adj. R^2	0.01161	0.00086	-0.00128	0.00744	0.01909

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0001	-0.0001	-0.0001	-0.0002
	(0.9257)	(0.9147)	(0.9512)	(0.9523)	(0.8890)
S&P	0.0276				0.0251
	(0.6362)				(0.7771)
BY		-0.0456			-0.0563
		(0.4175)			(0.3699)
CO			-0.0049		-0.0036
			(0.8385)		(0.8880)
VIX				-0.0067	-0.0103
				(0.4653)	(0.3940)
Adj. R^2	-0.00095	0.00332	-0.00122	-0.00057	0.00200

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0002	0.0000	0.0000	-0.0001	0.0001
	(0.8352)	(0.9757)	(0.9872)	(0.9574)	(0.9213)
S&P	-0.1940				-0.1332
	(0.0906)				(0.3434)
BY		-0.0066			0.0228
		(0.8642)			(0.5199)
CO			-0.0055		0.0307
			(0.8899)		(0.3266)
VIX				0.0334	0.0233
				(0.0523)	(0.2032)
Adj. R^2	0.01476	-0.00118	-0.00121	0.01614	0.01745

Table A9: Regression results for the correlation pair *Energy - Financials*

This table presents the results of regression models (21) - (24) for the correlation pair *Energy - Financials*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9617)	(0.9783)	(0.9799)	(0.9807)	(0.9917)
S&P	0.0464				-0.0410
	(0.2818)				(0.5394)
BY		-0.0026			-0.0152
		(0.9131)			(0.5696)
CO			-0.0120		-0.0202
			(0.5872)		(0.3963)
VIX				**-0.0161**	**-0.0240**
				(0.0190)	(0.0192)
Adj. R^2	0.00005	-0.00030	-0.00022	0.00138	0.00114

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0001	0.0000	0.0000	0.0000	0.0000
	(0.8645)	(0.9473)	(0.9910)	(0.9752)	(0.9791)
S&P	**-0.3945**				0.0156
	(0.0000)				(0.8519)
BY		**-0.0924**			0.0183
		(0.0034)			(0.5814)
CO			**-0.1095**		-0.0491
			(0.0003)		(0.1246)
VIX				**0.0847**	**0.0845**
				(0.0000)	(0.0000)
Adj. R^2	0.02537	0.00418	0.00719	0.04612	0.04657

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.8290)	(0.8434)	(0.8466)	(0.8481)	(0.8627)
S&P	0.0304				-0.0187
	(0.4014)				(0.7375)
BY		-0.0017			-0.0054
		(0.9164)			(0.7596)
CO			-0.0159		-0.0226
			(0.3505)		(0.2115)
VIX				-0.0107	-0.0156
				(0.0710)	(0.0746)
Adj. R^2	-0.00008	-0.00026	-0.00003	0.00059	0.00042

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0001	-0.0001	-0.0001	-0.0001
	(0.9928)	(0.8246)	(0.8860)	(0.8138)	(0.8190)
S&P	**-0.3208**				0.0208
	(0.0000)				(0.7491)
BY		**-0.0629**			-0.0049
		(0.0016)			(0.8087)
CO			**-0.0703**		-0.0214
			(0.0011)		(0.3219)
VIX				**0.0726**	**0.0728**
				(0.0000)	(0.0000)
Adj. R^2	0.02032	0.00363	0.00421	0.03874	0.03844

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0001	0.0000	0.0000	-0.0001	0.0005
	(0.9393)	(0.9883)	(0.9823)	(0.9727)	(0.7797)
S&P	-0.1691				-0.3697
	(0.2601)				(0.0983)
BY		0.0256			0.0727
		(0.4963)			(0.1652)
CO			**-0.0929**		-0.0817
			(0.0109)		(0.0623)
VIX				-0.0039	**-0.0460**
				(0.7450)	(0.0324)
Adj. R^2	0.00628	-0.00079	0.00809	-0.00132	0.02338

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0005	-0.0001	0.0000	-0.0001	0.0002
	(0.8003)	(0.9553)	(0.9860)	(0.9643)	(0.8878)
S&P	**-0.4166**				-0.1928
	(0.0009)				(0.2794)
BY		-0.0392			0.0609
		(0.2989)			(0.1311)
CO			-0.0684		-0.0097
			(0.2286)		(0.8556)
VIX				**0.0750**	**0.0579**
				(0.0003)	(0.0447)
Adj. R^2	0.04562	0.00012	0.00370	0.05696	0.05955

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	0.0001	0.0000	0.0000	0.0000	0.0001
	(0.9345)	(0.9535)	(0.9749)	(0.9977)	(0.9235)
S&P	-0.0448				-0.0534
	(0.4194)				(0.5705)
BY		-0.0366			-0.0327
		(0.2649)			(0.3808)
CO			-0.0358		-0.0286
			(0.0523)		(0.0799)
VIX				0.0004	-0.0124
				(0.9350)	(0.1696)
Adj. R^2	0.00186	0.00954	0.00788	-0.00126	0.01542

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0003	0.0000	0.0000	0.0000	0.0001
	(0.7027)	(0.9687)	(0.9719)	(0.9540)	(0.8508)
S&P	**-0.2025**				-0.1135
	(0.0032)				(0.1573)
BY		-0.0276			0.0040
		(0.2137)			(0.8253)
CO			-0.0335		0.0026
			(0.1733)		(0.8873)
VIX				**0.0344**	0.0216
				(0.0013)	(0.0594)
Adj. R^2	0.06266	0.00488	0.00674	0.06621	0.07198

Table A10: Regression results for the correlation pair *Energy - Health Care*

This table presents the results of regression models (21) - (24) for the correlation pair *Energy - Health Care*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9920)	(0.9942)	(0.9928)	(0.9920)	(0.9600)
S&P	0.0623				-0.1506
	(0.3840)				(0.1747)
BY		-0.0025			-0.0199
		(0.9509)			(0.6536)
CO			-0.0301		-0.0433
			(0.4130)		(0.2740)
VIX				**-0.0320**	**-0.0550**
				(0.0051)	(0.0012)
Adj. R^2	-0.00007	-0.00030	-0.00010	0.00209	0.00265

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0002	0.0000	0.0000	0.0000	0.0000
	(0.8208)	(0.9944)	(0.9586)	(0.9721)	(0.9882)
S&P	**-0.6215**				0.1553
	(0.0000)				(0.2507)
BY		**-0.1734**			-0.0104
		(0.0000)			(0.8354)
CO			**-0.1279**		-0.0202
			(0.0109)		(0.6994)
VIX				**0.1476**	**0.1634**
				(0.0000)	(0.0000)
Adj. R^2	0.02280	0.00542	0.00340	0.05076	0.05051

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0002	-0.0001	-0.0001	-0.0001	-0.0001
	(0.8403)	(0.8649)	(0.8634)	(0.8682)	(0.9175)
S&P	0.0768				-0.1176
	(0.1644)				(0.1492)
BY		0.0085			0.0010
		(0.7337)			(0.9693)
CO			-0.0386		**-0.0580**
			(0.0977)		(0.0187)
VIX				**-0.0333**	**-0.0525**
				(0.0036)	(0.0018)
Adj. R^2	0.00018	-0.00024	0.00025	0.00286	0.00398

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0001	-0.0001	-0.0001	-0.0002
	(0.9538)	(0.8579)	(0.9224)	(0.8459)	(0.8203)
S&P	**-0.5362**				0.1191
	(0.0000)				(0.2426)
BY		**-0.1142**			-0.0204
		(0.0008)			(0.5097)
CO			**-0.1073**		-0.0219
			(0.0017)		(0.5055)
VIX				**0.1301**	**0.1406**
				(0.0000)	(0.0000)
Adj. R^2	0.02157	0.00462	0.00369	0.04737	0.04727

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0001	-0.0001	-0.0001	0.0000
	(0.9870)	(0.9575)	(0.9740)	(0.9638)	(0.9869)
S&P	-0.0600				-0.0618
	(0.6891)				(0.6866)
BY		-0.0120			0.0230
		(0.8138)			(0.6821)
CO			**-0.1301**		**-0.1398**
			(0.0084)		(0.0098)
VIX				-0.0036	-0.0193
				(0.8215)	(0.4136)
Adj. R^2	-0.00095	-0.00140	0.00877	-0.00141	0.00591

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0006	-0.0001	-0.0001	-0.0001	0.0004
	(0.7841)	(0.9822)	(0.9821)	(0.9637)	(0.8667)
S&P	**-0.5386**				-0.2560
	(0.0024)				(0.2789)
BY		0.0070			**0.1408**
		(0.8902)			(0.0137)
CO			-0.0414		0.0284
			(0.6026)		(0.7062)
VIX				**0.1032**	**0.0901**
				(0.0000)	(0.0049)
Adj. R^2	0.04154	-0.00146	-0.00044	0.05902	0.06750

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0006	-0.0007	-0.0006	-0.0006	-0.0007
	(0.7041)	(0.6466)	(0.7138)	(0.6822)	(0.6445)
S&P	-0.0293				0.0626
	(0.6273)				(0.4828)
BY		**-0.0694**			**-0.0614**
		(0.0088)			(0.0289)
CO			**-0.0968**		**-0.0975**
			(0.0006)		(0.0014)
VIX				0.0029	-0.0064
				(0.7752)	(0.6532)
Adj. R^2	-0.00097	0.00743	0.01367	-0.00117	0.01685

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0007	-0.0006	-0.0007	-0.0004
	(0.9885)	(0.6564)	(0.7203)	(0.6356)	(0.8231)
S&P	**-0.4218**				-0.2188
	(0.0009)				(0.2081)
BY		**-0.0645**			0.0027
		(0.0150)			(0.9505)
CO			-0.0838		-0.0098
			(0.0759)		(0.7865)
VIX				**0.0720**	**0.0454**
				(0.0001)	(0.0334)
Adj. R^2	0.06071	0.00624	0.00991	0.06498	0.07010

Table A11: Regression results for the correlation pair *Energy* - *IT*

This table presents the results of regression models (21) - (24) for the correlation pair *Energy* - *IT*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	0.0000	0.0000	0.0000	0.0000
	(0.9424)	(0.9634)	(0.9666)	(0.9694)	(0.9912)
S&P	0.1078				-0.1583
	(0.1289)				(0.1499)
BY		-0.0162			-0.0628
		(0.6842)			(0.1538)
CO			0.0283		0.0206
			(0.4376)		(0.6003)
VIX				**-0.0410**	**-0.0641**
				(0.0003)	(0.0001)
Adj. R^2	0.00040	-0.00026	-0.00012	0.00370	0.00433

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0001	0.0000	0.0000	0.0000	-0.0001
	(0.8914)	(0.9768)	(0.9837)	(0.9966)	(0.9092)
S&P	**-0.4198**				**0.3821**
	(0.0000)				(0.0015)
BY		**-0.1405**			-0.0134
		(0.0004)			(0.7881)
CO			**-0.1399**		-0.0719
			(0.0001)		(0.1554)
VIX				**0.1229**	**0.1612**
				(0.0000)	(0.0000)
Adj. R^2	0.01043	0.00352	0.00421	0.03575	0.03901

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0002	-0.0001	-0.0002	-0.0001	-0.0001
	(0.7784)	(0.8355)	(0.8253)	(0.8314)	(0.8630)
S&P	0.1277				-0.1048
	(0.2038)				(0.3988)
BY		0.0548			0.0352
		(0.2369)			(0.4683)
CO			0.0400		0.0168
			(0.3155)		(0.6813)
VIX				-0.0355	-0.0432
				(0.1301)	(0.1717)
Adj. R^2	0.00021	0.00017	-0.00005	0.00109	0.00058

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0001	-0.0001	0.0000	-0.0002	-0.0002
	(0.9282)	(0.8362)	(0.9500)	(0.8249)	(0.7134)
S&P	**-0.5886**				**0.4140**
	(0.0000)				(0.0053)
BY		**-0.1582**			-0.0514
		(0.0012)			(0.2904)
CO			**-0.1771**		-0.0840
			(0.0011)		(0.1027)
VIX				**0.1661**	**0.2035**
				(0.0000)	(0.0000)
Adj. R^2	0.00977	0.00331	0.00385	0.02935	0.03134

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	-0.0001	-0.0001	0.0001
	(0.9888)	(0.9839)	(0.9781)	(0.9670)	(0.9620)
S&P	-0.1022				-0.0504
	(0.4770)				(0.8226)
BY		0.0298			0.0813
		(0.5386)			(0.1472)
CO			**-0.1039**		**-0.1144**
			(0.0270)		(0.0155)
VIX				0.0124	0.0061
				(0.4213)	(0.8274)
Adj. R^2	0.00023	-0.00092	0.00575	-0.00052	0.00491

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0004	-0.0001	0.0000	0.0000	0.0002
	(0.8482)	(0.9705)	(0.9996)	(0.9856)	(0.9273)
S&P	**-0.3750**				-0.1591
	(0.0001)				(0.3479)
BY		-0.0526			0.0345
		(0.2782)			(0.4935)
CO			-0.0636		-0.0072
			(0.3557)		(0.9186)
VIX				**0.0680**	0.0523
				(0.0021)	(0.0879)
Adj. R^2	0.02158	0.00026	0.00122	0.02756	0.02549

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0003	-0.0005	-0.0004	-0.0005	-0.0003
	(0.9363)	(0.7903)	(0.8510)	(0.8197)	(0.9023)
S&P	-0.1132				-0.0938
	(0.4941)				(0.7120)
BY		-0.0495			-0.0280
		(0.6439)			(0.8263)
CO			**-0.1188**		**-0.1123**
			(0.0405)		(0.0497)
VIX				0.0052	-0.0204
				(0.8542)	(0.6153)
Adj. R^2	-0.00044	-0.00044	0.00293	-0.00121	-0.00021

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0004	-0.0005	-0.0003	-0.0005	-0.0001
	(0.8747)	(0.8246)	(0.8842)	(0.8265)	(0.9720)
S&P	**-0.5118**				-0.2844
	(0.0056)				(0.1847)
BY		-0.0954			-0.0222
		(0.1946)			(0.7716)
CO			-0.0581		0.0423
			(0.4275)		(0.5455)
VIX				**0.0883**	0.0564
				(0.0102)	(0.1890)
Adj. R^2	0.01580	0.00180	-0.00026	0.01735	0.01636

Table A12: Regression results for the correlation pair *Energy - Utilities*

This table presents the results of regression models (21) - (24) for the correlation pair *Energy - Utilities*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0002	-0.0001	-0.0001	-0.0001	-0.0001
	(0.7815)	(0.8211)	(0.8117)	(0.8118)	(0.8280)
S&P	0.0893				-0.0159
	(0.0703)				(0.8326)
BY		0.0303			0.0208
		(0.2601)			(0.5061)
CO			-0.0382		**-0.0639**
			(0.1317)		(0.0149)
VIX				**-0.0236**	-0.0285
				(0.0027)	(0.0793)
Adj. R^2	0.00070	0.00006	0.00039	0.00245	0.00334

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0002	-0.0001	-0.0002	-0.0002
	(0.9020)	(0.7761)	(0.8119)	(0.7998)	(0.7523)
S&P	**-0.2827**				0.1223
	(0.0000)				(0.1522)
BY		**-0.0945**			-0.0211
		(0.0006)			(0.6023)
CO			-0.0636		-0.0124
			(0.0715)		(0.7319)
VIX				**0.0711**	**0.0826**
				(0.0000)	(0.0001)
Adj. R^2	0.00975	0.00327	0.00162	0.02462	0.02458

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0002	-0.0001	-0.0001	-0.0001	-0.0001
	(0.7794)	(0.8297)	(0.8314)	(0.8271)	(0.8682)
S&P	**0.1024**				-0.0245
	(0.0257)				(0.7084)
BY		0.0368			0.0309
		(0.0751)			(0.1919)
CO			-0.0420		**-0.0692**
			(0.0521)		(0.0009)
VIX				**-0.0276**	**-0.0333**
				(0.0002)	(0.0244)
Adj. R^2	0.00104	0.00057	0.00073	0.00326	0.00523

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0002	-0.0001	-0.0002	-0.0002
	(0.9444)	(0.7931)	(0.8482)	(0.7871)	(0.7427)
S&P	**-0.3264**				0.1253
	(0.0000)				(0.0980)
BY		**-0.0838**			-0.0260
		(0.0001)			(0.2963)
CO			**-0.0836**		-0.0317
			(0.0033)		(0.2354)
VIX				**0.0822**	**0.0919**
				(0.0000)	(0.0000)
Adj. R^2	0.01299	0.00404	0.00367	0.03088	0.03151

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0004	-0.0004	-0.0004	-0.0004	-0.0003
	(0.8619)	(0.8524)	(0.8533)	(0.8480)	(0.8936)
S&P	-0.0302				-0.0461
	(0.7157)				(0.7173)
BY		0.0084			0.0275
		(0.8424)			(0.5557)
CO			-0.0594		-0.0664
			(0.1471)		(0.1396)
VIX				-0.0022	-0.0098
				(0.8713)	(0.6165)
Adj. R^2	-0.00128	-0.00142	0.00164	-0.00144	-0.00178

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0005	-0.0004	-0.0004	-0.0001
	(0.9904)	(0.8099)	(0.8541)	(0.8379)	(0.9538)
S&P	**-0.3063**				-0.2149
	(0.0002)				(0.0992)
BY		-0.0665			0.0049
		(0.1155)			(0.9331)
CO			**-0.1061**		-0.0610
			(0.0095)		(0.1851)
VIX				**0.0407**	0.0112
				(0.0023)	(0.6637)
Adj. R^2	0.01879	0.00219	0.00846	0.01222	0.01759

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0005	-0.0007	-0.0005	-0.0005	-0.0007
	(0.7310)	(0.6404)	(0.7476)	(0.7293)	(0.6145)
S&P	-0.0054				0.0545
	(0.9272)				(0.6505)
BY		-0.1269			-0.1365
		(0.2348)			(0.2426)
CO			**-0.0631**		**-0.0530**
			(0.0227)		(0.0487)
VIX				-0.0039	-0.0179
				(0.6913)	(0.1716)
Adj. R^2	-0.00126	0.02892	0.00532	-0.00107	0.03387

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0006	-0.0005	-0.0006	-0.0003
	(0.9783)	(0.6628)	(0.7642)	(0.6850)	(0.8567)
S&P	**-0.3495**				**-0.2119**
	(0.0313)				(0.0235)
BY		-0.0951			-0.0430
		(0.1638)			(0.3565)
CO			**-0.1120**		-0.0525
			(0.0424)		(0.0708)
VIX				0.0504	0.0152
				(0.0946)	(0.5166)
Adj. R^2	0.04289	0.01569	0.01949	0.03241	0.04946

Table A13: Regression results for the correlation pair *Financials - Health Care*

This table presents the results of regression models (21) - (24) for the correlation pair *Financials - Health Care*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9558)	(0.9551)	(0.9612)	(0.9610)	(0.9800)
S&P	0.0180				-0.0977
	(0.7965)				(0.3660)
BY		-0.0197			-0.0247
		(0.6134)			(0.5679)
CO			-0.0410		-0.0459
			(0.2523)		(0.2340)
VIX				-0.0177	**-0.0351**
				(0.1124)	(0.0341)
Adj. R^2	-0.00029	-0.00023	0.00010	0.00047	0.00075

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0001	-0.0001	0.0000	0.0000	-0.0001
	(0.8913)	(0.9180)	(0.9724)	(0.9558)	(0.8850)
S&P	**-0.5912**				**0.2396**
	(0.0000)				(0.0483)
BY		**-0.1968**			-0.0429
		(0.0000)			(0.4194)
CO			**-0.1362**		-0.0299
			(0.0001)		(0.4386)
VIX				**0.1469**	**0.1688**
				(0.0000)	(0.0000)
Adj. R^2	0.02174	0.00747	0.00413	0.05304	0.05386

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9960)	(0.9972)	(0.9996)	(0.9910)	(0.9563)
S&P	0.0299				-0.1257
	(0.6353)				(0.1592)
BY		-0.0066			-0.0093
		(0.8147)			(0.7653)
CO			-0.0311		-0.0402
			(0.2621)		(0.1622)
VIX				-0.0233	**-0.0431**
				(0.0640)	(0.0132)
Adj. R^2	-0.00021	-0.00025	-0.00002	0.00087	0.00118

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0002	0.0000	0.0000	0.0000	-0.0001
	(0.8253)	(0.9821)	(0.9589)	(0.9717)	(0.8854)
S&P	**-0.6125**				**0.2995**
	(0.0000)				(0.0055)
BY		**-0.1392**			-0.0286
		(0.0011)			(0.5007)
CO			**-0.1400**		-0.0429
			(0.0000)		(0.1503)
VIX				**0.1635**	**0.1929**
				(0.0000)	(0.0000)
Adj. R^2	0.02080	0.00510	0.00472	0.05537	0.05695

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0002	-0.0001	-0.0001	-0.0001	0.0003
	(0.9324)	(0.9778)	(0.9476)	(0.9483)	(0.9034)
S&P	0.0256				-0.2152
	(0.8746)				(0.3997)
BY		0.0613			0.0670
		(0.1467)			(0.2467)
CO			-0.0477		-0.0680
			(0.2447)		(0.1835)
VIX				**-0.0301**	**-0.0536**
				(0.0244)	(0.0413)
Adj. R^2	-0.00134	0.00164	0.00053	0.00602	0.01257

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0004	-0.0003	-0.0001	-0.0002	0.0001
	(0.8270)	(0.9000)	(0.9534)	(0.9272)	(0.9477)
S&P	**-0.4821**				-0.2061
	(0.0005)				(0.4602)
BY		-0.0807			0.0336
		(0.0563)			(0.5620)
CO			-0.1098		-0.0390
			(0.0530)		(0.4191)
VIX				**0.0841**	**0.0604**
				(0.0000)	(0.0399)
Adj. R^2	0.04860	0.00392	0.00914	0.05693	0.05921

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0004	-0.0004	-0.0003	-0.0003	-0.0003
	(0.7656)	(0.7917)	(0.8227)	(0.8184)	(0.8392)
S&P	0.0492				-0.0100
	(0.3453)				(0.8968)
BY		-0.0212			-0.0296
		(0.3537)			(0.2234)
CO			-0.0443		**-0.0588**
			(0.0690)		(0.0255)
VIX				**-0.0186**	**-0.0291**
				(0.0300)	(0.0187)
Adj. R^2	-0.00014	-0.00018	0.00293	0.00470	0.01115

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0002	-0.0004	-0.0003	-0.0004	-0.0002
	(0.9018)	(0.7511)	(0.8405)	(0.7546)	(0.8922)
S&P	**-0.3467**				-0.1390
	(0.0009)				(0.3620)
BY		**-0.0804**			-0.0251
		(0.0004)			(0.5318)
CO			**-0.0915**		-0.0302
			(0.0002)		(0.2435)
VIX				**0.0606**	**0.0383**
				(0.0000)	(0.0218)
Adj. R^2	0.05506	0.01445	0.01669	0.06185	0.06849

Table A14: Regression results for the correlation pair *Financials - IT*

This table presents the results of regression models (21) - (24) for the correlation pair *Financials - IT*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9581)	(0.9948)	(0.9862)	(0.9874)	(0.9959)
S&P	0.1077				-0.0188
	(0.2576)				(0.9048)
BY		0.0297			0.0090
		(0.5858)			(0.8831)
CO			-0.0114		-0.0355
			(0.8186)		(0.5242)
VIX				-0.0268	-0.0309
				(0.1858)	(0.3262)
Adj. R^2	0.00002	-0.00023	-0.00029	0.00048	-0.00030

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0002	0.0000	0.0000	0.0000	-0.0001
	(0.8274)	(0.9549)	(0.9820)	(0.9982)	(0.9172)
S&P	**-0.6389**				0.2967
	(0.0000)				(0.0831)
BY		**-0.2192**			-0.0676
		(0.0020)			(0.3700)
CO			-0.0803		0.0466
			(0.1273)		(0.3954)
VIX				**0.1661**	**0.1984**
				(0.0000)	(0.0000)
Adj. R^2	0.01115	0.00399	0.00038	0.03005	0.03067

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	0.0000	0.0000	0.0000	0.0001
	(0.9314)	(0.9946)	(0.9597)	(0.9798)	(0.9345)
S&P	0.1254				-0.2085
	(0.2024)				(0.1260)
BY		**0.1105**			**0.1049**
		(0.0370)			(0.0495)
CO			0.0153		-0.0204
			(0.7089)		(0.6324)
VIX				-0.0424	-0.0585
				(0.0533)	(0.0514)
Adj. R^2	0.00018	0.00141	-0.00023	0.00159	0.00235

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0002	-0.0001	0.0000	-0.0001	-0.0002
	(0.8118)	(0.9445)	(0.9756)	(0.9394)	(0.7536)
S&P	**-0.6773**				**0.5113**
	(0.0000)				(0.0015)
BY		**-0.2234**			-0.1188
		(0.0004)			(0.0520)
CO			**-0.1199**		0.0046
			(0.0336)		(0.9251)
VIX				**0.1959**	**0.2455**
				(0.0000)	(0.0000)
Adj. R^2	0.01251	0.00659	0.00155	0.03931	0.04255

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	-0.0001	-0.0001	0.0003
	(0.9960)	(0.9882)	(0.9627)	(0.9584)	(0.8766)
S&P	-0.0925				-0.2314
	(0.5778)				(0.3676)
BY		0.0505			0.0825
		(0.2079)			(0.1470)
CO			-0.0457		-0.0469
			(0.3493)		(0.2155)
VIX				-0.0029	-0.0251
				(0.8167)	(0.3488)
Adj. R^2	0.00057	0.00087	0.00057	-0.00140	0.00585

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0004	-0.0003	-0.0001	-0.0001	0.0002
	(0.8150)	(0.8922)	(0.9674)	(0.9483)	(0.9273)
S&P	**-0.4413**				-0.2763
	(0.0000)				(0.1105)
BY		**-0.1196**			-0.0379
		(0.0028)			(0.4277)
CO			-0.0679		0.0168
			(0.0814)		(0.6659)
VIX				**0.0684**	0.0332
				(0.0000)	(0.2153)
Adj. R^2	0.04514	0.01170	0.00302	0.04142	0.04738

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0002	-0.0003	-0.0002	-0.0002	0.0001
	(0.9150)	(0.9050)	(0.9133)	(0.9175)	(0.9691)
S&P	-0.0109				-0.2016
	(0.9453)				(0.4018)
BY		-0.0064			-0.0127
		(0.8688)			(0.8248)
CO			-0.0244		-0.0282
			(0.5535)		(0.4610)
VIX				-0.0230	-0.0511
				(0.1138)	(0.0669)
Adj. R^2	-0.00125	-0.00124	-0.00082	0.00191	0.00295

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0005	-0.0004	-0.0002	-0.0004	0.0001
	(0.8304)	(0.8668)	(0.9307)	(0.8681)	(0.9795)
S&P	**-0.5205**				-0.2961
	(0.0000)				(0.0688)
BY		**-0.1060**			-0.0302
		(0.0060)			(0.5447)
CO			**-0.0886**		0.0094
			(0.0312)		(0.8082)
VIX				**0.0859**	0.0485
				(0.0000)	(0.0761)
Adj. R^2	0.04326	0.00830	0.00463	0.04324	0.04765

Table A15: Regression results for the correlation pair *Financials - Utilities*

This table presents the results of regression models (21) - (24) for the correlation pair *Financials - Utilities*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0002	-0.0001	-0.0001	-0.0001	-0.0001
	(0.7994)	(0.8463)	(0.8333)	(0.8356)	(0.8751)
S&P	**0.1055**				-0.1059
	(0.0325)				(0.1660)
BY		0.0363			0.0094
		(0.1896)			(0.7597)
CO			0.0114		-0.0097
			(0.6524)		(0.7234)
VIX				**-0.0332**	**-0.0456**
				(0.0000)	(0.0001)
Adj. R^2	0.00109	0.00022	-0.00024	0.00513	0.00492

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0002	-0.0001	-0.0001	-0.0002
	(0.9541)	(0.7661)	(0.8372)	(0.8216)	(0.7373)
S&P	**-0.3670**				0.1457
	(0.0000)				(0.1934)
BY		**-0.1919**			**-0.1114**
		(0.0002)			(0.0406)
CO			**-0.0963**		-0.0178
			(0.0001)		(0.5260)
VIX				**0.0862**	**0.0915**
				(0.0000)	(0.0007)
Adj. R^2	0.01662	0.01441	0.00411	0.03628	0.04028

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	0.0000	0.0000	0.0000	0.0000
	(0.9223)	(0.9689)	(0.9621)	(0.9701)	(0.9652)
S&P	**0.1007**				-0.1234
	(0.0405)				(0.1027)
BY		0.0327			0.0205
		(0.1397)			(0.3962)
CO			-0.0073		-0.0296
			(0.7517)		(0.2278)
VIX				**-0.0358**	**-0.0510**
				(0.0000)	(0.0000)
Adj. R^2	0.00084	0.00031	-0.00024	0.00488	0.00541

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0001	-0.0001	0.0000	-0.0001	-0.0001
	(0.8924)	(0.9189)	(0.9983)	(0.9255)	(0.8532)
S&P	**-0.4047**				0.1943
	(0.0000)				(0.0529)
BY		**-0.1441**			**-0.0792**
		(0.0000)			(0.0215)
CO			**-0.1112**		-0.0413
			(0.0000)		(0.0746)
VIX				**0.1020**	**0.1136**
				(0.0000)	(0.0000)
Adj. R^2	0.01748	0.01084	0.00580	0.04151	0.04537

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0004	-0.0004	-0.0004	-0.0004	-0.0003
	(0.5559)	(0.5401)	(0.5421)	(0.5403)	(0.6215)
S&P	-0.0139				-0.0545
	(0.6127)				(0.1969)
BY		0.0007			0.0041
		(0.9599)			(0.7899)
CO			-0.0140		-0.0130
			(0.3053)		(0.3820)
VIX				-0.0035	-0.0105
				(0.4349)	(0.1092)
Adj. R^2	-0.00110	-0.00148	0.00008	-0.00058	-0.00024

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0002	-0.0005	-0.0004	-0.0004	-0.0003
	(0.7680)	(0.4693)	(0.5477)	(0.5257)	(0.7151)
S&P	**-0.1798**				-0.1586
	(0.0000)				(0.1107)
BY		**-0.0608**			-0.0328
		(0.0290)			(0.2971)
CO			**-0.0294**		0.0092
			(0.0309)		(0.5766)
VIX				**0.0223**	0.0009
				(0.0000)	(0.9383)
Adj. R^2	0.06178	0.02637	0.00542	0.03573	0.06452

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0002	-0.0001	-0.0001	-0.0002
	(0.8795)	(0.7818)	(0.9010)	(0.8871)	(0.7684)
S&P	0.0017				0.0201
	(0.9566)				(0.8086)
BY		-0.0799			-0.0888
		(0.2516)			(0.2450)
CO			**-0.0294**		-0.0222
			(0.0489)		(0.1135)
VIX				-0.0045	**-0.0142**
				(0.3943)	(0.0441)
Adj. R^2	-0.00127	0.04006	0.00366	-0.00035	0.04769

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0002	-0.0002	-0.0001	-0.0002	0.0000
	(0.7973)	(0.7872)	(0.9244)	(0.8313)	(0.9781)
S&P	**-0.2465**				-0.1458
	(0.0213)				(0.0581)
BY		-0.0801			-0.0474
		(0.0755)			(0.1280)
CO			-0.0592		-0.0113
			(0.0922)		(0.5040)
VIX				0.0371	0.0135
				(0.0563)	(0.3747)
Adj. R^2	0.07454	0.04022	0.01873	0.06176	0.09137

Table A16: Regression results for the correlation pair *Health Care - IT*

This table presents the results of regression models (21) - (24) for the correlation pair *Health Care - IT*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0001
	(0.9836)	(0.9809)	(0.9993)	(0.9962)	(0.9249)
S&P	0.0756				**-0.2422**
	(0.2417)				(0.0232)
BY		0.0682			0.0460
		(0.0717)			(0.3114)
CO			0.0392		0.0210
			(0.2748)		(0.5858)
VIX				**-0.0362**	**-0.0588**
				(0.0027)	(0.0022)
Adj. R^2	0.00004	0.00060	0.00005	0.00282	0.00354

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0001	-0.0001	0.0000	0.0000	-0.0001
	(0.8964)	(0.9533)	(0.9989)	(0.9851)	(0.8752)
S&P	**-0.4662**				**0.3995**
	(0.0000)				(0.0009)
BY		**-0.1671**			-0.0400
		(0.0004)			(0.4231)
CO			**-0.1087**		-0.0233
			(0.0016)		(0.5040)
VIX				**0.1361**	**0.1777**
				(0.0000)	(0.0000)
Adj. R^2	0.01295	0.00511	0.00242	0.04397	0.04715

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0002
	(0.9963)	(0.9568)	(0.9818)	(0.9687)	(0.8425)
S&P	0.0640				**-0.3469**
	(0.3122)				(0.0016)
BY		**0.0963**			**0.0969**
		(0.0055)			(0.0176)
CO			0.0245		0.0007
			(0.3834)		(0.9827)
VIX				**-0.0425**	**-0.0740**
				(0.0002)	(0.0000)
Adj. R^2	-0.00001	0.00251	-0.00010	0.00379	0.00746

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0002	0.0000	0.0000	0.0000	-0.0001
	(0.8506)	(0.9929)	(0.9637)	(0.9818)	(0.8702)
S&P	**-0.4770**				**0.3353**
	(0.0000)				(0.0011)
BY		**-0.1095**			-0.0235
		(0.0017)			(0.4715)
CO			**-0.1015**		-0.0241
			(0.0003)		(0.3356)
VIX				**0.1383**	**0.1741**
				(0.0000)	(0.0000)
Adj. R^2	0.01354	0.00332	0.00257	0.04273	0.04489

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9496)	(0.9769)	(0.9908)	(0.9874)	(0.9874)
S&P	0.0264				0.0185
	(0.5078)				(0.7589)
BY		0.0217			0.0251
		(0.1183)			(0.0998)
CO			-0.0189		**-0.0317**
			(0.1955)		(0.0333)
VIX				-0.0052	-0.0028
				(0.3658)	(0.7593)
Adj. R^2	-0.00030	0.00158	0.00100	0.00026	0.00356

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0001	-0.0001	0.0000	0.0000	-0.0001
	(0.8479)	(0.9287)	(0.9908)	(0.9671)	(0.8949)
S&P	**-0.1214**				0.0602
	(0.0025)				(0.3184)
BY		-0.0302			0.0044
		(0.0813)			(0.7894)
CO			**-0.0365**		-0.0212
			(0.0454)		(0.2530)
VIX				**0.0317**	**0.0376**
				(0.0000)	(0.0000)
Adj. R^2	0.02345	0.00444	0.00774	0.06367	0.06375

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	0.0000	0.0000	0.0000	-0.0001
	(0.9370)	(0.9919)	(0.9788)	(0.9785)	(0.9493)
S&P	0.0685				0.0589
	(0.1885)				(0.4747)
BY		-0.0220			-0.0336
		(0.5365)			(0.3876)
CO			-0.0180		-0.0304
			(0.3562)		(0.1428)
VIX				-0.0133	-0.0132
				(0.0789)	(0.2631)
Adj. R^2	0.00183	0.00039	-0.00030	0.00304	0.00605

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0004	0.0000	0.0001	-0.0001	0.0000
	(0.7579)	(0.9940)	(0.9551)	(0.9559)	(0.9819)
S&P	**-0.2413**				0.0144
	(0.0003)				(0.8399)
BY		-0.0159			0.0348
		(0.5141)			(0.1138)
CO			**-0.0668**		-0.0298
			(0.0112)		(0.1847)
VIX				**0.0566**	**0.0591**
				(0.0000)	(0.0000)
Adj. R^2	0.03720	-0.00041	0.01222	0.07641	0.07817

Table A17: Regression results for the correlation pair *Health Care - Utilities*

This table presents the results of regression models (21) - (24) for the correlation pair *Health Care - Utilities*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	0.0000	-0.0001	-0.0001	0.0000
	(0.9213)	(0.9569)	(0.9373)	(0.9386)	(0.9690)
S&P	0.0652				-0.0436
	(0.2299)				(0.6212)
BY		**0.0725**			0.0700
		(0.0231)			(0.0678)
CO			0.0043		-0.0196
			(0.8800)		(0.5328)
VIX				-0.0157	-0.0157
				(0.1543)	(0.3437)
Adj. R^2	0.00001	0.00094	-0.00030	0.00041	0.00046

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0001	-0.0001	-0.0001	-0.0001
	(0.9766)	(0.9048)	(0.9484)	(0.9405)	(0.8862)
S&P	**-0.3055**				0.1122
	(0.0004)				(0.3566)
BY		**-0.1560**			-0.0948
		(0.0054)			(0.1176)
CO			-0.0510		0.0183
			(0.1105)		(0.6010)
VIX				**0.0728**	**0.0785**
				(0.0003)	(0.0066)
Adj. R^2	0.00664	0.00546	0.00043	0.01516	0.01616

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0001
	(0.9998)	(0.9816)	(0.9845)	(0.9858)	(0.9391)
S&P	0.0288				-0.0809
	(0.5180)				(0.2295)
BY		0.0295			0.0314
		(0.1269)			(0.1431)
CO			-0.0151		-0.0267
			(0.4094)		(0.1742)
VIX				-0.0141	-0.0228
				(0.1263)	(0.0819)
Adj. R^2	-0.00018	0.00018	-0.00016	0.00050	0.00061

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0001	0.0000	0.0000	0.0000	0.0000
	(0.8768)	(0.9948)	(0.9503)	(0.9935)	(0.9529)
S&P	**-0.3058**				0.1302
	(0.0000)				(0.1500)
BY		**-0.0852**			-0.0350
		(0.0080)			(0.2962)
CO			**-0.0652**		-0.0132
			(0.0049)		(0.5486)
VIX				**0.0788**	**0.0898**
				(0.0000)	(0.0000)
Adj. R^2	0.00947	0.00346	0.00174	0.02372	0.02410

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0003	-0.0002	-0.0002	-0.0002	-0.0002
	(0.5666)	(0.5986)	(0.5938)	(0.5911)	(0.5939)
S&P	0.0125				0.0018
	(0.5042)				(0.9696)
BY		0.0044			0.0052
		(0.6420)			(0.6130)
CO			-0.0140		-0.0193
			(0.1495)		(0.1436)
VIX				-0.0039	-0.0047
				(0.1942)	(0.4096)
Adj. R^2	-0.00082	-0.00116	0.00192	0.00102	0.00219

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0003	-0.0002	-0.0002	-0.0001
	(0.8145)	(0.5786)	(0.6051)	(0.5878)	(0.8818)
S&P	-0.1064				-0.1256
	(0.0635)				(0.1658)
BY		-0.0119			0.0083
		(0.3321)			(0.6753)
CO			-0.0151		0.0031
			(0.3852)		(0.7960)
VIX				**0.0112**	-0.0024
				(0.0378)	(0.7612)
Adj. R^2	0.04648	0.00083	0.00248	0.01900	0.04404

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0001	0.0001	0.0000
	(0.9514)	(0.9893)	(0.8954)	(0.9075)	(0.9385)
S&P	0.0157				0.0352
	(0.4004)				(0.4471)
BY		-0.0410			-0.0470
		(0.2990)			(0.2756)
CO			-0.0165		-0.0157
			(0.0579)		(0.0953)
VIX				-0.0033	-0.0059
				(0.2784)	(0.1585)
Adj. R^2	-0.00037	0.03070	0.00330	0.00022	0.04069

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0002	0.0000	0.0001	0.0000	0.0002
	(0.6421)	(0.9578)	(0.8726)	(0.9429)	(0.7046)
S&P	**-0.1339**				-0.1002
	(0.0425)				(0.0976)
BY		-0.0280			-0.0089
		(0.2528)			(0.6028)
CO			-0.0313		-0.0078
			(0.1379)		(0.4585)
VIX				0.0185	0.0049
				(0.0900)	(0.5768)
Adj. R^2	0.06437	0.01365	0.01512	0.04487	0.06533

Table A18: Regression results for the correlation pair *IT* - *Utilities*

This table presents the results of regression models (21) - (24) for the correlation pair *IT - Utilities*. In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A, C, E, and G) or $t-1$ (Panels B, D, F, and H). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0001	-0.0001	-0.0001	-0.0001	0.0000
	(0.8760)	(0.9235)	(0.9094)	(0.9108)	(0.9443)
S&P	**0.0889**				-0.0615
	(0.0439)				(0.3682)
BY		0.0369			0.0215
		(0.1354)			(0.4330)
CO			-0.0109		-0.0334
			(0.6292)		(0.1707)
VIX				**-0.0261**	**-0.0339**
				(0.0002)	(0.0012)
Adj. R^2	0.00094	0.00038	-0.00023	0.00389	0.00399

Panel B: daily data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0001	-0.0001	-0.0001	-0.0001
	(0.9954)	(0.8776)	(0.9218)	(0.9129)	(0.8478)
S&P	**-0.2268**				0.1027
	(0.0008)				(0.2044)
BY		**-0.1065**			-0.0603
		(0.0000)			(0.0923)
CO			-0.0271		0.0242
			(0.2312)		(0.3314)
VIX				**0.0572**	**0.0655**
				(0.0002)	(0.0028)
Adj. R^2	0.00778	0.00536	0.00013	0.01982	0.02100

Panel C: daily data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0001
	(0.9816)	(0.9734)	(0.9816)	(0.9783)	(0.8900)
S&P	0.0677				**-0.1262**
	(0.0979)				(0.0445)
BY		**0.0434**			**0.0415**
		(0.0183)			(0.0383)
CO			-0.0206		**-0.0414**
			(0.2845)		(0.0423)
VIX				**-0.0277**	**-0.0422**
				(0.0000)	(0.0000)
Adj. R^2	0.00046	0.00120	0.00004	0.00421	0.00642

Panel D: daily data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0001	0.0000	0.0000	0.0000	0.0000
	(0.8563)	(0.9952)	(0.9485)	(0.9929)	(0.9440)
S&P	**-0.2822**				0.1126
	(0.0000)				(0.1359)
BY		**-0.0754**			-0.0280
		(0.0000)			(0.2348)
CO			**-0.0615**		-0.0145
			(0.0049)		(0.4712)
VIX				**0.0721**	**0.0815**
				(0.0000)	(0.0000)
Adj. R^2	0.01223	0.00414	0.00242	0.02994	0.03040

Panel E: weekly data, 2007 - 2019

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002
	(0.5475)	(0.5134)	(0.5072)	(0.5030)	(0.6464)
S&P	-0.0198				**-0.0440**
	(0.1608)				(0.0418)
BY		0.0040			0.0100
		(0.5761)			(0.2076)
CO			-0.0120		-0.0111
			(0.0914)		(0.1444)
VIX				-0.0006	-0.0056
				(0.7985)	(0.0952)
Adj. R^2	0.00143	-0.00102	0.00291	-0.00138	0.00673

Panel F: weekly data, 2007 - 2019, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	-0.0002	-0.0002	-0.0002	-0.0002	-0.0001
	(0.6613)	(0.4940)	(0.5209)	(0.5095)	(0.6879)
S&P	**-0.0573**				**-0.0661**
	(0.0167)				(0.0252)
BY		-0.0092			0.0012
		(0.2033)			(0.8923)
CO			-0.0084		0.0020
			(0.3258)		(0.7819)
VIX				0.0061	-0.0014
				(0.0849)	(0.7117)
Adj. R^2	0.02297	0.00092	0.00065	0.00898	0.01905

Panel G: weekly data, 2007 - 2022

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	-0.0001	0.0000	0.0000	0.0000
	(0.9646)	(0.9574)	(0.9776)	(0.9931)	(0.9788)
S&P	-0.0263				-0.0304
	(0.4855)				(0.7048)
BY		-0.0508			-0.0521
		(0.3241)			(0.3599)
CO			-0.0309		-0.0239
			(0.0930)		(0.1405)
VIX				-0.0019	-0.0137
				(0.7568)	(0.1396)
Adj. R^2	-0.00065	0.01069	0.00265	-0.00115	0.01184

Panel H: weekly data, 2007 - 2022, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0003	0.0000	0.0001	0.0000	0.0002
	(0.7723)	(0.9956)	(0.9543)	(0.9916)	(0.8471)
S&P	**-0.1886**				**-0.1194**
	(0.0238)				(0.0267)
BY		-0.0285			0.0009
		(0.4024)			(0.9694)
CO			-0.0416		-0.0096
			(0.1517)		(0.5952)
VIX				0.0294	0.0143
				(0.0536)	(0.2536)
Adj. R^2	0.03055	0.00250	0.00580	0.02701	0.03051

Table A19: Regression results for the correlation pair *Energy - IT* (2007 - 2011)

This table presents the results of regression models (21) - (24) for the correlation pair *Energy - IT* from 2007 to 2011.[a] In these models, changes in the correlation in time t were regressed on log-returns of independent variables in time t (Panels A and C) or $t-1$ (Panels B and D). Columns (1) - (4) show the results of simple regression models. Column (5) contains the results of the multivariate regression. P-values, corrected (if necessary) for the effect of heteroskedasticity and/or autocorrelation, are in the brackets. Coefficients of regressors significant at least at 5% level are in bold.

Panel A: daily data, 2007 - 2011

	(1)	(2)	(3)	(4)	(5)
Const.	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.9718)	(0.9630)	(0.9825)	(0.9629)	(0.9639)
S&P	0.0738				-0.0685
	(0.1536)				(0.4245)
BY		0.0233			-0.0053
		(0.5317)			(0.8994)
CO			0.0100		-0.0045
			(0.7491)		(0.8961)
VIX				**-0.0297**	**-0.0426**
				(0.0102)	(0.0205)
Adj. R^2	0.00083	-0.00048	-0.00071	0.00445	0.00275

Panel B: daily data, 2007 - 2011, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0001	0.0000	0.0001	0.0000	0.0000
	(0.9411)	(0.9965)	(0.8944)	(0.9695)	(0.9747)
S&P	**-0.2278**				**0.3010**
	(0.0019)				(0.0158)
BY		**-0.1139**			-0.0235
		(0.0021)			(0.4851)
CO			**-0.0661**		-0.0192
			(0.0344)		(0.5357)
VIX				**0.0973**	**0.1449**
				(0.0001)	(0.0007)
Adj. R^2	0.01472	0.00672	0.00277	0.05601	0.06362

Panel C: weekly data, 2007 - 2011

	(1)	(2)	(3)	(4)	(5)
Const.	0.0003	0.0005	0.0006	0.0002	0.0010
	(0.9099)	(0.8472)	(0.8208)	(0.9266)	(0.6748)
S&P	-0.1243				0.0035
	(0.3102)				(0.9836)
BY		0.0392			**0.1556**
		(0.4573)			(0.0387)
CO			**-0.0916**		**-0.1169**
			(0.0249)		(0.0045)
VIX				**0.0345**	0.0443
				(0.0428)	(0.1004)
Adj. R^2	0.00670	-0.00173	0.01562	0.01204	0.03849

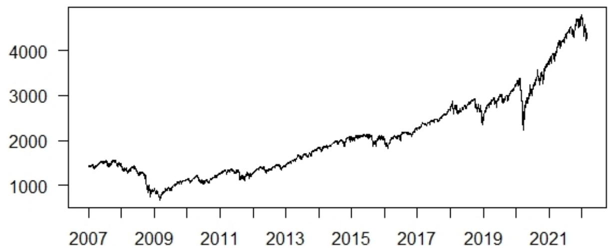
Panel D: weekly data, 2007 - 2011, forecasting

	(1)	(2)	(3)	(4)	(5)
Const.	0.0004	0.0004	0.0005	0.0004	0.0004
	(0.8767)	(0.8746)	(0.8331)	(0.8751)	(0.8585)
S&P	**-0.2072**				**-0.2498**
	(0.0058)				(0.0320)
BY		-0.0258			0.0384
		(0.6266)			(0.5359)
CO			-0.0188		0.0203
			(0.6462)		(0.6612)
VIX				0.0328	-0.0014
				(0.0546)	(0.9570)
Adj. R^2	0.02561	-0.00298	-0.00308	0.01050	0.01730

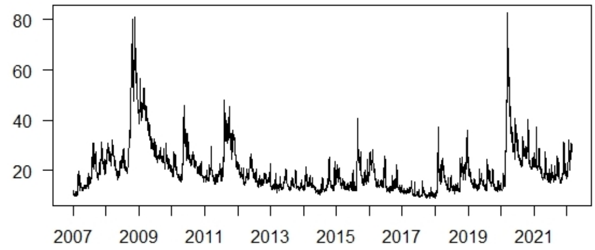
[a] The optimal models were as follows. ARMA(2,0)-eGARCH(2,1) for daily log-returns of *Energy*, ARMA(0,1)-eGARCH(2,1) for daily log-returns of *IT*, ARMA(1,1)-eGARCH(1,1) for weekly log-returns of *Energy*, ARMA(1,0)-eGARCH(1,1) for weekly log-returns of *IT*. The optimal DCC order was always (1,1).

Figure A1: Independent Variables

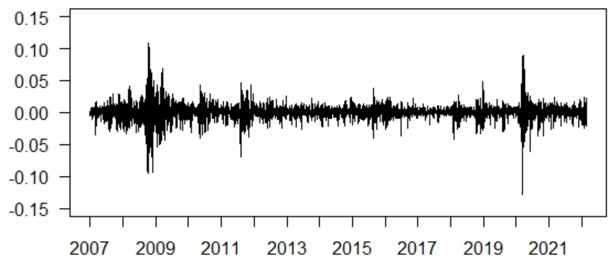
This figure shows values (prices) as well as daily log-returns of the following independent variables: S&P 500 Index, 10-year US Treasury Note yield, crude oil, and VIX. Subfigure (e) depicts the price drop into the negative territory on April 20, 2020. However, in subfigure (g), log-returns on April 20 and April 21, 2020 are replaced by median values (0.1%).



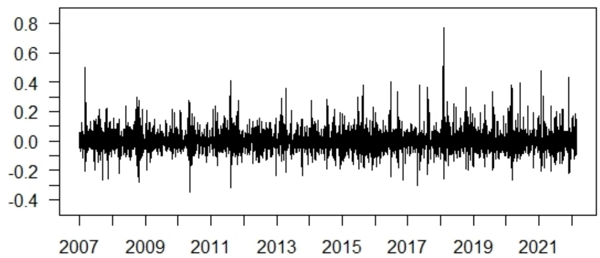
(a) S&P 500 Index - value



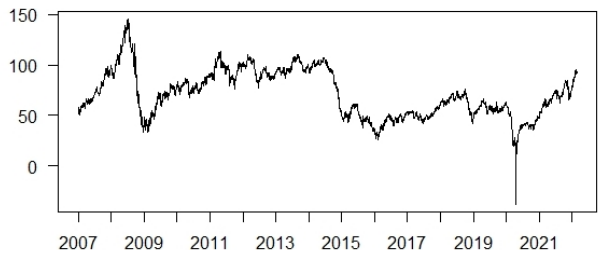
(b) VIX - value



(c) S&P 500 - log-returns

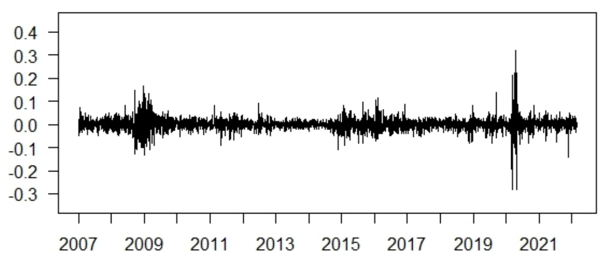


(d) VIX - log-returns

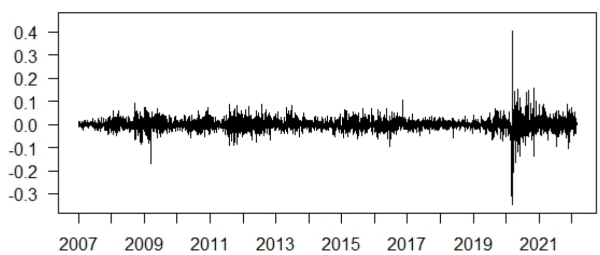


(e) Crude oil - price

(f) 10-year US T-Note yield



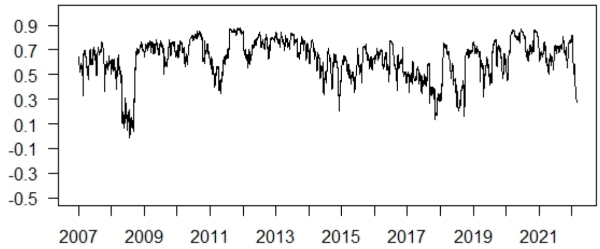
(g) Crude oil - log-returns



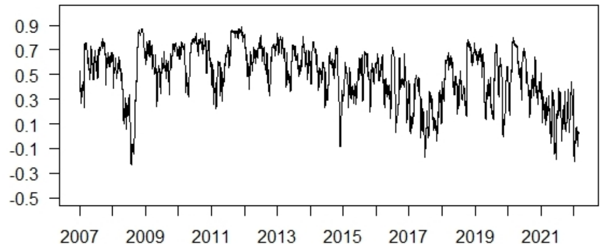
(h) 10-year US T-Note yield - log-returns

Figure A2: DCC of *Energy*

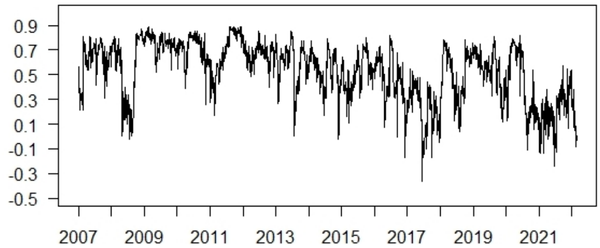
This figure shows the daily DCC values for correlation pairs between *Energy* and (a) *Financials*, (b) *Health Care*, (c) *IT*, (d) *Utilities*.



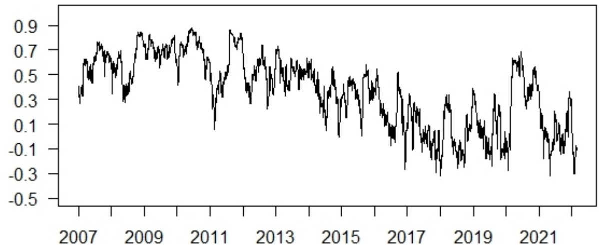
(a) *Financials*



(b) *Health Care*



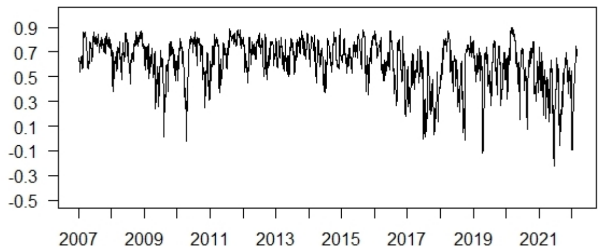
(c) *IT*



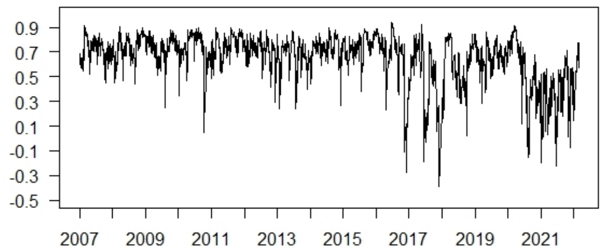
(d) *Utilities*

Figure A3: DCC of *Financials*

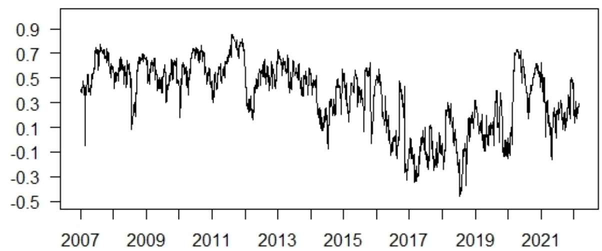
This figure shows the daily DCC values for correlation pairs between *Financials* and (a) *Health Care*, (b) *IT*, (c) *Utilities*.



(a) *Health Care*



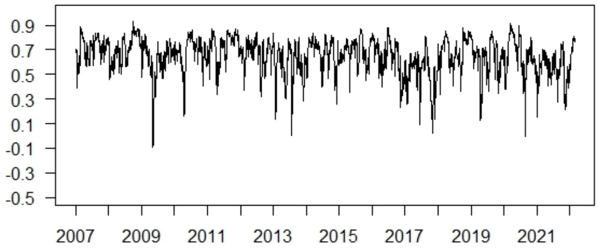
(b) *IT*



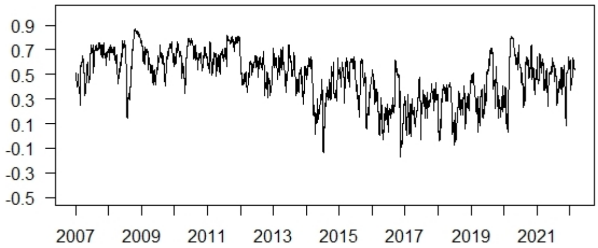
(c) *Utilities*

Figure A4: DCC of *Health Care*

This figure shows the daily DCC values for correlation pairs between *Health Care* and (a) *IT*, (b) *Utilities*.



(a) *IT*



(b) *Utilities*

Figure A5: DCC of *IT*

This figure shows the daily DCC values for the correlation pair *IT* - *Utilities*.