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Volatility spillovers between Cocoa Futures markets and selected currency pairs

Bachelor's thesis

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Declaration of Authorship

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Abstract

This thesis explores spillover dynamics between cocoa futures and currency pairs. Intercontinental Exchange U.S. and Intercontinental Exchange Europe cocoa futures contracts are both included in the analysis. United States dollar, British pound, and Swiss franc are selected as global currencies, and Ghanaian cedi is chosen as the currency of Ghana, a cocoa-dependent country. The empirical analysis covers a period from July 2007 to May 2024. Univariate GARCH modeling confirms that cocoa futures contracts have been experiencing unprecedented volatility in 2024. VAR-DCC-GARCH model is used to explore conditional correlations between the assets. The correlation between cocoa contracts is very strong, with occasional episodes of temporary decline. Conditional correlations between cocoa futures and currency pairs are weak and vary over time. Bivariate VAR-BEKK-GARCH models are applied to explore the presence of spillovers in mean, shocks, and volatility across assets. Additionally, the models are estimated for four subsample periods. The degree of spillover differs in full sample and subsample analysis and varies across individual periods. Notably, spillovers between cocoa futures and the currency pairs are the most widespread during the most volatile period covering the Great Financial Crisis and the European Sovereign Debt Crisis, confirming that spillover between the asset classes increases substantially in periods of financial stress.

JEL Classification	F12, F21, F23, H25, H71, H87
Keywords	volatility, spillover, cocoa futures, currency pairs

Title	Volatility spillovers between Cocoa Futures markets and selected currency pairs

Abstrakt

Tato práce se zabývá dynamikou přelévání mezi kakaovými futures a měnovými páry. Intercontinental Exchange U.S. a Intercontinental Exchange Europe kakaové futures kontrakty jsou zahrnuty v analýze. Americký dolar, britská libra a švýcarský frank jsou vybrány jakožto důležité globální měny a ghanský cedi jakožto měna Ghany, země závislé na exportu kakaa. Empirický výzkum je proveden pro období od července 2007 do května 2024. GARCH modely jedné proměnné potvrzují, že kakaové futures v roce 2024 zaznamenaly bezprecedentní úroveň volatility. VAR-DCC-GARCH model je použit pro studium podmíněných korelací mezi jednotlivými instrumenty. Korelace mezi kakaovými futures je velice silná až na výjimečná období náhlého poklesu. Podmíněné korelace mezi kakaovými futures a měnovými páry jsou velice slabé a proměnlivé v čase. VAR-BEKK-GARCH modely o dvou proměnných jsou aplikovány na studium výskytu přelévání ve střední hodnotě, šoku a volatilitě mezi jednotlivými instrumenty. Model je dále postupně aplikován na čtyři časové podintervaly. Míra přelévání v analýze celého intervalu se liší od analýz podintervalů, stejně tak jako se liší míra přelévání mezi jednotlivými podintervaly. Je pozoruhodné, že přelévání dosahuje nejvyšší intenzity v podintervalu zahrnujícím období finanční krize roku 2008 a počátečních fází krize eurozóny. Tento poznatek potvrzuje, že přelévání mezi jednotlivými trhy se významně prohlubuje v dobách paniky na finančních trzích.

Klasifikace JEL	F12, F21, F23, H25, H71, H87
Klíčová slova	volatilita, přelévání, kakaové futures, měnové páry

Název práce	Přelévání volatility mezi termínovými kontrakty na kakao a vybranými měnovými páry

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Acronyms

AIC Akaike information criterion

ADF Augmented Dickey-Fuller

ARCH Autoregressive Conditional Heteroskedasticity

ARMA Autoregressive Moving Average

BEKK Babba, Engle, Kraft, Kroner

BIC Bayes Information Criterion

CBOE Chicago Board Options Exchange

CCC Constant Conditional Correlation

CFTC Commodities Futures Trading Commission

CHF Swiss Franc

CIF Cost, insurance, and freight

COCOBOD Ghana Cocoa Board

Conseil Conseil du Café et du Cacao

CMC Cocoa Marketing Company

CSCE Coffee, Sugar and Cocoa Exchange

DCC Dynamic Conditional Correlation

DSTCC Double Smooth Transition Conditional Correlation

ES Expected Shortfall

EUR Euro

EWMA Exponentially Weighted Moving Average

FOB Free on Board

GARCH Generalized Autoregressive Conditional Heteroskedasticity

GBP British Pound

GHS Ghanian Cedi

GFC Great Financial Crisis

HIC Hannan information criterion

i.i.d independent, identically distributed

ICE Intercontinental Exchange

KPSS Kwiatkowski-Phillips-Schmidt-Shin

LM Lagrange Multiplier

LBC Licensed Buying Company

LCE London Commodity Exchange

LIFFE London International Financial Futures and Options Exchange

LPCH London Produce Clearing House

MGARCH Multivariate Generalized Conditional Heteroskedasticity

NASDAQ National Association of Securities Dealers Automated Quotations

NYBOT New York Board of Trade

NYSE New York Stock Exchange

OECD Organisation for Economic Co-operation and Development

OLS Ordinary Least Squares

PP Phillips-Perron

PVAM Programme de Vente Anticipyées a la moyenne

SIC Schwarz information criterion

UGX Ugandan Shilling

US United States

USD United States Dollar

VAR Vector Autoregressive

VaR Value at Risk

VIX CBOE Volatility Index

WAMCO West African Mills Company

USD United States Dollar

Chapter 1

Introduction

Volatility of an asset is the crucial input of many decision-making processes in finance. As a measure of risk, it is applied in various stages of risk management, portfolio management, or derivative pricing. In the asset allocation discipline, the volatility of an asset will enter as an input within a mean-variance framework. In the sphere of financial risk management, the volatility estimates are employed within the concepts of Value at Risk (VaR) or Expected Shortfall (ES). Derivative pricing is another field where volatility estimates find their application. An example is the pricing of options using the Black-Scholes formula (see Black & Scholes 1973) that requires the volatility estimate. While the volatility sometimes does not receive the same level of attention as the mean of return, it is just as important. Furthermore, from the econometric perspective, modeling volatility or variance may be even more attractive since it is often an onerous task to explain the mean of returns empirically (Hurn *et al.* 2021).

Volatility may be seen as a reflection of risk conditions pertaining to a particular asset, an asset class, or broader segments of financial markets. Risk, in general, cannot be expressed as a single measurable quantity. Instead, we must resolve to treat it as a latent variable that can never be observed directly. To overcome this hindrance, various means of risk modeling have been proposed. Typically, trade-offs between parsimony and complexity have to be made. This thesis capitalizes on the framework of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) volatility models, expanding on Bollerslev (1986), which produces the estimate of variance by using past information about shocks and variance values. The resulting product, an estimate of conditional volatility, may be utilized in a wide array of financial applications. Therefore, the outcomes of the empirical analysis have the potential not only to be of theoretical importance but also to be of practical value.

Agricultural commodities will be the asset class of primary interest, namely cocoa beans futures. Following the financialization of the commodity industry that has taken place since the beginning of the 21st century, commodities have become just another asset class that may be found in portfolios of investors with no direct link to the industry itself. The annual volume of US exchange-traded futures and futures options increased from 630 million contracts in 1998 to 3.2 billion contracts in 2007 (CFTC 2008). Trading in commodities is no longer the domain of specialized commodity trading houses taking on the role of a speculator or a producer entering the market to hedge against adverse price movements. Nowadays, both institutional and retail investors may access derivative commodity markets with ease, or they may use commodity-oriented investment vehicles such as exchange-traded funds tracking commodity futures that offer even greater convenience. The rapid pace of financialization prior to the Great Financial Crisis (GFC) was reflected in the value of institutional holdings of commodity index-related investments, which grew from 15 billion United States Dollar (USD) in 2003 to 200 billion USD in 2008 (Tang & Xiong 2012; CFTC 2008).

One of the significant motivating factors for participating in the commodity market is diversification. While the price dynamics of any commodity cannot be immune from developments in other sectors of the economy, commodities have historically evinced relatively low negative correlation with other asset classes (Gorton & Rouwenhorst 2006). After all, the price of every commodity should be a reflection of its supply and demand and the information the market participants have concerning future developments. However, it is argued that following commodity financialization and the integration into more traditional financial structures, such as commodity index funds, the correlation with other asset classes has increased. Such evidence is presented by ECB (2011). Furthermore, they offer a theoretical rationale for this development. They argue that financial investors may be more responsive to macroeconomic news than specific commodity fundamentals. Therefore, the rising correlation emerged as the news regarding the macroeconomic cycle became the joint driver for commodities and other asset classes. The effects of commodity financialization on interconnectedness and correlations with conventional asset classes were also confirmed by Tang & Xiong (2012), Irwin & Sanders (2011), Silvennoinen & Thorp (2013), with possible structural breaks arising in the period leading to the GFC. Furthermore, Basak & Pavlova (2016) provide a theoretical framework for commodity financialization mechanism that is largely in accordance with the empirical results.

The ramification for the commodity market participants is that it is no longer reasonable to rely entirely on the diversifying characteristics. Significant spillovers and correlations with other asset classes need to be recognized. Such correlations may vary over time and depend on the overall risk environment. The commodity that is very little correlated with other asset classes during tranquil periods in financial markets may suddenly become highly correlated with other assets in the portfolio in times of stress. Such an occurrence may be detrimental to the diversifying potential of the given asset. Tang & Xiong (2012) present evidence that commodities included in popular indices (e.g., S&P GSCI, DJ-UBSCI) show larger responses to shocks during the financial crisis. Therefore, time-varying correlations and spillovers are among the phenomena that we strive to explore, and particular focus is placed on whether the degree of spillover differs in times of financial crisis.

Futures markets have been widely adopted throughout different sectors of the commodity industry. Prices quoted on futures exchanges typically serve as global benchmarks for prices of given commodities. Significant volatility has historically been a defining feature of the agricultural commodities space. The futures market provides the market participants with a toolset to navigate this environment. Generally, hedgers and speculators are the two types of players that meet in the futures market. A speculator bets on the directional move in the futures price without direct participation in the market for the underlying asset. A hedger, on the other hand, participates directly in the market for the underlying asset. Therefore, the futures market provides the hedger with an opportunity to lock in input or output prices. Such protection is of crucial importance as it enables the producer to conduct operations and plan for the future, even in times of extreme volatility in the spot market.

The specificity of the cocoa market resides in the high geographical concentration of production. Only a handful of countries in West Africa account for the vast majority of cocoa bean production. The supply-side vulnerability is further exacerbated by the significant proneness of the cocoa plant to adverse weather conditions and various pests and diseases. The perfect example of such vulnerability has unfolded in the cocoa beans market since the autumn of 2023. Unseasonal severe rains have gravely impacted bean production in both pre-harvest and post-harvest stages (ICCO 2023). The drying process was disrupted, leading to degradation of the bean quality. Furthermore, due to the excess rainfall, black pod disease and swollen shoot virus cases have been detected. Consequently, the resulting supply deficit and negative crop outlook led to the price of the ICE US front month futures contract increasing from 3400 USD on October 5, 2023, to 11461 USD on April 19, 2024. Moreover, it is necessary to highlight the substantial dependence of the cocoa exporting countries on price fluctuations, which is in sharp contrast with the cocoa importing countries for which the price of cocoa is of little importance. The high reliance on the price of one commodity plays a fundamental role in the economic development of these countries.

Despite the heterogeneity of actors participating in various stages of the cocoa supply chain, exposure to the cocoa price and foreign exchange rates is a common factor for all of them. To explore the risks this exposure entails, inspecting the volatility of univariate series one by one does not suffice. The degree of correlation and information transmission between the assets is likely to be time-varying. Understanding how cocoa futures prices and exchange rates interrelate proves vital, especially in times when the volatility environment changes abruptly. In such situations, a part of the portfolio may be subject to substantial price fluctuations, and the survival of the business rests on the performance of the remaining exposures. In order to model the cross-asset dynamics and to provide a detailed description of the interrelations, multivariate GARCH models are applied in this thesis.

The foreign exchange market is the largest market in the world by volume. According to a survey by NY FED (2023), the average daily volume of spot transactions was 436,092 million USD. When the adjacent derivative transactions were considered, the average daily volume amounted to 1,021,008 million USD. Furthermore, foreign exchange markets are closely tied to the global economy. Price moves in the currency markets may be interpreted beyond simple supply and demand forces. They carry informational values about interest rate differentials between countries, macroeconomic performance, or risk sentiment pertinent either to a particular country or the global economy. On the other hand, cocoa futures are a considerably smaller market that will only exercise limited influence outside the producing countries. Therefore, the transmission of information is expected to flow predominantly from currency pairs to cocoa futures. However, the situation may differ for Ghanian Cedi (GHS), the currency of Ghana. Cocoa production is an important sector of the Ghanaian economy. Therefore, it is not unlikely that the cocoa futures price is among the important factors priced in by the currency markets. Consequently, it may be hypothesized that, unlike the global currency pairs, the transmission mechanism between GHS and cocoa futures works in either opposite or two-way direction.

The objective of the thesis is to provide a comprehensive overview of cross-asset dynamics between both cocoa futures contracts and selected currency pairs. The selected currencies are USD, Euro (EUR), British Pound (GBP), Swiss Franc (CHF), and GHS. Own volatility dynamics of cocoa futures will be examined in the process. Furthermore, time-varying correlation between the assets is to be explored to determine whether stable patterns exist in the correlation structure of the data. Conditional correlation will be examined with the use of Vector Autoregressive (VAR)-Dynamic Conditional Correlation (DCC)-GARCH model, first for cocoa futures contracts exclusively and consequently for USD and GBP-denominated assets. A similar structure will be followed in the study of spillovers. However, in response to the limitations of VAR-Babba, Engle, Kraft, Kroner (BEKK)-GARCH model, the entirety of the spillover analysis will be restricted to bivariate modeling. The purpose of the spillover study is to explore the transmission between different markets. The structure of the model enables us to test for mean, shock, and volatility spillovers. On top of the presence of the spillovers, their direction is of great interest as well. Therefore, we will be able to confirm or refute the expectation that the majority of transmission will flow from foreign exchange markets to cocoa futures, possibly with the exception of GHS. Finally, we strive to explore how the degree of transmission varies across different time periods. A question of particular interest is whether such dynamics are more or less pronounced in times of severe stress in financial markets. Therefore, aside from the analysis of the full sample, the data series is partitioned into four subsamples, one representing the period of the GFC and the early stages of the European Sovereign Debt Crisis. The presented research objectives are summarized by the following hypotheses, answers to which will be given over the course of the thesis and summarized in the concluding chapter (Chapter 7).

> Hypothesis 1: There is little or no correlation between cocoa futures and currency pairs.

> Hypothesis 2: The spillover between currency pairs and cocoa futures varies over time, depending on macroeconomic and financial conditions.

Hypothesis 3: The most significant spillover will occur during severe stress in financial markets, represented by Period 1 of the subsample analysis.

Hypothesis 4: The predominant direction of spillovers is from the much larger currency markets to smaller cocoa futures markets in the case of global currency pairs.

Hypothesis 5: The transmission exists in the direction from the cocoa futures market to the currency market in the case of GHS.

Hypothesis 6: London Cocoa futures contract is more closely oriented to the African production and the European processing industry. Therefore, it leads the US Cocoa futures in terms of price.

Hypothesis 7: The degree of transmission between cocoa futures and currencies is greater for US Cocoa as it attracts more speculative activity, and therefore, it will be more responsive to impulses originating from global financial markets.

The remaining parts of the thesis are organized in the following manner. Chapter 2 presents the literature review relevant to the research field of the thesis, and it serves a dual purpose. First, it provides foundations of the integral theoretical framework and outlines the literature in which the methodological tools applied in the later chapters were developed. The second part of the chapter focuses on empirical research relevant to the area of interest, which is the interrelation of commodities and currencies. Chapter 3 summarizes the basic characteristics of cocoa futures trading and the cocoa supply chain. In Chapter 4, methodological tools are described in greater detail. Univariate GARCH is presented. Next, the VAR model is outlined since it is used as a mean specification for the multivariate GARCH models. DCC and BEKK models and details of the estimation technique are introduced in the remainder of the chapter. Chapter 5 concerns the dataset used in the empirical analysis. The construction of the dataset is described. Furthermore, basic descriptive analysis and statistical tests are conducted in order to provide the first insight into the data and to ensure its readiness for further analysis. Chapter 6 is comprised of the empirical research, which is structured into three parts. First, univariate GARCH modeling is carried out for cocoa futures contracts. Second, the time-varying correlation between the assets is modeled. Third, the spillover between assets in terms of mean, shocks, and volatility is explored. Chapter 7 concludes the analysis and summarizes the results in a concise manner. Limits of the applied tools are emphasized, and the avenues for future research are proposed.

Chapter 2

Literature Review and Fundamental Theoretical Framework

This chapter provides an extensive overview of the body of literature and the current state of knowledge concerning the crucial concepts that appear in the latter stages of the thesis. The overview is divided into two sections.

The first section (Section 2.1) summarizes the literature in which the methods applied in the empirical analysis of Chapter 6 were developed. Those are mainly methods that originated in the second half of the 20$^{\text{th}}$ century to provide a framework for studying the dynamics concerning higher moments of random variables in the financial time series. Since we attempt to capture the process of volatility spillovers and the contagion between different segments of financial markets, both univariate and multivariate volatility models are of interest. Volatility models enable the study of the time-varying nature of variance, covariance, and correlation of asset return series. However, they vary significantly in terms of the econometric concepts on which they capitalize and the degree of their complexity. Perhaps the most important theoretical concepts are conditional variance and covariance. High priority is placed on a thorough grasp of these terms as it is a prerequisite for carrying out the empirical analysis and its sound interpretation. It is not the objective of this overview to explain the methods used in empirical analysis in greater detail. A more rigorous treatment of the model specifications and the process of estimation will be provided in Chapter 3, which focuses exclusively on the methodology.

In the second section (Section 2.2), we turn to the existing body of empirical research surrounding the volatility dynamics of the commodity markets. Particular focus is placed on studies concerning the spillovers between the asset classes of commodities and foreign exchange markets. In spite of the fact that the amount of research exploring the volatility spillovers in financial markets is abundant, the focus on the linkages between agricultural commodities markets and foreign exchange has been relatively limited. Therefore, the survey of existing empirical literature is not limited to research that deploys methodological tools identical to this thesis.

2.1 Development of Key Theoretical Concepts

The spillovers of volatility are the primary concern of the empirical analysis conducted in this thesis. The volatility of the return series interests all actors in the financial markets. As a primary measure of risk, the volatility of the asset returns needs to be constantly evaluated by financial market participants. It plays a crucial part in any decision-making and risk-management practices. However, volatility is not a single quantity that can be directly observed. With the genesis of financial theory, the variable representing the risk of an asset became an integral input. Consequently, the need for a reliable measurement of risk became exigent. Until the 1980s, the widespread practice was to assume that the volatility does not vary over time (Engle & Granger 2003). However, the problem with this approach is to be easily identified even when we conduct a simple visual inspection of an asset return times series (see Figure A.1, Figure A.3, Figure A.5). We typically observe periods of low volatility characterized by relatively small returns in both directions and periods of high volatility during which the magnitude of returns increases sharply in both directions (Engle 2001). This notion may be internalized as a stylized fact pertinent to the financial return series. Such phenomenon is known as volatility clustering, and it represents a critical realization that there is a degree of autocorrelation in the volatility of asset returns (Engle 2001). We can encapsulate this crucial observation in the following simple statement. There are riskier periods in financial markets and less risky periods. For any model to be satisfactory, it should be able to generate this dynamic that manifests itself as dependence in the data, for example, as a serial correlation in the squared returns.

The naive and most rudimentary approach to measuring volatility is the concept of historical volatility. Historical variance (volatility squared), defined as

$$\sigma_t^2 = \frac{1}{T}\sum_{i=1}^{T} r_{t-i}^2, \tag{2.1}$$

is based on a fixed window (T) of observations that are assigned the same weight, regardless of how far in the past they occurred. The time-varying feature of volatility, in combination with a discretionary choice of model parameters, disqualifies historical volatility as a model that would be able to capture the volatility dynamics in accordance with reality. The fact that it is up to our choice to decide on the length of the time window represents a significant deficiency. The most widely used values for the parameter T correspond to the number of trading days in a month, 22, or the number of trading days in a year, 252 (Hurn *et al.* 2021). Despite the aforementioned imperfections of the historical volatility model, the measure retains an attractive characteristic due to its simplicity. Furthermore, it is easy to implement either on its own or as mere input into more sophisticated models, such as spillover index models of Diebold & Yilmaz (2009; 2012).

Another unsophisticated approach that partially responds to the shortcomings of historical volatility is the Exponentially Weighted Moving Average (EWMA) model, which measures the variance (volatility squared) as

$$\sigma_t^2 = (1-\lambda)\sum_{i=1}^{\infty} \lambda^i r_{t-i-1}^2 = \cdots = (1-\lambda) r_{t-1}^2 + \lambda \sigma_{t-1}^2. \tag{2.2}$$

Unlike the historical volatility approach, it attaches more weight to more recent observations. However, the parameter λ still depends on the discretionary choice of the practitioner. Such a choice is typically made to fit the modeled data. However, the model does not allow us to estimate the model parameter, value $\lambda = 0.94$ is the most widely used option (Hurn *et al.* 2021).

Engle (1982) laid the foundations of the new approach to volatility modeling by introducing the Autoregressive Conditional Heteroskedasticity (ARCH) process. Many models that expand on this breakthrough have since been developed, and Robert Engle has continued contributing to the field of volatility modeling (see Engle *et al.* 1985; Engle & Gonzalez-Rivera 1991; Engle & Mustafa 1992; Bollerslev *et al.* 1994; Engle & Kroner 1995; Engle 2001; 2002b;a; 2004). Unlike the historical and EWMA volatility models, the ARCH-based framework does not suffer from the choice of arbitrary window length and lost information. Furthermore, the parameters of the model are to be estimated. Therefore, we do not have to make a decision about which portion of past data points is relevant and which is not.

Engle (2001) outlines a basic intuition about the need for more advanced methods by first looking at the deficiencies of the Ordinary Least Squares (OLS) model. The OLS model often takes on the assumption of homoskedasticity, meaning that the expected value of the error term is constant. The violation of the homoskedasticity assumption does not cause the estimates of the coefficients to be biased. However, the bias will arise in the standard errors obtained by the OLS procedure, resulting in the confidence intervals being too narrow and giving us a false sense of precision. One of the possible solutions to the heteroskedasticity problem is the introduction of heteroskedasticity-robust standard errors (see Eicker 1963; White 1980). However, Engle (1982) does not attempt to correct for the heteroskedasticity. Instead, he takes the variance as an object to be modeled, which is interesting for many financial modeling applications. The ARCH(1) model is specified as

$$u_t = \epsilon_t h_t^{1/2} \tag{2.3}$$

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2. \tag{2.4}$$

The model takes advantage of the concept of conditional variance that is defined with respect to I_{t-1} as

$$h_t = Var(u_t|I_{t-1}) = \mathbb{E}[(u_t - \mathbb{E}(u_t|I_{t-1}))^2|I_{t-1}], \tag{2.5}$$

where I_{t-1} is σ-algebra that may be interpreted as an information set containing all information available up to the time $t-1$.

Conditional moments are integral to the GARCH framework from both theoretical and practical perspective. The definition of conditional moments allows us to capture the time-varying nature of the modeled quantity as we define conditional moment relative to a set of available information I_{t-1}. We are focused on the evolution of conditional variance, described by the variance equation (see Equation 2.5). In order to obtain the shocks u_t that enter the variance equation, we need to specify the evolution of the conditional mean as well. The conditional mean equation specifies the link between the return, conditional mean, and shock variable u_t (innovation or error are alternative terms for u_t that are regularly found in literature). Moreover, from Equation 2.3, we may see how the shock variable provides the channel by which the conditional variance affects the magnitude of the asset return.

While the unconditional (long-term) variance, provided it exists, is still assumed to be constant in the ARCH model, the conditional variance does vary over time. Consequently, the parameters of conditional variance can be jointly estimated with the parameters of the conditional mean. Engle (1982) defined the ARCH model by an equation in which he essentially expressed the conditional variance as a function of past squared shocks with different weights that are to be estimated. Furthermore, it is assumed that the shocks can be expressed as $u_t = \epsilon_t h_t^{1/2}$, where ϵ_t is an independent, identically distributed (i.i.d) random variable with the mean equal to zero and the variance equal to one, normal distribution is assumed most frequently. Engle (1982) builds up the estimation theory for the ARCH model, specifies the characteristics regarding the maximum likelihood estimator, and introduces Lagrange Multiplier (LM) test in order to test for the presence of ARCH effects in the shocks u_t.

Engle (1982) successfully captured key dynamics describing the conditional variance of asset returns. However, in empirical practice, the ARCH model often requires a large number of lagged shocks to be included (Bollerslev 1986). Bollerslev (1986) introduced GARCH model, which imposes a structure on the conditional variance that resembles a specification of the Autoregressive Moving Average (ARMA) model. Aside from the lagged shocks, lagged values of conditional variances are included as well. Therefore, the equation for the conditional variance takes the form of

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j}^2. \tag{2.6}$$

In empirical practice, the order of the GARCH model does not exceed two for either p or q in Equation 2.6. Engle (2004) points out that the GARCH(1,1) model is able to model the conditional volatility of most financial series. The success of the GARCH model is demonstrated by the immense quantity of extensions that have been introduced over the years (see Bauwens *et al.* 2006; Bollerslev 2008). The extensions emerged either to augment the original model in order to accommodate nuances of the financial returns time series (e.g., leverage effects) or to allow the modeling of phenomena that the model had previously been incapable of. An example of the latter is the generalization of the GARCH model from univariate into multivariate setting.

Multivariate generalization of the GARCH models brings another quantity into consideration, conditional covariance. This extension is not only of a technical nature. It is a reaction to the real-world setting in which participants hold a large number of assets in their portfolios. Therefore, the generalization to multivariate framework comes as a natural extension that will enable us to model the dynamics between the assets. The evolution of the covariance and correlation measures follows a similar pattern as univariate variance measures. Basic measures such as historical correlation

$$\rho_{12,t} = \frac{\sum_{i=t-T-1}^{t-1} r_{1,i} r_{2,i}}{\sqrt{(\sum_{i=t-T-1}^{t-1} r_{1,i}^2)(\sum_{i=t-T-1}^{t-1} r_{2,i}^2)}} \tag{2.7}$$

or exponential smoother correlation

$$\rho_{12,t} = \frac{\sum_{i=t-T-1}^{t-1} \lambda^{t-i-1} r_{1,i} r_{2,i}}{\sqrt{(\sum_{i=t-T-1}^{t-1} \lambda^{t-i-1} r_{1,i}^2)(\sum_{i=t-T-1}^{t-1} \lambda^{t-i-1} r_{2,i}^2)}} \tag{2.8}$$

rely on our choice of the length of the rolling window T and the weighting parameter λ in the case of Equation 2.8. Similar to the univariate EWMA (see Equation 2.2), the value $\lambda = 0.94$ is the common choice (Engle 2002a). These basic measures derive value from their simplicity and may be used as a simple descriptive tool. However, they fail to capture the dynamics between assets in a more sophisticated manner, and they do not allow for the estimation of the model parameters. Conditional covariance matrix, defined as

$$\boldsymbol{H_t} = \mathbb{E}(\boldsymbol{u_t}\boldsymbol{u_t}^T | I_{t-1}), \tag{2.9}$$

forms the cornerstone of the multivariate GARCH analysis, and it will be the object to be modeled. Conditional variances of single assets form the diagonal of the conditional covariance matrix, and the off-diagonal elements are the conditional covariances between the assets.

The VEC model by Engle & Kroner (1995) offers a straightforward way to parametrize the multivariate model,

$$vec(\boldsymbol{H_t}) = vec(\boldsymbol{\Omega}) + \boldsymbol{A} vec(\boldsymbol{u_{t-1}}\boldsymbol{u_{t-1}}^T) + \boldsymbol{B}\boldsymbol{H_{t-1}}, \tag{2.10}$$

where vec is an operator that stacks the elements of the matrix into a column vector, $\boldsymbol{u_{t-1}}$ is $n \times 1$ vector of shocks at the time $t-1$ and $\boldsymbol{A}$, $\boldsymbol{B}$ are $n^2 \times n^2$ parameter matrices. VEC model translates the GARCH(1,1) model into multivariate setting in the most direct manner, with a conditional covariance matrix depending on the outer product of shocks and the lagged value of the conditional matrix. However, two problems arise in the case of this specification. First, the problem of dimensionality is evident as the number of parameters will be inconveniently large, particularly for a large number of assets. Second, the conditional covariance matrix $\boldsymbol{H_t}$ will not always be positive definite (Engle 2002a).

The issue of positive definiteness is addressed by the BEKK model of Engle & Kroner (1995), who parametrize the model such that

$$\boldsymbol{H_t} = \boldsymbol{\Omega} + \boldsymbol{A u_{t-1} u_{t-1}}^T \boldsymbol{A}^T + \boldsymbol{B H_{t-1} B}^T. \tag{2.11}$$

The BEKK model and its versions (asymmetric BEKK, diagonal BEKK, scalar BEKK) continue to be used in multivariate volatility modeling to this day. While the parameters of the model cannot be interpreted directly (Tsay 2005), we can examine the significance of the cross-parameters to explore whether volatility spillover between assets or markets exists. The deficiency that is common to both VEC and BEKK models is the curse of dimensionality. With an increasing number of assets, the number of parameters to estimate sharply increases. Therefore, in practice, the BEKK model can be effectively applied only if the number of assets remains relatively small. However, financial practice demands the ability to model hundreds of assets in the portfolio. Therefore, in such applications, the ability of the BEKK model will be significantly constrained.

Bollerslev (1990) took a different approach to the parametrization by specifying the conditional covariance matrix as

$$\boldsymbol{H_t} = \boldsymbol{D_t R D_t}, \tag{2.12}$$

where $\boldsymbol{D_t}$ is a diagonal matrix with conditional volatilities on the diagonal (obtained from first step univariate modeling) and $\boldsymbol{R}$ is a correlation matrix. The Constant Conditional Correlation (CCC) model assumes a constant conditional correlation between assets. It is conceivable that this restriction does not necessarily reflect the reality of the financial markets as market conditions change over time and, with them, the correlations and covariances between different assets. To reflect such eventuality, Engle (2002a) augments the CCC model by allowing the conditional correlation to vary over time, such as

$$\boldsymbol{H_t} = \boldsymbol{D_t R_t D_t}. \tag{2.13}$$

The DCC model has several properties that make it attractive for empirical applications. Engle (2002a) specifies the model and its estimation in a way that enables the estimation of large conditional covariance or correlation matrices. Estimation is conducted in two steps. The first step is obtaining conditional volatilities from univariate GARCH models. The second step utilizes the output of the first step, and estimates of the conditional covariance matrix are obtained by indirect specification.

The DCC model does not allow for the same interpretation of volatility spillovers as in the case of the BEKK model since conditional volatilities only enter as univariate processes and direct spillovers are not considered. However, the effective parametrization of the DCC model makes it appropriate for the study of time-varying conditional correlations between a larger number of different assets. Therefore, it is not necessary to be restricted to modeling of a lower number of variables as in the case of the BEKK model. Engle (2002a) emphasizes that adding new assets into the model has no effect on the volatility forecasts of the other assets, and there will be very limited effect on the conditional correlation estimates as well. The possibility of including a large number of assets makes the model attractive for risk management applications such as dynamic hedging ratios (see Ku *et al.* 2007).

Among the mentioned multivariate volatility models, BEKK and DCC are used in the multivariate empirical analysis in Chapter 6. There are several publications that employ a similar approach in terms of the applied methodological tools. Li & Majerowska (2008) use the BEKK model to test for spillovers between the emerging markets of Poland and Hungary and the developed global stock markets of Germany and the United States. Also Worthington & Higgs (2004) uses the BEKK model to study spillovers between developed and emerging markets, the dynamics are investigated for Asia, and the research is focused on the period including the Asian financial crisis. Various specifications of BEKK and DCC are also estimated by Bala & Takimoto (2017), who once again focus on developed and emerging markets. The spillover is studied separately among the developed, emerging and combined markets, and the emphasis is placed on how these dynamics differ in times of crisis. Liu *et al.* (2017) combine the BEKK model with a wavelet-based approach to explore spillovers between the oil and the stock markets of Russia and the US. Furthermore, they consider different time periods and different wavelets for the study, an approach partially followed in this thesis, albeit using less sophisticated tools. Bivariate BEKK models are also used to explore spillovers in exotic asset classes.

Katsiampa *et al.* (2019) model the spillover dynamics between pairs of leading cryptocurrencies (Bitcoin, Ether, Litecoin) and find significant shock and volatility spillovers.

2.2 Current State of Empirical Research

This section provides an overview of the existing literature that explores the spillovers between currency pairs and commodity markets in a broader sense. The main field of interest is the research of volatility dynamics between the agricultural commodity futures market and foreign exchange pairs. However, the field of agricultural commodities has yet to be the subject of such intensive research as the other commodity markets. Therefore, literature exploring interrelations between currencies and broader commodity markets is also outlined.

In this thesis, we study the volatility spillovers between the cocoa futures markets and currency pairs. The body of literature and research concerning the dynamics of the cocoa futures markets is, however, somewhat limited. Therefore, we start with a closer inspection of the findings related directly to the area of interest. The volatility dynamics between these two financial markets have been studied by Jumah & Kunst (2001), who explore the volatility dynamics between the dollar/sterling (USDGBP) forward exchange rates and futures markets for coffee and cocoa in both London and New York. In this paper, the authors present evidence that the USDGBP exchange rate volatility affects coffee and cocoa futures prices on the London International Financial Futures and Options Exchange (LIFFE) and Coffee, Sugar and Cocoa Exchange (CSCE). These effects are explored in four cases, for coffee and cocoa futures in both London and New York. In each case, the exchange rate arises as a major source of risk for the price of the futures contracts. The interactions between the LIFFE and CSCE futures contracts were also examined, and the statistical evidence shows that volatility spillover across the exchanges is strong and works in both directions. This relationship is stronger in the case of the coffee futures contracts than in the case of the cocoa futures contracts. Since the studied phenomenon is closely related to the interest of this thesis, it will be contributive to compare these findings with the results of our empirical analysis and update the understanding of these dynamics 23 years after the original paper of Jumah and Kunst was published.

Katusiime (2018) employs the volatility spillover framework by Diebold & Yilmaz (2009; 2012) and the multivariate GARCH model to explore the volatility spillover dynamics between food, oil, and Ugandan Shilling (UGX)USD nominal exchange rate which is flagged by the study as a critical macroeconomic financial stability indicator. DCC is used along with the spillover index by Diebold & Yilmaz (2012) to explore time-varying correlation and volatility spillover. The level of spillover is found to be weak during calm market conditions. However, it sharply intensifies during periods of significant market turbulence, such as the GFC or European sovereign debt crisis. Uganda shares many characteristics with countries that heavily depend on the export of cocoa beans. Therefore, it is highly relevant to the research subject of this thesis. The author suggests revenue stabilization funds as a policy arrangement to bolster macroeconomic stability and intergenerational equity and to mitigate the exchange rate volatility.

Also Kassouri & Altıntaş (2020) recognize the importance of exchange rate dynamics for commodity-exporting African countries. They investigate the effects of terms of trade shocks on the dynamics between the prices of a wide range of primary commodities and real exchange rates across twenty-three African countries. Using the nonlinear panel Autoregressive Distributive Lag technique, it is discovered that the effect is asymmetric and differs in the short run and in the long run. Notably, the evidence suggests that a positive response of the real exchange rates to positive terms of trade shocks is prevalent in the long run. On the other hand, in the short run, there is a pronounced negative response of the real exchange rates to negative terms of trade shocks.

The body of literature becomes substantially more copious if a broader commodity space is considered. Antonakakis & Kizys (2015) use the theoretical framework of Diebold & Yilmaz (2009; 2012) to analyze the dynamic returns and volatility spillovers between precious metals, crude oil, and currency markets. They are motivated by the preceding body of literature that studies the resilience of precious metals in times of financial crisis and shows their benefits as a way to reduce systematic risk in the portfolio and as a diversification element, especially in times of elevated market volatility. Furthermore, they compare the results of static and dynamic analysis. They show that the assets' role as net transmitters or net receivers may weaken or reverse entirely in specific periods. On the other hand, Arezki *et al.* (2014) point out that despite their undisputed benefit as a means to store wealth securely, the precious metals markets may also experience periods of heightened volatility.

More recently, Yıldırım *et al.* (2022) proceeded in a similar line of research to analyze the volatility spillover between crude oil, precious metals, and real exchange rates, but they focus on the G-20 emerging market economies, namely Mexico, Indonesia, and Turkey. In harmony with the preceding strand of literature, the transmission is found to be bidirectional during most of the observed period (1993 - 2021). However, this phenomenon dissipates during crisis periods. These findings offer evidence of protection characteristics that commodities possess in relation to exchange rates and their potential use in the diversification of portfolios. Additionally, precious metals demonstrate a safe haven behavior against exchange rates, which can be observed during the period of extreme volatility following the outbreak of COVID-19.

Apart from investigating these interrelations, Yıldırım *et al.* (2022) summarize two possible perspectives on the directionality of the contagion between commodity prices and exchange rates. The first perspective comes from Chen & Rogoff (2003), who study three Organisation for Economic Co-operation and Development (OECD) economies with a large share of primary commodity exports, and they find that the USD price of the exported commodities evinces significant influence on their real exchange rates. They effectively introduce a concept of commodity currency that aligns with the view that fluctuations in commodity prices lead to movements in the exchange rate. The second perspective highlights possible causality in the opposite direction, from exchange rates to the commodity markets (Chen *et al.* 2010). Belasen & Demirer (2019) give evidence in favor of such contagion, focusing on a wide range of export commodities and export countries. They find strong causal effects from currencies to commodities in both returns and volatility, and these effects become more widespread after the GFC. Examples of such significant dynamics are found, especially between gold and the New Zealand dollar, Brent oil and the Brazilian real, and copper and the Chilean peso. In some cases, these relations are even found to be bidirectional. Furthermore, Belasen & Demirer (2019) utilize these findings to present a case for hedging opportunities that would capitalize on the informative value provided by the foreign exchange market to hedge the commodity exposure.

The presence of bidirectional causalities between the currency and commodity prices is in partial accordance with Zhang *et al.* (2016). Unlike other authors, they employ a more robust approach by examining various time horizons for potential causality that, they argue, allows to account for indirect causal links and helps to curtail spurious findings of causation and time-aggregation effects. Moreover, the evidence provided by the multi-horizontal approach enables valuable comparison of the strength of causal relationships, therefore further enhancing the understanding of the directionality of such relationships. Zhang *et al.* (2016) present results showing that bidirectional causalities exist across various time horizons. However, the direction from commodity prices to the exchange rates displays significantly greater strength, suggesting that macroeconomic/trade-based mechanism evinces a central role in the contagion.

Overall, the presented evidence suggests that even though bidirectional relationships of varying magnitude are often found, the macroeconomic/trade-based mechanism described by Chen & Rogoff (2003) continues to play the deciding role in understanding the dynamics that govern the interrelations between commodities and currencies of commodity-exporting countries. As can be seen, certain patterns may be spotted across the existing research works. However, the nuances occurring across the different markets and geographical regions hint that studying the individual effects in greater detail is worthwhile.

Chapter 3

Cocoa Market Overview

3.1 Cocoa Futures Trading

A cocoa futures contract is an agreement to buy or sell a given quantity and grade of cocoa beans in accordance with contract specifications provided by the futures exchange. There are well-established futures contracts trading in London and New York under the auspices of the Intercontinental Exchange (ICE). Cocoa Futures (symbol CC) are traded on the ICE Futures US platform, and they are commonly referred to as US Cocoa. Price quotation is published in USD per metric tonne, and the contract size is 10 metric tonnes. London Cocoa Futures (symbol C) are traded on ICE Futures Europe, and they are commonly referred to as London Cocoa. Prices of London Cocoa are quoted in GBP per metric tonne, and the size of a contract is 10 metric tonnes. The dominant position of these contracts has been tested in recent years by the introduction of new products (see CME Group 2015; ICE 2015). However, these attempts have failed to attract significant volume. Both contracts are accepted as benchmarks for the global price of cocoa beans.

Table 3.1: ICE Cocoa Futures contracts

Contract	*Symbol*	*Contract Size*	*Price Quotation*
Cocoa Futures	CC	10 metric tonnes	USD/metric tonne
London Cocoa Future	C	10 metric tonnes	GBP/metric tonne

Source: https://www.ice.com/products; ICE (2024a), ICE (2024b)

London market tends to be oriented toward African cocoa production and the European processing industry (Darhei Noam Ltd 2023). Eligible delivery points are located in proximity to major ports in northwestern Europe. Possible delivery locations are Amsterdam, Antwerp, Bremen, Hamburg, Liverpool, London and Rotterdam (ICE 2024a). On the other hand, the US Cocoa futures market holds the position of global benchmark, it is oriented toward processing industries of America and Asia, and it is viewed to have attracted more speculative activity than the London market (Darhei Noam Ltd 2023). The locations for the physical delivery of US Cocoa are situated in the major ports on the northeastern coast of the United States. The eligible delivery locations are licensed warehouses in the ports of New York, Delaware, Hampton Roads, Albany, and Baltimore (ICE 2024b).

The difference between both markets has varied throughout history depending on miscellaneous factors that may have had an effect on the migration of participants between the contracts. According to Bertilorenzi (2023), the London and New York markets were very similar in terms of the two key terminal markets' competitive qualities, geographical proximity to commodity production sites, and maturity and reliability of the contracts. The regulatory environment has always had a significant influence on the competition between New York and London futures markets. Futures exchanges in London developed as self-regulating. In the United States, imported soft commodities such as sugar, coffee, and cocoa had functioned in a relatively light regulatory environment, unlike domestic agricultural commodities, until the Commodities Futures Trading Commission (CFTC) was established in 1974. The weak regulation was appealing particularly to the most speculative market participants (Markham 1991). Following the regulation by the CFTC, London captured a competitive edge, becoming suddenly more attractive to those who previously relied on lenient regulation in the US. The accommodative environment of London was further enhanced by the growth of the eurodollar markets, and many US financial firms involved in commodity trading opened branches in London during this period (Altamura 2016). This episode highlights the critical influence of factors originating purely from financial markets rather than the cocoa industry itself.

Both cocoa futures contracts have been trading for nearly a century. Both contracts are settled by physical delivery, and both allow for the delivery of a wide range of cocoa bean grades. Even though the contracts are currently traded on the ICE platforms, that has not always been the case, it is an outcome of a long series of mergers and acquisitions. This development was not exclusive to the soft commodity futures space. The consolidation of the financial exchange industry has accelerated significantly in the years following the introduction of electronic trading, leading to the ICE and National Association of Securities Dealers Automated Quotations (NASDAQ) emerging as dominant players. As a result, a vast majority of soft commodity futures volume has ended up under the umbrella of the ICE.

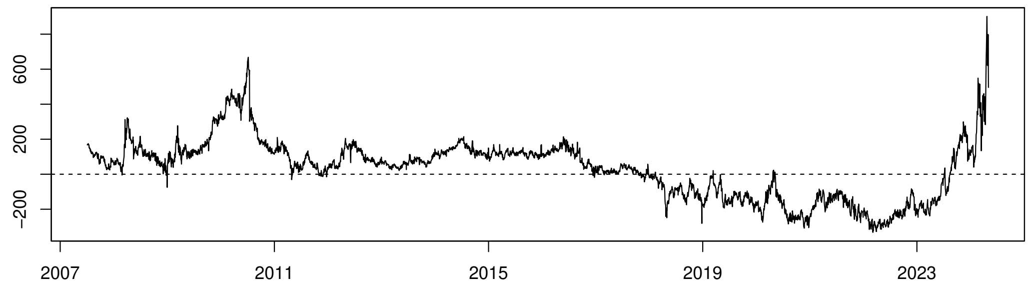
US Cocoa Futures contracts are universally regarded as the primary global benchmark of cocoa beans and dominate in terms of open interest. The contract has a long tradition, and its origin can be traced back to October 1, 1925, when the New York Cocoa Exchange first opened for trading, and it had been thriving from the start. Early president of the Cocoa Exchange, Eugene Canalizo, cites the main reasons that motivated the establishment of the exchange in Canalizo (1931). First, a hedging market was desired to allow businesses to obtain insurance against unexpected price developments by transferring the risk from the hedger to the speculator. The second motivating factor was establishing a centralized market where the information would be aggregated and effective price consensus formed. Furthermore, greater liquidity, access to financing, and fostering of cocoa trade were also emphasized as highly desirable. In 1979, the New York Cocoa Exchange merged with the New York Coffee and Sugar Exchange, forming the CSCE (Paul 1982). In 1998, the CSCE and the New York Cotton Exchange became a part of the New York Board of Trade (NYBOT), which was acquired by the ICE in 2007 during the consolidation of the exchange industry (Hall *et al.* 2006; Brown 2013).

London Cocoa Futures started trading in London in 1928, following the model of other futures exchanges that were established in the City in the second half of the 19th century in the era of increasing international trade and globalization (Bertilorenzi 2023). Unlike in the US, commodity exchanges in London have long maintained their independence and specialization. In the self-regulatory environment of London City, they cooperated in areas of common interest, such as establishing the London Produce Clearing House (LPCH) in 1888 when raw sugar and robusta coffee futures started trading (Rees 1972). The first wave of consolidation occurred in the 1980s when the independent exchanges merged into the London Commodity Exchange (LCE). In 1996, LCE merged with the financial futures exchanges of the City, leading to the creation of the LIFFE (Bertilorenzi 2023). LIFFE itself was acquired by Euronext in 2002, which then completed a merger with the New York Stock Exchange (NYSE) in 2007 (Euronext 2024). The latest step of the consolidation in the trading of soft commodity futures space took place in 2013 with the acquisition of the

NYSE Euronext by ICE, leading to the creation of ICE Europe (ICE 2013).

Today, the specifications of contracts differ only marginally. However, there are differentiating features that are typical for each market. Darhei Noam Ltd (2023) lists the differences as of 2023. US Cocoa tends to be more volatile, attracting more speculative players. On the other hand, London Cocoa is more closely linked to fundamental forces of supply and demand in the European market, and it is used by hedgers and exporters more than the US contract. London Cocoa offers greater flexibility in terms of deliverable origins of the cocoa beans. Generally, the quality standards of the London contract are higher, causing the contract to trade at a premium to its US counterpart. However, the existence and the size of the quality premium are influenced by the foreign exchange market conditions. The size of the premium in USD may be seen in Figure 3.1. The magnitude of the premium was computed by converting the price of London Cocoa to USD at the daily spot exchange rate close and computing the difference between contracts. It can be seen that the size of the premium is time-varying. Even though London Cocoa has been trading at a premium over US Cocoa for the larger part of the sample period, there has been an extended period in recent years during which the premium was negative (approximately from 2018/1 to 2023/7).

Figure 3.1: London Cocoa premium (USD)



Source: Author's computations

Market structure and participants changed substantially with the onset of electronic trading and the financialization of the commodity industry. The new entrants included hedge funds, algorithmic traders, and a varied set of financial intermediaries. New entrants brought benefits regarding market liquidity, efficiency, and price discovery. Chaboud *et al.* (2014) show the positive effects of algorithmic trading on the foreign exchange market. The new participants have possibly given rise to negative effects of their activity as well. Typically, debates regarding the negative impacts arise in times of greater price moves, which develop initially in response to the fundamental dynamics of the market. The evidence of significant destabilization of commodity markets by futures speculation is either weak or nonexistent. Kim (2015) shows that futures speculation does not exacerbate spot commodity price volatility, and, at times, speculators even have a stabilizing effect. Managed futures is a trading strategy closely associated with large speculative actors in commodity markets. The possible effect of such activity on price volatility has been examined for the 1988-1989 period by Irwin & Yoshimaru (1999), who find no evidence of the causality.

3.2 Cocoa Production

Cocoa beans, the underlying asset of cocoa futures, originate from the Theobroma Cacao plant that grew originally in South America. The earliest proofs of native populations using the plant date back to 5450-5300 years ago, various parts of the plant were used as a food ingredient, currency, ritual object, or medicine (Zarrillo *et al.* 2018). The first European to encounter cocoa and the chocolate drink prepared by the indigenous population, xocoatl, was Columbus in 1502 (Bergmann 1969). In 1528, Hernán Cortés brought cocoa back to Spain (Afoakwa 2016). Even though the demand for the commodity grew very slowly at first, the cultivation area began to spread during the era of colonization to areas near the equator throughout the world. The crop was introduced to Africa during the 19th century, and in 1912, Africa surpassed Latin America as the largest producer of cocoa beans (Chauveau 1997). By the late 20th century, Africa had established its dominant position in the production of cocoa beans.

Cocoa flourishes in the lower story of the evergreen rainforest, where it receives only limited sunlight. This indigenous way of growing cocoa under the shade of native forest (agroforestry method) is beneficial based on ecological considerations (Franzen & Borgerhoff Mulder 2007). The other alternative is to grow cocoa monoculture under full sun. Such an approach results in higher yields. However, it is demanding for both the environment and the farmer as a large amount of mineral fertilizer is necessary to sustain the production (Niether *et al.* 2017). Despite the agroforestry method often being presented as more resilient, Abdulai *et al.* (2018) presents evidence that in the presence of weather conditions of extreme drought and heat, the method proves to be less resilient than the production under full sun.

For the cocoa plant to thrive, the rainfall should be smoothly distributed over the year. Cocoa requires a minimum rainfall level of 1200-1500 mm per year, and the number of days without precipitation should be limited to under ninety (Yoroba *et al.* 2019). While the cocoa plant is susceptible to the dearth of soil water, excessive rainfall may be just as detrimental. The negative effect of excessive rainfall on cocoa in Nigeria was confirmed by Lawal & Omonona (2014), who found a significant negative relationship between rainfall and yield. The vulnerability of cocoa production to excessive rainfall has been on display since September 2023. The confluence of the bad weather and the lack of supply in the storage facilities has materialized in cocoa futures prices exhibiting unprecedented volatility (see Figure 6.1) and reaching all-time highs (ICCO 2023). The vulnerability of cocoa production to drought, on the other hand, was demonstrated during the 2015/16 season, when the meteorological phenomenon El Niño resulted in the most severe drought in decades and a significant decrease in cocoa production (Abdulai *et al.* 2018).

One of the consequential characteristics of cocoa is the extreme geographical concentration of its production. The concentration of such magnitude is unparalleled in other agricultural commodity markets and poses a major vulnerability for the entire industry. Data on seasonal production starting 2016/17 collected by ICCO (2024) are to be found in Table 3.2. It is estimated that

Table 3.2: Seasonal production of cocoa beans by regions (000s MT)

Region	16/17	17/18	18/19	19/20	20/21	21/22	22/23	23/24
Africa	3617	3494	3645	3549	4056	3589	3669	3168
Cameroon	246	250	280	280	292	295	290	300
Côte d'Ivoire	2020	1964	2154	2105	2248	2121	2241	1800
Ghana	969	905	812	771	1047	683	654	580
Nigeria	245	250	279	250	290	280	280	270
Africa others	137	125	129	143	178	210	204	218
Americas	758	835	846	909	935	973	1061	1035
Brazil	174	204	176	201	200	220	220	220
Ecuador	290	287	322	342	365	365	454	430
Americas others	294	344	349	366	369	388	387	385
Asia & Oceania	357	319	303	283	254	265	266	247
Indonesia	270	240	220	200	170	180	180	160
Papua N.G	38	36	40	41	42	42	41	42
A&O others	49	43	43	42	42	43	45	45
World total	4731	4648	4794	4741	5245	4826	4996	4449

Source: https://www.icco.org/statistics/; ICCO (2024)

during the 2022/23 season, 73.4% of the world's cocoa beans were grown in Africa. Production is situated particularly in the western equatorial area. The four African countries with the biggest production are Côte d'Ivoire, Ghana, Cameroon, and Nigeria. Côte d'Ivoire and Ghana alone account for nearly 58%

of the world's total production of cocoa beans. In the case of the three largest African producers, Côte d'Ivoire, Ghana, and Cameroon, cocoa products represent an important share of the exports. In the case of the biggest producer, Côte d'Ivoire, cocoa products account for 30.7% of total exports (OEC 2024). In the case of Ghana and Cameroon, cocoa products account for nearly 10% of the total export volume (OEC 2024). Therefore, just as the producing countries are essential for the world cocoa supply chain, cocoa is just as vital for their export revenues. While it is likely that African production will retain its dominant position for the foreseeable future, the second most significant region, the Americas, has been steadily increasing production in the past decade. In the 2016/17 season, the total production of the Americas was 760,000 tonnes, accounting for 16 % of the total production. In 2022/23, it is estimated that the total production in the Americas rose to 1,061,000 tonnes, which now accounts for 21.2% of the total production in the world. The region's most significant producer is Ecuador, which, in the latest season, produced 454,000 tonnes of cocoa beans, making it the third-largest producer in the world. Unlike Africa's biggest producers, the producing countries in the Americas are not significantly dependent on cocoa production. In the case of Ecuador, the export share of cocoa products is just 3%, which is considerably lower than in the case of African producers (OEC 2024).

Table 3.3: Seasonal grindings of cocoa beans by regions (000s MT)

Region	15/16	16/17	17/18	18/19	19/20	20/21	21/22	22/23	23/24
Europe	1595	1628	1703	1718	1706	1807	1771	1784	1710
Germany	430	410	448	445	430	460	440	450	440
Netherlands	534	565	585	600	600	610	610	600	590
Others	631	653	670	673	676	738	721	734	680
Africa	767	901	959	1017	998	1050	1135	1178	1094
Côte d'Ivoire	492	577	559	605	614	620	710	793	750
Ghana	202	250	310	320	292	322	295	250	210
Others	74	73	90	92	92	108	130	135	134
America	889	880	875	903	893	970	935	937	913
Brazil	225	227	230	235	221	240	223	251	253
United States	398	390	385	400	380	390	380	350	340
Others	266	262	260	268	292	340	333	336	320
Asia & Oceania	876	988	1048	1146	1109	1122	1154	1121	1063
Indonesia	382	455	483	487	480	462	460	450	430
Malaysia	194	216	236	327	318	338	375	364	345
Others	301	317	329	332	311	322	319	307	288
World total	4127	4397	4585	4784	4706	4949	4994	5020	4780

Source: https://www.icco.org/statistics/; ICCO (2024)

To complete the cocoa supply chain overview, it is instructive to outline where the cocoa bean grinding takes place (see Table 3.3). Grinding is a process of pulverizing cocoa cake into powder, which is commonly referred to as cocoa. However, since various post-harvest steps take place in the processing plant, grinding is often used in a broader context to describe the industrial processing of cocoa beans. This value-added process has not historically taken place at the location of production. However, this dynamic has begun to reverse as producing countries attempt to capture a greater proportion of the cocoa value chain by expanding domestic processing capacity. Early attempts to establish domestic processing capacity occurred in the 1960s, first by West African Mills Company (WAMCO) and then by Cocoa Processing Company, which was established by the government and privatized in the 1980s (Darhei Noam Ltd 2023). However, a more sustained trend has only been apparent in recent years. Seasonal grindings may be observed in Table 3.3. In the 2015/16 season, African producers accounted for 18.6% of the world's cocoa grindings. In the 2022/23 season, it is estimated that African cocoa grindings accounted for 23.5% of the total. The effort to increase the domestic processing capacity is even more apparent from the data on total grindings in individual countries. In the 2015/16 season, domestic grindings amounted to 492,000 tonnes in Côte d'Ivoire and 202,000 tonnes in Ghana. Seven years later, in the 2022/23 season, grindings in Côte d'Ivoire increased to 793,000 tonnes, and grindings in Ghana increased to 250,000 tonnes.

3.3 Cocoa Marketing

In the previous section, it was outlined that the main producing countries exercise a high level of control over the supply of cocoa beans. Therefore, marketing systems play an essential role in understanding the upstream dynamics of the cocoa industry. The purpose of the marketing system is to provide a framework that will determine how a crop makes its way from a farmer to the terminal markets. Marketing systems differ in approach to price setting, support for farmers, and a wide range of internal market workings, such as quality control and transport of the product. Both Côte d'Ivoire and Ghana experimented with different systems after gaining independence from France (1960) and the United Kingdom (1957). Currently, both countries insulate domestic actors from intra-seasonal price variations. Therefore, the governing organizations are heavily involved in the transfer of risk away from the producers.

Côte d'Ivoire depends on cocoa production like no other country in the world. Therefore, the functioning of the marketing system does not only impact the well-being of more than 993,000 farmers, it also contributes significantly to the national economy (Kouassi 2023). The main governing body of the cocoa sector is the Conseil du Café et du Cacao (Conseil). The country adopted reforms aimed at liberalization of the industry in the 1990s. However, the course has been reversed since then, and tighter regulations have been reestablished (Leissle 2018). Farmers sell cocoa at the farm gate to either a cooperative or a pisteur, an agent who acts as an intermediary between farmers and buyers of beans (Kouassi 2023). The minimum price that the farmer receives for his crop is determined by the Conseil. Cocoa beans are then transported by various intermediary agents to regional hubs before the product finally makes its way to packaging and processing facilities in the port cities of Abidjan or San Pedro. Conseil bears responsibility for the sale of the collected crop. The sales are currently conducted in two stages under the umbrella of the Programme de Vente Anticipyées a la moyenne (PVAM) program (Kouassi 2023). The first stage is carried out at the start of each season by forward sales of 70-80% of the forecasted crop. In the second stage, the residual crop is sold on the spot market. Furthermore, both forward and spot prices are then used to determine Cost, insurance, and freight (CIF) price, which is further used to obtain the minimum farm gate price.

Ghana shares the general characteristics of the marketing system with Côte d'Ivoire. On the whole, the involvement of Ghanaian authorities is considered to be successful. Kolavalli & Vigneri (2011) lists favorable price regime, ameliorated partially liberalized marketing, and the effort of the government organizations to enhance productivity as the main contributors to the country's success. Ghana produces bulk cocoa beans of the highest quality, which is demonstrated by the premium at which the Ghanaian cocoa beans have been historically traded. According to Gilbert *et al.* (2009), the premium relative to Côte d'Ivoire origin has been increasing since the 1990s. It reached 5.7% in 2007 and 6.9% in 2008. The private-public partnership is the foundation of the marketing system that is governed by the Ghana Cocoa Board (COCOBOD). Private actors are responsible for the production and internal flow of the commodity. Meanwhile, the public sector provides support for the farmers and conducts external sales. The internal journey of cocoa beans follows the same pattern as in Côte d'Ivoire. The farmer sells the crop to Licensed Buying Company (LBC) for the producer price determined by the government (Kolavalli & Vigneri 2011). LBC conducts the process of collecting and bagging of the cocoa beans. Furthermore, cocoa undergoes various quality assurance checks, and it is transported to the warehouse where it is stored until COCOBOD sells the product to either domestic or external buyers (Aning 2023). Cocoa sales and export rights are executed at the trading desk of Cocoa Marketing Company. The producer price for the season is determined by the government that effectively absorbs any intraseasonal price risk. Aning (2023) describes the main factors that enter the price-setting process. First, the projection of the Free on Board (FOB) price is made by COCOBOD. Second, the Bank of Ghana supplies the projection of the USDGHS exchange rate. Third, COCOBOD conducts a forecast of crop size for the coming season.

Chapter 4

Methodology

This chapter provides an overview of the necessary tools used in the empirical analysis of Chapter 6, where conditional volatilities, covariances, and correlations are modeled. To establish the necessary theoretical foundations, we first start with a brief overview of the GARCH model framework that will be used in univariate volatility modeling in the form of the GARCH(1,1) process. The univariate model is used to estimate the conditional volatility as well as an input into the multivariate DCC model. Next, the multivariate tools are introduced. In order to proceed with the multivariate GARCH methods, we first outline the VAR framework that is used in the multivariate analysis to describe the dynamics between returns and as the first estimation step of the multivariate volatility analysis. Finally, DCC and BEKK models, the salient tools applied in the empirical analysis of Chapter 6, are described jointly with the estimation process.

While it is argued by Caporin & McAleer (2012) that DCC and BEKK models provide very similar results, we deploy both to take advantage of specific characteristics of each model to extract the desired information. DCC requires estimates of conditional volatility from univariate GARCH processes as inputs. However, the generalization to multivariate case is not trivial because certain reparametrization steps are necessary. Furthermore, it must be emphasized that the basic DCC specification does not directly model spillovers of shocks or volatility. First-step estimates of conditional volatilities are estimated as univariate processes that do not depend on conditional volatilities of other assets or covariances. While such parametrization may lead to neglecting certain cross-effects between assets, the number of parameters remains under control even for a very large number of assets. BEKK model specification, on the other hand, suffers from a dimensionality problem, the number of parameters grows rapidly for a large number of included series. Therefore, we are restricted solely to BEKK(1,1) bivariate models. The advantage of the BEKK specification, on the other hand, is that it will allow us to model spillovers of shocks and volatility between two assets. Therefore, we can test for the presence of such cross-effects by examining the statistical significance of the particular parameter estimates.

4.1 GARCH(1,1) Model

4.1.1 Model Specification

Conditional random variables and conditional moments form the foundations of the time-varying volatility models. The first and the second conditional moments are to be found in every stage of our analysis, and therefore, before we proceed any further, we first define these foundational concepts. Conditional mean is defined as

$$\mu_t = \mathbb{E}(r_t|I_{t-1}), \tag{4.1}$$

where r_t is a random variable of interest, log-return, in our case. Analogically conditional variance is defined as

$$h_t = \mathbb{E}((r_t - \mathbb{E}(r_t|I_{t-1}))^2|I_{t-1}) = \mathbb{E}((r_t - \mu_t)^2|I_{t-1}) = \mathbb{E}(u_t^2|I_{t-1}), \tag{4.2}$$

where u_t denotes a shock variable, demeaned return in the simplest case. Shock, error, or innovation are terms used interchangeably for u_t. Generally, as we will outline in model specifications in Section 4.4 and Section 4.3, shocks $\{u_t\}$ are obtained as residuals from the conditional mean equation. The σ-field I_{t-1} is an information set that contains all the available information up to the time $t-1$. In a practical setting, by all available information, we mean all past returns and their linear combinations (Tsay 2005). Throughout the thesis, conditional variance h_t is used predominantly to describe the second conditional central moment of a random variable generating the return series $\{r_t\}$. Occasionally, we will refer to the square root of the conditional variance, $\sqrt{h_t}$, conditional volatility. Volatility is more frequently used in financial applications as it offers benefits when interpreting the results compared to the variance.

The GARCH model was introduced by Bollerslev (1986) as an extension of the ARCH model by Engle (1982). The GARCH model treats conditional volatility as a time-varying process that proves its ability to emulate the salient stylized facts pertinent to financial returns series. Examples of such characteristics are leptokurtic asset returns, volatility clustering and leverage effects (see Bollerslev *et al.* 1994). GARCH(1,1) is the most widely used specification of the GARCH models. It is used both as a model for univariate analysis (see Section 6.1) and as the first-step model for the DCC specification (see Section 6.2). Several equivalent ways to specify the GARCH(1,1) model do exist. In this thesis, the following specification consisting of three equations is used

$$r_t = \mu_t + u_t \tag{4.3}$$

$$u_t = {h_t}^{1/2}\epsilon_t \tag{4.4}$$

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1}. \tag{4.5}$$

Furthermore, Bollerslev (1986) imposes the following parameter restrictions, $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, $\alpha_1 + \beta_1 < 1$, the first three conditions ensure positive h_t, and the fourth is sufficient condition for a wide-sense stationarity. The relation between conditional mean μ_t, shock u_t, and the return variable r_t is specified in Equation 4.3. The purpose of the conditional mean equation is to dispose of linear dependencies that may be found in the raw series of returns $\{r_t\}$. Therefore, the ARMA model may be utilized in the place of μ_t. In the simplest case, when no linear dependencies are to be found in the data, μ_t is modeled as a constant μ_0, and u_t is interpreted as a demeaned return.

Equation 4.4 describes the dynamic between the innovation u_t, conditional variance in the given period h_t and i.i.d process $\{\epsilon_t\}$ with zero mean and variance equal to one. The distributional assumption for the random variable ϵ_t is made based on the knowledge of the idiosyncratic characteristics of the data. The most frequently used are the normal distribution, Student's t-distribution, or Student's skewed distribution. Empirical practice hints that either Student's t or Skewed Student's t distributions provide a more appropriate model (see Bala & Takimoto 2017). Nevertheless, normal distribution is widely used due to its convenience and ubiquity in econometric applications.

Equation 4.5 defines the evolution of the conditional variance h_t. We can see that the magnitude of the shock in the previous period u_{t-1} and the value of conditional variance in the previous period h_{t-1} will impact the current level of the conditional variance h_t. It is straightforward how the equation translates into the volatility dynamics of a given asset. When a large innovation occurs, the value of the next period's conditional variance increases as well. Consequently, the shock in the next period will also tend to be larger. Furthermore, the lagged value of the conditional variance feeds into the process. The resulting dependence in the volatility series manifests itself by alternating periods of relative calm and periods of higher volatility. This behaviour corresponds to the stylized fact of the financial returns series called volatility clustering that may be observed in the return series in different asset classes across financial markets.

4.1.2 Model Estimation

The GARCH model is estimated using the maximum likelihood method, as outlined by Bollerslev (1986). The likelihood function will take the form of

$$\begin{aligned} \mathcal{L}(\boldsymbol{\theta}|u_1,...,u_n) &= f(u_1,...,u_n|\boldsymbol{\theta}) \\ &= f(u_T|I_{T-1},\boldsymbol{\theta})f(u_{T-1}|I_{T-2},\boldsymbol{\theta})\dots f(u_2|I_1,\boldsymbol{\theta})f(u_1|\boldsymbol{\theta}), \end{aligned} \tag{4.6}$$

where $\boldsymbol{\theta}$ is a parameter vector. The marginal density of u_1, $f(u_1|\boldsymbol{\theta})$, is often disregarded since its form is too complicated (especially for GARCH models of higher orders), the resulting effect will not be significant when a large sample is available (Tsay 2010). The form of Equation 4.6 without the marginal density, conditional likelihood function, will be used for the remainder of the chapter. In order to proceed, conditional maximum likelihood estimation requires a distributional assumption to be made for ϵ_t in Equation 4.4.

First, the estimation of the model with the assumption of normal distribution is outlined. Parameter vector $\boldsymbol{\theta} = [\alpha_0, \alpha_1\, \beta_1]^T$ is to be estimated. A shock in the model was defined in Equation 4.4 as $u_t = {h_t}^{1/2}\epsilon_t$. The random variable ϵ_t is assumed to be i.i.d. Therefore, when $\epsilon_t \sim N(0,1)$ is assumed, it also holds that $u_t|I_{t-1} \sim N(0, h_t)$. Therefore, the conditional likelihood function will take the following form

$$L(\boldsymbol{\theta}) = \prod_{t=2}^{T} \frac{1}{\sqrt{2\pi h_t}} exp\left(-\frac{u_t^2}{2h_t}\right). \tag{4.7}$$

The conditional likelihood function can be transformed by natural logarithm, and the optimization will be equivalent since the natural logarithm is a strictly monotonic function. Therefore, after the transformation, we obtain the conditional log-likelihood function

$$l(\boldsymbol{\theta}) = logL(\boldsymbol{\theta}) = -\frac{1}{2}\sum_{t=2}^{T}\left(log(2\pi) + log(h_t) + \frac{u_t^2}{h_t}\right). \tag{4.8}$$

Alternatively, one may assume that ϵ follows standardized Student's t-distribution, $\epsilon_t \sim St(0, 1, \nu)$, where ν (shape parameter) is the number of degrees of freedom of the Student's t-distribution. Therefore, the parameter vector $\boldsymbol{\theta} = [\alpha_0, \alpha_1\, \beta_1, \nu]^T$ is to be estimated. Standardized t-distribution is obtained in the following way. If y_t^ν is an i.i.d random variable following Student's t-distribution with ν degrees of freedom, then

$$\epsilon_t = y_t^\nu \sqrt{\frac{\nu - 2}{\nu}} \tag{4.9}$$

will follow the said standardized Student's t-distribution.
Consequently, $u_t | I_{t-1} \sim St(0, h_t, \nu)$. Therefore, conditional likelihood function with t-distributed shocks will be

$$L(\boldsymbol{\theta}) = \prod_{t=2}^{T} \frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\frac{\nu}{2})\sqrt{\nu - 2}} \frac{1}{\sqrt{h_t}} \left(1 + \frac{u_t^2}{h_t(\nu - 2)}\right)^{\frac{-\nu+1}{2}}. \tag{4.10}$$

When the conditional likelihood function is transformed by the natural logarithm, conditional log likelihood function will be obtained, such as

$$\begin{aligned} l(\boldsymbol{\theta}) = logL(\boldsymbol{\theta}) = (T-2)log\left(\frac{\Gamma(\frac{\nu+1}{2})}{\Gamma(\frac{\nu}{2})\sqrt{\nu - 2}}\right) - \frac{1}{2}\sum_{t=2}^{T} logh_t \\ -\frac{\nu+1}{2}\sum_{t=2}^{T} log\left(1 + \frac{u_t^2}{(\nu - 2)h_t}\right). \end{aligned} \tag{4.11}$$

Regardless of whether the conditional log-likelihood with the assumption of normal (see Equation 4.8) or t-distribution (see Equation 4.11) is used, the maximum likelihood estimate $\widehat{\boldsymbol{\theta}}_{ML}$ is obtained by solving the following optimization problem

$$\widehat{\boldsymbol{\theta}}_{ML} = \arg\max_{\theta} l(\boldsymbol{\theta}). \tag{4.12}$$

Numerical optimization methods are usually applied, Bollerslev (1990) proposed BHHH algorithm by Hall *et al.* (1974) as a convenient option. In our case, the augmented Lagrange solver solnp by Ye (1997) is used within the *rugarch* R package by Galanos (2023).

4.2 Vector Autoregressive Model

VAR is used to model the spillover across different return series and as a mean equation in the case of both BEKK and DCC models. The VAR model is a straightforward generalization of the univariate autoregressive process. In the multivariate setting of the VAR model, an asset's returns are explained not only by its past values but also by the past values of the remaining assets included in the model. Therefore, each regression equation contains the same set of independent variables, with p lags included for each variable. The VAR(p) model with n assets will be specified by the following set of n equations

$$\begin{aligned} r_{1t} &= \mu_{10} + \sum_{i=1}^{p} \phi_{11,i} r_{1t-i} + \sum_{i=1}^{p} \phi_{12,i} r_{2t-i} + \ldots + \sum_{i=1}^{p} \phi_{1n,i} r_{nt-i} + u_{1t} \\ &\vdots \\ r_{nt} &= \mu_{n0} + \sum_{i=1}^{p} \phi_{n1,i} r_{1t-i} + \sum_{i=1}^{p} \phi_{n2,i} r_{2t-i} + \ldots + \sum_{i=1}^{p} \phi_{nn,i} r_{nt-i} + u_{nt}. \end{aligned} \tag{4.13}$$

Alternatively, we can express the equations in a matrix form. We obtain

$$\boldsymbol{r_t} = \boldsymbol{\mu}_0 + \boldsymbol{\Phi}_1 \boldsymbol{r}_{t-1} + \ldots + \boldsymbol{\Phi}_p \boldsymbol{r}_{t-1} + \boldsymbol{u}_t, \tag{4.14}$$

where $\boldsymbol{r}_t$ is $n \times 1$ vector of returns at time t, $\boldsymbol{\mu}_0$ is a constant $n \times 1$ vector, $\boldsymbol{\Phi}_i, i = 1, \ldots, p$ are $n \times n$ parameter matrices, and $\boldsymbol{u}_t$ is $n \times 1$ vector of errors.

Estimation of the VAR(p) model is conducted by either OLS for individual equations or maximum likelihood. Both options are asymptotically equivalent (Tsay 2005). The benefit of using conditional maximum likelihood estimation rests in the availability of information criteria to determine the appropriate lag length. The error vector $\boldsymbol{u}_t$ is of particular interest to the empirical part of our analysis, and it may be interpreted as a vector of shocks that will enter the multivariate GARCH models. Furthermore, the VAR model is used to explore spillover between assets that can be captured by the conditional mean equation (unlike shock and volatility spillover that is derived from the conditional covariance equation of multivariate GARCH model). Since the spillover modeled by the VAR model takes place in the mean equation of the VAR-BEKK model, we term this phenomenon a mean spillover in accordance with empirical literature (see Liu *et al.* 2017).

An important step in VAR model construction is the selection of the lag length p. Such choice is made based on the information criteria such as Akaike information criterion (AIC) (Akaike 1974), Hannan information criterion (HIC) (Hannan & Quinn 1979) or Schwarz information criterion (SIC) (Schwarz 1978). AIC is used in our case. The general form of the AIC is defined as

$$AIC(\hat{\theta}) = -2log(\hat{L}) + 2k, \tag{4.15}$$

where $\hat{L}$ is the value of likelihood and k is the number of parameters to be estimated. When applied to the VAR model, the AIC may be expressed as

$$AIC = log|\hat{\Sigma}| + \frac{2pn^2}{T}, \tag{4.16}$$

where $\hat{\Sigma}$ is the estimate of the covariance matrix of residuals from Equation 4.13, p is the given lag length, n is the number of equations in the VAR system, and T is the number of observations (Hurn *et al.* 2021).

If the lag length p in Equation 4.13 or Equation 4.14 is chosen to be $p = 1$, we only consider dependence between assets to be limited to one lagged return. Furthermore, in Section 6.3, only bivariate models are considered, therefore, $n = 2$ is assumed. In such case, the VAR model will have the following form

$$\begin{bmatrix} r_{1t} \\ r_{2t} \end{bmatrix} = \begin{bmatrix} \mu_{10} \\ \mu_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} r_{1t-1} \\ r_{2t-1} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} \tag{4.17}$$

$$= \begin{bmatrix} \mu_{10} \\ \mu_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11} r_{1t-1} + \phi_{12} r_{2t-1} \\ \phi_{21} r_{1t-1} + \phi_{22} r_{2t-1} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}. \tag{4.18}$$

The lag length p is chosen to be 1 in the vast majority of applications that use the VAR-BEKK specification for spillover modeling. In our case, the lag length is not fixed in order to achieve greater flexibility for the mean equation. However, in order to keep the number of parameters within reasonable bounds, the maximum lag length is restricted to $p = 4$. To avoid any potential ambiguity of parameter notation, the model for $n = 2$ and $p = 4$ is explicitly stated in Equation 4.19 and Equation 4.20.

$$\begin{aligned}
\begin{bmatrix} r_{1t} \\ r_{2t} \end{bmatrix} &= \begin{bmatrix} \mu_{10} \\ \mu_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} r_{1t-1} \\ r_{2t-1} \end{bmatrix} + \begin{bmatrix} \phi_{13} & \phi_{14} \\ \phi_{23} & \phi_{24} \end{bmatrix} \begin{bmatrix} r_{1t-2} \\ r_{2t-2} \end{bmatrix} \\
&+ \begin{bmatrix} \phi_{15} & \phi_{16} \\ \phi_{25} & \phi_{26} \end{bmatrix} \begin{bmatrix} r_{1t-3} \\ r_{2t-3} \end{bmatrix} + \begin{bmatrix} \phi_{17} & \phi_{18} \\ \phi_{27} & \phi_{28} \end{bmatrix} \begin{bmatrix} r_{1t-4} \\ r_{2t-4} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} \qquad (4.19) \\
&= \begin{bmatrix} \mu_{10} \\ \mu_{20} \end{bmatrix} + \begin{bmatrix} \phi_{11} r_{1t-1} + \phi_{12} r_{2t-1} \\ \phi_{21} r_{1t-1} + \phi_{22} r_{2t-1} \end{bmatrix} + \begin{bmatrix} \phi_{13} r_{1t-2} + \phi_{14} r_{2t-2} \\ \phi_{23} r_{1t-2} + \phi_{24} r_{2t-2} \end{bmatrix} \\
&+ \begin{bmatrix} \phi_{15} r_{1t-3} + \phi_{16} r_{2t-3} \\ \phi_{25} r_{1t-3} + \phi_{26} r_{2t-3} \end{bmatrix} + \begin{bmatrix} \phi_{17} r_{1t-4} + \phi_{18} r_{2t-4} \\ \phi_{27} r_{1t-4} + \phi_{28} r_{2t-4} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} \qquad (4.20)
\end{aligned}$$

To assess whether there is spillover in the mean equation of the included assets, the notion of Granger causality by Granger (1969) is used. The concept of Granger causality signifies the informational value of one variable for the prediction of future values of the other. Therefore, it does not automatically imply a causal relationship. However, if the causal relationship is, in fact, present, then it is also reasonable to expect that such a variable will play a role in the prediction of the other (Hurn *et al.* 2021).

Testing for Granger causality can be reduced to either testing for statistical significance of the coefficient ϕ_{21}, resp. ϕ_{12} in the case of the bivariate model with one lag (see Equation 4.18) or testing for joint statistical significance of multiple parameters that correspond to p lagged values of one variable. In the most general case, when there are n variables and p lags in the VAR model (see Equation 4.13), to test whether variable i Granger-causes variable j means to test the following hypothesis

$$H_0 : \phi_{ji,1} = \phi_{ji,1} = \ldots = \phi_{ji,p} = 0. \qquad (4.21)$$

Alternatively, for the concrete case of two variables and four lags, defined by Equation 4.20, the null hypothesis to determine whether variable r_2 Granger-causes variable r_1 has the form of

$$H_0 : \phi_{12} = \phi_{14} = \phi_{16} = \phi_{18} = 0. \qquad (4.22)$$

There are several alternative ways of testing the joint significance in the Granger causality test, F-test is applied in our case.

4.3 Dynamic Conditional Correlation Model

4.3.1 Model Specification

The generalization of GARCH models to a multivariate setting is not trivial in most cases. Therefore, it is necessary to describe the procedure with diligence. While the DCC model by Engle (2002a) does not allow for direct modeling of spillovers, it is the most widely used and effective instrument for modeling time-varying conditional correlations between different assets. The foundation of the multivariate specification is obtained by a straightforward generalization of the univariate counterparts (see Equation 4.3, Equation 4.4), such as

$$\boldsymbol{r_t} = \boldsymbol{\mu_t} + \boldsymbol{u_t} \tag{4.23}$$

$$\boldsymbol{u_t} = \boldsymbol{H_t^{1/2}} \boldsymbol{\epsilon_t}. \tag{4.24}$$

In Equation 4.23, the vector of raw asset returns $\boldsymbol{r_t}$ is decomposed into conditional mean specification $\boldsymbol{\mu_t}$ and the vector of innovations $\boldsymbol{u_t}$ at the time t. The vector of returns $\boldsymbol{r_t}$ has dimension of $n \times 1$, where n is the number of asset return series. Conditional mean specification $\boldsymbol{\mu_t}$ may take on various forms. In the simplest case, $\boldsymbol{\mu}$ is assumed to be a constant vector. Then, the innovations $\boldsymbol{u_t}$ may be interpreted as plain mean corrected returns. The flexibility of the DCC model resides in the possibility of applying different specifications to each univariate series. One such possibility is applying multivariate specification for the conditional mean, allowing for interaction between the return series. Such procedure is applied in Section 6.2. The multivariate specification, VAR model, is described in Section 4.2. Equation 4.24 defines how the conditional covariance matrix $\boldsymbol{H_t}$ influences the vector of innovations $\boldsymbol{u_t}$ in a manner analogous to the univariate counterpart described by Equation 4.4. $\boldsymbol{\epsilon_t}$ is $n \times 1$ i.i.d random variable vector with elements ϵ_{it}.

The generalization to multivariate setting has been straightforward so far. However, the integral part of the DCC model is to impose a concrete structure on the conditional covariance matrix. The conditional covariance matrix $\boldsymbol{H_t}$ ($[\boldsymbol{H_t}]_{ij} = h_{ijt}$), defined by Equation 2.9, is assumed to take on the form of

$$\boldsymbol{H_t} = \boldsymbol{D_t R_t D_t}, \tag{4.25}$$

where $\boldsymbol{D_t} = diag\{\sqrt{h_{1t}}, ..., \sqrt{h_{nt}}\}$ is $n \times n$ diagonal matrix of conditional volatilities originating from the first step of the estimation, typically univariate GARCH(1,1) processes, as in Equation 4.5.

In the vast majority of empirical applications that employ the DCC model, the $n \times n$ matrix of conditional correlations $\boldsymbol{R_t}$ is the object of main interest. Before proceeding any further, there are two issues that need to be addressed. First, the conditional covariance matrix $\boldsymbol{H_t}$ needs to be positive definite. Since it was defined as $\boldsymbol{H_t} = \boldsymbol{D_t R_t D_t}$ and the diagonal matrices $\boldsymbol{D_t}$ are positive definite by definition (diagonal elements of $\boldsymbol{D_t}$ are positive), we can see that $\boldsymbol{R_t}$ needs to be positive definite for each t. Second, all elements of the conditional correlation matrix $\boldsymbol{R_t}$ ($[\boldsymbol{R_t}]_{ij} = \rho_{ijt}$) need to lie in the interval $[-1, 1]$ to preserve the interpretation of its elements ρ_{ij} as correlation coefficients.

In order to satisfy the aforementioned requirements, the indirect specification by Engle (2002a) proceeds with the following steps. Standardized innovation may be expressed as $\boldsymbol{\epsilon_t} = \boldsymbol{D_t}^{-1}\boldsymbol{u_t}$, and each element is computed as $\epsilon_{it} = u_{it}/\sqrt{h_{it}}$. Furthermore, the ij-th element of the conditional covariance matrix of $\boldsymbol{\epsilon_t}$ ($\mathbb{E}(\boldsymbol{\epsilon_t}\boldsymbol{\epsilon_t}^T|I_{t-1})$) will be

$$\mathbb{E}(\epsilon_{it}\epsilon_{jt}|I_{t-1}) = \frac{\mathbb{E}(u_{it}u_{jt}|I_{t-1})}{\sqrt{h_{it}h_{jt}}} = \frac{h_{ijt}}{\sqrt{h_{it}h_{jt}}} = \rho_{ijt}. \tag{4.26}$$

Therefore, the conditional covariance of the standardized innovations $\boldsymbol{\epsilon_t}$ will be $\boldsymbol{R_t}$, conditional correlation of innovations $\boldsymbol{u_t}$. Then, the conditional correlation is modeled indirectly as a matrix $\boldsymbol{Q_t}$ ($[\boldsymbol{Q_t}]_{ij} = q_{ijt}$) that is described by the equation

$$\boldsymbol{Q_t} = (1 - a - b)\overline{\boldsymbol{Q}} + a\boldsymbol{\epsilon_{t-1}}\boldsymbol{\epsilon_{t-1}}^T + b\boldsymbol{Q_{t-1}}. \tag{4.27}$$

Similarly to the univariate GARCH model, Engle (2002a) imposes restrictions on the parameters such that $a \geq 0$, $a \geq 0$ and $a + b < 1$. The last restriction is particularly important as it ensures mean reversion to the long-run value. $\overline{\boldsymbol{Q}}$ is unconditional covariance matrix of the standardized innovations. A natural estimator of $\overline{\boldsymbol{Q}}$, using all T observations in the sample, is

$$\widehat{\overline{\boldsymbol{Q}}} = \frac{1}{T}\sum_{t=1}^{T} \boldsymbol{\epsilon_t}\boldsymbol{\epsilon_t}^T. \tag{4.28}$$

Finally, it is necessary to state how the auxiliary correlation matrix $\boldsymbol{Q_t}$ relates to $\boldsymbol{R_t}$. Let's define $\boldsymbol{Q_t^D} = diag\{\sqrt{q_{11t}}, ..., \sqrt{q_{nnt}}\}$, a diagonal matrix of square roots of diagonal elements of $\boldsymbol{Q_t}$.

Then, the following expression highlights how the matrix $\boldsymbol{Q_t}$ is standardized to obtain the original conditional correlation matrix $\boldsymbol{R_t}$,

$$\boldsymbol{R_t} = (\boldsymbol{Q_t^D})^{-1}\boldsymbol{Q}_t(\boldsymbol{Q_t^D})^{-1}, \tag{4.29}$$

therefore, for element-wise expression, it will hold that

$$\rho_{ij} = \frac{q_{ijt}}{\sqrt{q_{it}q_{jt}}} \in [-1, 1]\,. \tag{4.30}$$

4.3.2 Model Estimation

Estimation of the DCC model is conducted by means of maximum likelihood. Since the maximum likelihood is a parametric estimation method, a distributional assumption for either innovations $\boldsymbol{u_t}$ or standardized innovations $\boldsymbol{\epsilon_t}$ needs to be made. Both normal and Student's t-distribution are considered in the empirical analysis in Section 6.2. Therefore, both likelihood functions are formulated. Engle (2002a) proposes a two-step estimation of the parameter vector $\boldsymbol{\theta} = \{\boldsymbol{\theta_1}, \boldsymbol{\theta_2}\}$.

First, we start with the assumption of normal distribution for our model. Let

$$\boldsymbol{\epsilon_t} \sim N(\boldsymbol{0}, \boldsymbol{I}), \tag{4.31}$$

then, since $\boldsymbol{u_t} = \boldsymbol{H_t}^{\boldsymbol{1/2}}\boldsymbol{\epsilon_t}$, the following holds for the innovation vector,

$$\boldsymbol{u_t}|I_{t-1} \sim N(\boldsymbol{0}, \boldsymbol{H_t}). \tag{4.32}$$

The first stage estimation concerns parameters of the univariate GARCH(1,1) model $\boldsymbol{\theta_{1i}} = \{\alpha_{0i}, \alpha_{1i}, \beta_{1i}\}$ for $i = 1, ..., n$, where n is the number of assets in the model. In the second stage, parameters of the DCC model $\boldsymbol{\theta_2} = \{a, b\}$ are estimated. Likelihood function takes the form of

$$L(\boldsymbol{\theta}) = \prod_{t=1}^{T} \frac{1}{(2\pi)^{n/2}|\boldsymbol{H_t}|^{1/2}} exp\left(-\frac{1}{2}\boldsymbol{u_t}^{\boldsymbol{T}}\boldsymbol{H_t}^{-1}\boldsymbol{u_t}\right), \tag{4.33}$$

where $|\boldsymbol{H_t}|$ denotes the determinant of the conditional covariance matrix $\boldsymbol{H}_t$.

Furthermore, when the likelihood function is transformed by natural logarithm, the log-likelihood function is obtained,

$$l(\boldsymbol{\theta}) = logL(\boldsymbol{\theta}) = -\frac{1}{2}\sum_{t=1}^{T}\left(nlog(2\pi) + log|\boldsymbol{H_t}| + \boldsymbol{u_t}^{\boldsymbol{T}}\boldsymbol{H_t}^{-1}\boldsymbol{u_t}\right), \tag{4.34}$$

where we can substitute for $\boldsymbol{H_t}$ according to Equation 4.25, therefore

$$l(\boldsymbol{\theta}) = -\frac{1}{2}\sum_{t=1}^{T}\left(nlog(2\pi) + log|\boldsymbol{D_t R_t D_t}| + \boldsymbol{u_t}^{\boldsymbol{T}}\boldsymbol{D_t}^{\boldsymbol{-1}}\boldsymbol{R_t}^{-1}\boldsymbol{D_t}^{-1}\boldsymbol{u_t}\right). \tag{4.35}$$

Using properties of logarithm, $\boldsymbol{D_t}$ can be isolated. The first term in Equation 4.35 and the isolated elements with $\boldsymbol{D_t}$ may be treated as constants (they were already estimated in the first stage of estimation), and they are redundant for the optimization process of the second stage. Furthermore, we can substitute $\boldsymbol{u_t} = \boldsymbol{H_t}^{\boldsymbol{1/2}}\boldsymbol{\epsilon_t}$ for $\boldsymbol{u_t}$ in Equation 4.35. Therefore, we obtain the second stage log-likelihood with normally distributed innovations such as

$$l(\boldsymbol{\theta}) = -\frac{1}{2}\sum_{t=1}^{T} log|\boldsymbol{R_t}| + \boldsymbol{\epsilon_t}\boldsymbol{R_t}^{\boldsymbol{-1}}\boldsymbol{\epsilon_t}. \tag{4.36}$$

Alternatively, it may be assumed that the innovations are t-distributed. Such an assumption may be formulated with the use of standardized innovations $\boldsymbol{\epsilon_t}$ as

$$\boldsymbol{\epsilon_t} \sim St(\boldsymbol{0}, \boldsymbol{I}, \nu), \tag{4.37}$$

or with the use of innovations $\boldsymbol{u_t}$ as

$$\boldsymbol{u_t}|I_{t-1} \sim St(\boldsymbol{0}, \boldsymbol{H_t}, \nu). \tag{4.38}$$

The first stage estimation concerns parameters of the univariate GARCH(1,1) model $\boldsymbol{\theta_{1i}} = \{\alpha_{0i}, \alpha_{1i}, \beta_{1i}, \nu_i\}$ for $i = 1, ..., n$, where n is the number of assets in the model. In the second stage, parameters of the DCC model $\boldsymbol{\theta_2} = \{a, b, \nu\}$ are estimated. Then, the likelihood function takes the form of

$$L(\boldsymbol{\theta}) = \prod_{t=1}^{T} \frac{\Gamma\left(\frac{\nu+n}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)\left(\sqrt{\pi(\nu-2)}\right)^{n/2}|\boldsymbol{H_t}|^{1/2}} \left(\frac{\boldsymbol{u_t}^{\boldsymbol{T}}\boldsymbol{H_t}^{-1}\boldsymbol{u_t}}{\nu-2}\right)^{-\frac{n+\nu}{2}}, \tag{4.39}$$

where Γ denotes the gamma function, and ν is the degrees of freedom in the second step likelihood function. By taking the logarithm and using the DCC structure for the conditional covariance matrix defined in Equation 4.25, we can substitute for $\boldsymbol{H_t}$, and we obtain log-likelihood function such as

$$\begin{aligned} l(\boldsymbol{\theta}) = logL = \sum_{t=1}^{T} log\Gamma\left(\frac{\nu+n}{2}\right) - log\Gamma\left(\frac{\nu}{2}\right) - \frac{n}{2}log(\pi(\nu-2)) - \\ -\frac{1}{2}log|\boldsymbol{D_t}\boldsymbol{R_t}\boldsymbol{D_t}| - \frac{\nu+n}{2}log\left(1+\frac{\boldsymbol{u_t}^{\boldsymbol{T}}\boldsymbol{D_t}^{\boldsymbol{-1}}\boldsymbol{R_t}^{\boldsymbol{-1}}\boldsymbol{D_t}^{\boldsymbol{-1}}\boldsymbol{u_t}}{\nu-2}\right). \end{aligned} \tag{4.40}$$

Finally, we use the product and power properties of the natural logarithm function and the fact that $\boldsymbol{\epsilon_t} = \boldsymbol{H_t}^{-1/2}\boldsymbol{u_t}$. Furthermore, the matrix $\boldsymbol{D_t}$ is redundant for the second stage of the estimation. Therefore, the second stage log-likelihood function for t-distributed innovations is

$$\begin{aligned} l(\boldsymbol{\theta}) = \sum_{t=1}^{T} log\Gamma\left(\frac{\nu+n}{2}\right) - log\Gamma\left(\frac{\nu}{2}\right) - \frac{n}{2}log(\pi(\nu-2)) - \\ -\frac{1}{2}log|\boldsymbol{R_t}| - \frac{\nu+n}{2}log\left(1+\frac{\boldsymbol{\epsilon_t}^{\boldsymbol{T}}\boldsymbol{R_t}^{\boldsymbol{-1}}\boldsymbol{\epsilon_t}}{\nu-2}\right). \end{aligned} \tag{4.41}$$

Regardless of whether we use the log-likelihood with the assumption of normal or t-distribution, the maximum likelihood estimate $\widehat{\boldsymbol{\theta}}_{ML}$ is obtained by solving the following optimization problem

$$\widehat{\boldsymbol{\theta}}_{ML} = \arg\max_{\theta} l(\boldsymbol{\theta}). \tag{4.42}$$

The optimization is conducted within the *rmgarch* R package by Galanos (2022). Similarly, as in the case of univariate GARCH estimation (see Section 6.1), the augmented Lagrange solver solnp by Ye (1997) is used.

4.4 BEKK Model

4.4.1 Model Specification

BEKK model by Engle & Kroner (1995) is a model specification used to model a conditional covariance matrix. Unlike CCC or DCC models that impose concrete structure for the conditional covariance matrix (see Equation 4.25), BEKK specification is constructed in a more direct manner. Similar to the most direct multivariate vec-GARCH specification, it suffers from an excessive number of parameters. However, the dimensionality problem can be contained when the number of assets in the model is significantly constrained. Therefore, to address the problem of dimensionality and to allow for reasonable interpretation of the estimation results, only bivariate BEKK models are considered. Therefore, we assume that N = 2 and the conditional covariance matrix takes the following form

$$\boldsymbol{H_t} = \begin{pmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{pmatrix}. \tag{4.43}$$

The following equations state the conditions for such a matrix to be positive definite

$$h_{11t} > 0 \tag{4.44}$$

$$h_{11t}h_{22t} - h_{21t}h_{12t} > 0. \tag{4.45}$$

The first condition (see Equation 4.44) is straightforward as it states that the conditional variance of the first series is positive. The second condition (see Equation 4.45) is more sophisticated. Hurn *et al.* (2021) offer an interpretation of Equation 4.45 as a range condition for the correlation coefficient between the two series. Therefore,

$$-1 < \frac{h_{12t}}{\sqrt{h_{11t}}\sqrt{h_{22t}}} < 1. \tag{4.46}$$

General form of BEKK(1,1,1) model by Engle & Kroner (1995) for N assets is

$$\boldsymbol{H_t} = \boldsymbol{C}^T\boldsymbol{C} + \boldsymbol{A}^T\boldsymbol{u_{t-1}}\boldsymbol{u_{t-1}^T}\boldsymbol{A} + \boldsymbol{G}^T\boldsymbol{H_{t-1}}\boldsymbol{G}, \tag{4.47}$$

where $\boldsymbol{C}$ is a lower triangular $N \times N$ matrix, $\boldsymbol{C}^T\boldsymbol{C}$ may be seen as a decomposition of the constant matrix. Therefore, the parameters of the matrix $\boldsymbol{C}$ have no practical interpretation. The $n \times 1$ vector $\boldsymbol{u_{t-1}}$ contains shocks lagged by one period, and $\boldsymbol{H_{t-1}}$ is a lagged $N \times N$ conditional covariance matrix. $\boldsymbol{A}$, $\boldsymbol{G}$

are $N \times N$ parameter matrices that will be estimated.

The fact that the BEKK model is a relatively straightforward generalization of the univariate GARCH(1,1) model may be demonstrated when we set N = 1. In such case, the model simplifies to

$$h_{11t} = c_{11}^2 + a_{11}^2 u_{t-1}^2 + b_{11}^2 h_{11t-1}, \tag{4.48}$$

which is equivalent to the univariate GARCH(1,1) model (with the exception of squared parameters).

4.4.2 Model Estimation

Similar to other GARCH model specifications, the maximum likelihood framework is applied in the process of model estimation. Only bivariate models are considered in the empirical analysis (see Section 6.3). BEKK model with the assumption of normally distributed shocks is applied. Therefore, we assume

$$\boldsymbol{u_t} | I_{t-1} \sim N(\boldsymbol{0}, \boldsymbol{H_t}), \tag{4.49}$$

where $\boldsymbol{u_t}$ is a 2×1 vector of shocks and $\boldsymbol{H_t}$ is a 2×2 conditional covariance matrix. The likelihood function based on the multivariate normal distribution is

$$L(\boldsymbol{\theta}) = \prod_{t=1}^{T} (2\pi)^{-1} |\boldsymbol{H_t}|^{-1/2} exp\left(-\frac{1}{2} \boldsymbol{u_t}^T \boldsymbol{H_t}^{-1} \boldsymbol{u_t}\right). \tag{4.50}$$

After transformation by natural logarithm is conducted, we obtain the log-likelihood function of the following form

$$l(\boldsymbol{\theta}) = logL(\boldsymbol{\theta}) = -Tlog(2\pi) - \frac{1}{2}\sum_{t=1}^{T} log|\boldsymbol{H_t}| - \frac{1}{2}\sum_{t=1}^{T} \boldsymbol{u_t}^T \boldsymbol{H_t}^{-1} \boldsymbol{u_t}. \tag{4.51}$$

The estimate of the parameter vector is then obtained by solving the following optimization problem

$$\widehat{\boldsymbol{\theta}}_{ML} = \arg\max_{\theta} l(\boldsymbol{\theta}). \tag{4.52}$$

Engle & Kroner (1995) recommend the BHHH algorithm by Hall *et al.* (1974) for the estimation. In this thesis, *BEKKs* package is applied for the estimation process. Within the *BEKKs*, Fülle *et al.* (2022) use the BHHH-based method inspired by the study of Hafner & Herwartz (2008).

4.4.3 Equations of Bivariate BEKK Models

In the empirical analysis of spillovers between currency pairs and cocoa futures (see Section 6.3), the bivariate BEKK model is used. In order to outline how the spillovers are modeled, it is instructive to break down the model in greater detail. The BEKK model contains information about the dynamics of conditional variances h_{11}, h_{22} and the conditional covariance term h_{21}. For $N = 2$ in Equation 4.47, the BEKK model becomes

$$\begin{bmatrix} h_{11t} & h_{12t} \\ h_{21t} & h_{22t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{21} \\ 0 & c_{22} \end{bmatrix} \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \end{bmatrix} \begin{bmatrix} u_{1t-1} \\ u_{2t-1} \end{bmatrix} \begin{bmatrix} u_{1t-1} & u_{2t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{21} \\ g_{12} & g_{22} \end{bmatrix} \begin{bmatrix} h_{11t-1} & h_{12t-1} \\ h_{21t-1} & h_{22t-1} \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}. \tag{4.53}$$

Then, simple matrix multiplication in 4.53 gives Equation 4.54, Equation 4.55, and Equation 4.56 for h_{11t}, h_{12t}, and h_{22t}, respectively. The elements of the constant matrix $\boldsymbol{C}^T\boldsymbol{C}$ are disregarded as they carry no informational value for the purpose of our analysis.

$$\begin{aligned} h_{11t} &= a_{11}^2 u_{1t-1}^2 + 2a_{11}a_{21}u_{1t-1}u_{2t-1} + a_{21}^2 u_{2t-1}^2 \\ &+ g_{11}^2 h_{11t-1} + 2g_{11}g_{21}h_{12t-1} + g_{21}^2 h_{22t-1} \end{aligned} \tag{4.54}$$

$$\begin{aligned} h_{12t} &= a_{11}a_{12}u_{1t-1}^2 + u_{1t-1}u_{2t-1}(a_{11}a_{22} + a_{12}a_{21}) + a_{21}a_{22}u_{2t-1}^2 \\ &+ g_{11}g_{21}h_{11t-1} + h_{12t-1}(g_{11}g_{22} + g_{21}g_{12}) + g_{21}g_{22}h_{22t-1} \end{aligned} \tag{4.55}$$

$$\begin{aligned} h_{22t} &= a_{12}^2 u_{1t-1}^2 + 2a_{12}a_{22}u_{1t-1}u_{2t-1} + a_{22}^2 u_{2t-1}^2 \\ &+ g_{12}^2 h_{11t-1} + 2g_{12}g_{22}h_{21t-1} + g_{22}^2 h_{22t-1} \end{aligned} \tag{4.56}$$

From the equations above, the evolution of conditional variances h_{11t}, h_{22t}, and conditional covariance h_{12t} (note that $h_{12t} = h_{21t}$) may be observed. In Section 6.3, spillovers are studied between two assets at the time. By testing for the significance of a_{12} and a_{21}, we examine the presence of shock spillover from asset 1 to asset 2 and from asset 2 to asset 1, respectively. In the same way, by testing for the significance of g_{12} and g_{21}, we examine the presence of volatility (or variance) spillover from asset 1 to asset 2 and from asset 2 to asset 1, respectively. Therefore, only Equation 4.54 for h_{11t} and Equation 4.56 for h_{22t}

are of interest to the empirical analysis of spillovers conducted in Section 6.3, and we may disregard Equation 4.55 for h_{12t} from the consideration altogether.

Chapter 5

Data Description and Preliminary Analysis

5.1 Construction of the Dataset

This chapter provides details on the construction of the dataset, together with a preliminary analysis comprising a variety of descriptive measures and tests for the data used in the empirical analysis. The price data on two asset classes, cocoa futures, and spot currency rates, were collected from Refinitiv Eikon on May 4, 2024. Data on closing prices are sampled with daily and weekly frequency for a period from July 5, 2007 to May 3, 2024. The choice of the time span for the analysis is made with consideration to the availability of data and the fact that Third GHS was instituted as the legal tender in Ghana starting on July 2, 2007, and it remains in place to this day.

Futures contracts expire when the delivery month approaches. Therefore, continuous futures price series need to be constructed. We use a continuation price series that uses the second to earliest futures contract for both US Cocoa Futures and London Cocoa Futures. Rolling to the next contract is conducted on the last trading day of delivery months (March, May, July, September, December), one day before the last notice day. The last notice day occurs ten business days prior to the last business day of the delivery month (ICE 2024b). Therefore, in both cases, the rolling procedure occurs eleven days before the last business day of the delivery month. We avoid using the contract with the earliest delivery month, the front month, because the informational value of the futures price may get distorted as the contract nears its delivery. Such distortions may occur in the period close to the contract expiry as both volume and open interest tend to plummet. On the other hand, the second to earliest contract displays greater stability in terms of open interest and volume, and it even dominates the front-month contract in these measures for a significant portion of time.

Closing prices are used for both daily and weekly data. For weekly data, the closing Friday price is used. US Cocoa Futures daily close is at 13:30 New York local time or 18:30 London local time, respectively. London Cocoa Futures daily close is at 16:55 London local time or 11:55 New York local time, respectively. The foreign exchange market opens on Sunday at 17:00 New York local time and stays open until 17:00 New York local time on Friday. Therefore, the trading hours of the considered assets are not synchronous. The difference in the trading hours between both futures contracts is not too large, as trading in both contracts overlaps to a great extent.

The difference in the trading hours between ICE futures markets and foreign exchange is more problematic. However, even though the potential effects of these discrepancies need to be acknowledged, they will not cause serious detriment to our analysis. First, the models focus on the effects of the previous day's data on the next day's data, therefore, the distortion will be limited. Second, only pairs of European currencies, GHS, and USD are considered. In practice, a large part of the traded volume in these foreign exchange pairs will occur during London and New York trading sessions. Consequently, major currency moves tend to take place during these hours as well, overlapping with the trading hours of the cocoa futures contracts. In empirical work, the problem of nonsynchronous trading hours is addressed depending on its severity. One solution is to use lower frequency data, such as weekly returns, which will alleviate the problem significantly. However, such action comes with a trade-off as we disregard the dynamics of the higher time-frequency, which may be of greater interest than those of lower frequency. The approach adopted in this thesis is to work with both daily and weekly data, not only to address the aforementioned phenomena but also to explore the studied dynamics from different time frequency perspectives.

The price series for the spot currency rates are constructed using the daily mid price, obtained as an average of daily closing bid and ask prices. Currencies of interest for the analysis are USD, GBP, EUR, CHF, and GHS. The choice of currencies has been made based on their importance for the global financial system (EUR, GBP, CHF) and their relevance to the study of the cocoa sector (GHS). The currency pairs are then formed to obtain USD and GBP-denominated currency pairs suitable for the empirical analysis. Therefore, eight currency pairs are used in total. EURUSD, GBPUSD, CHFUSD, GHSUSD, USDGBP, EURGBP, CHFGBP and GHSGBP. Currency rates are expressed such that they convey how much of the second currency we need to buy one unit of the first currency in the given pair. Therefore, the price of EURUSD equal to 1.5 means that 1.5 units of USD are necessary in order to purchase 1 unit of EUR.

Days for which cocoa futures data are unavailable, typically US or UK market holidays, are disregarded from the analysis altogether. Visual inspection of price plots (see Figure 5.1, Figure 5.2, Figure 5.3) hints that the price series most likely contain some form of unit root. In order to obtain weakly stationary time series, price data points need to be differenced. Therefore, the series of returns are obtained. In accordance with empirical practice, continuously compounded returns r_t are used. Continuously compounded returns are computed as

$$r_t = log\frac{P_t}{P_{t-1}}, \tag{5.1}$$

where log is a natural logarithm, and P_t is the price of an instrument at the time t. Plots of daily return series for cocoa futures may be found in Figure A.1, for USD-denominated currency pairs in Figure A.3, and for GBP-currency pairs in Figure A.5. Plots of weekly returns for cocoa futures may be found in Figure A.2, for USD-denominated currency pairs in Figure A.4, and for GBP-denominated currency pairs in Figure A.6. Based on the visual inspection, it is likely that the return series satisfy the properties of constant mean, variance, and covariance necessary for the time series to be weakly (covariance) stationary. To confirm such a conclusion, stationarity tests will be carried out in Section 5.3.

5.2 Descriptive Statistics

Table 5.1: Descriptive statistics for daily returns

Statistic	N	Mean	St. Dev.	Min	Max	Skewness	Kurtosis
US Cocoa	4,175	0.032	1.757	−17.076	9.191	-0.38	7.601
London Cocoa	4,175	0.044	1.510	−15.653	9.640	-0.251	9.134
EURUSD	4,175	−0.005	0.584	−2.785	3.733	0.087	5.362
GBPUSD	4,175	−0.009	0.619	−8.402	3.090	-0.85	13.862
CHFUSD	4,175	0.009	0.668	−9.090	17.141	3.59	116.803
USDGBP	4,175	0.009	0.619	−3.086	8.408	0.845	13.836
EURGBP	4,175	0.004	0.528	−3.142	6.003	0.505	9.364
CHFGBP	4,175	0.017	0.699	−8.015	17.456	3.684	104.962
GHSUSD	4,175	−0.061	1.027	−15.338	15.954	0.336	47.385
GHSGBP	4,175	−0.051	1.211	−15.233	15.413	0.414	27.666

Note: All presented descriptive statistics are for returns as %, i.e. $log(P_t/P_{t-1}) \times 100$.
The values are rounded to 3 decimal places.

Daily sample return series data span from July 6, 2007, to May 3, 2024. Therefore, after all adjustments, there are 4175 observations of daily returns. To make the results more suitable for interpretation, descriptive statistics in Table 5.1 are computed for log returns multiplied by 100 to enable interpretation of the values as daily % returns. For both cocoa futures contracts, the basic characteristics are qualitatively and quantitatively alike. The mean returns, though positive, are close to 0%. Standard deviation is larger for the US Cocoa, meaning that the US contract is more volatile than its London counterpart. Maximum returns are within the bounds of 10% for both futures contracts. Maximum returns for US Cocoa occurred on April 18, 2024, and for London Cocoa on March 25, 2024. Minimum returns are of larger magnitude for US Cocoa (-17.076%) than for London Cocoa (-15.653%), both occurred on April 29, 2024. Both futures contracts are moderately negatively skewed and exhibit excess kurtosis, indicating that the distribution of returns is leptokurtic. Based on the values of kurtosis, the distributional properties of cocoa futures returns are likely to be nonnormal. Fat tails are present, and extreme values will occur with higher frequency than in the case of normal distribution.

In the case of foreign exchange returns, the values of the descriptive statistics are significantly more diverse. It can be observed that the descriptive statistics get progressively more tilted towards extreme values as we shift from the most traded currency pairs of the developed world, such as EURUSD, GBPUSD, and EURGBP, to pairs with less volume that involve CHF and GHS in particular. EURUSD and EURGBP share similar characteristics. They are the least volatile of all considered instruments, the mean of returns is close to 0, and they are both positively skewed. However, the skewness of EURGBP (0.505) is of significantly larger magnitude, and based on the values of minimum (-3.142%), maximum (6.003%), and kurtosis (9.364), it may be stated that more extreme values exist in EURGBP series. USDGBP evinces similar behaviour to that of EURGBP, but its tendency towards more extreme moves is even more pronounced with the higher values of standard deviation (0.619), skewness (0.845), and kurtosis (13.836). It is necessary to note that USDGBP and GBPUSD are mere inverse values of each other, representing the exchange rate between GBP and USD. However, both GBPUSD and USDGBP are used in Chapter 6 in their respective forms, therefore, it is useful to conduct descriptive analysis and statistical tests for both series. Any minor discrepancies between the two, apart from the inverse relation, are consequences of bid-ask spread and rounding of the data.

CHFUSD and CHFGBP exhibit more volatile behaviour than the aforementioned pairs, and both manifest highly similar dynamics that may be explained by the unique role of the Swiss Franc as a safe haven asset (see Antonakakis & Kizys 2015). Therefore, it is a desirable investment in times of financial stress, which was demonstrated during the period of GFC and the European Sovereign Debt Crisis when CHF appreciated immensely against both USD and GBP (see Figure 5.2, Figure 5.3). Both CHFUSD and CHFGBP are more volatile based on the values of standard deviation than previously examined pairs. Returns of larger magnitudes are present in both directions, e.g., the largest return for CHFUSD is 17.141%, and the smallest return is -9.090%. The occurrence of extreme returns manifests itself through the high magnitude of kurtosis, which is 116.803 for CHFUSD and 104.962 for CHFGBP. Furthermore, the distribution of returns for both pairs is highly positively skewed.

GHS is the only developing currency that is considered in the empirical analysis in Chapter 6. Both GHSUSD and GHSGBP have a negative mean of return, which is in accordance with the long-term negative trend of GHS depreciation (see Figure 5.2, Figure 5.3). Both pairs are the most volatile among the currency pairs, with a standard deviation of GHSUSD equal to 1.027 and a standard deviation of GHSGBP equal to 1.212. Returns are positively skewed. Extreme values are present in both series, which can also be observed in minimum and maximum values of returns exceeding 15%. The large values of the kurtosis measure also indicate the presence of extreme values in the return series and distributional properties that are likely different from normal distribution.

Figure 5.1: Daily price of cocoa futures contracts

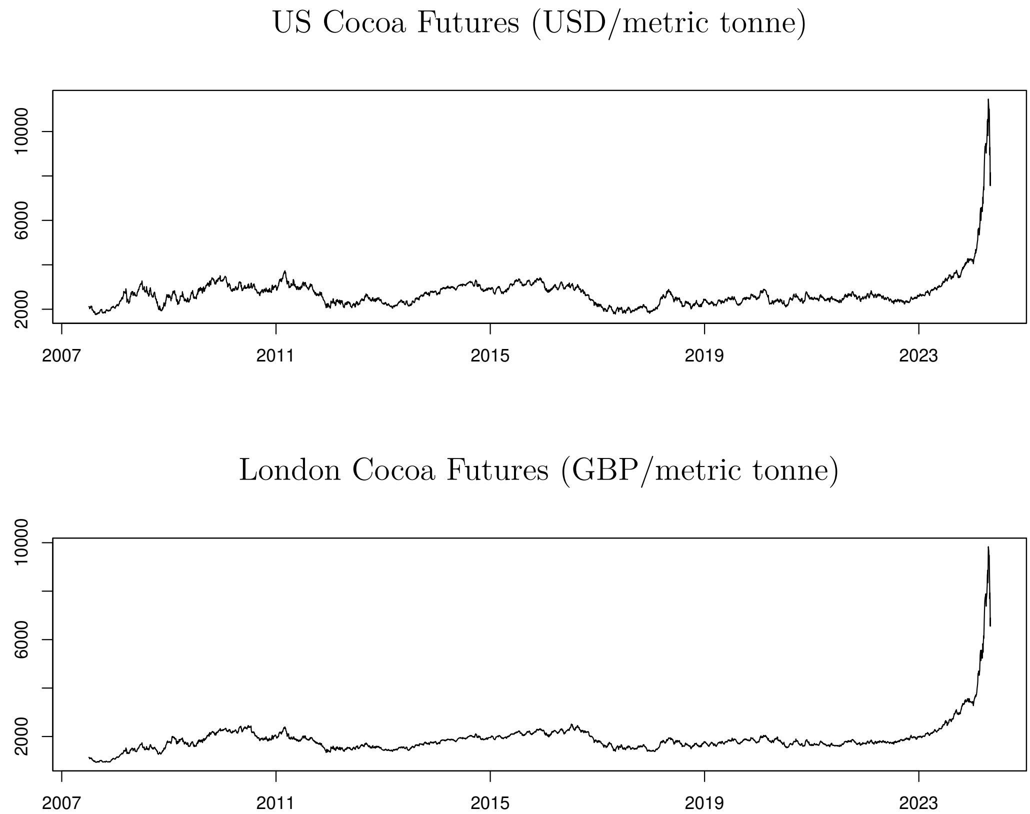


Table 5.2: Descriptive Statistics for weekly returns

Statistic	N	Mean	St. Dev.	Min	Max	Skewness	Kurtosis
US Cocoa	878	0.153	3.937	−26.288	15.813	−0.347	6.884
London Cocoa	878	0.205	3.520	−26.525	16.733	−0.084	8.791
EURUSD	878	−0.027	1.274	−6.033	4.966	−0.249	4.869
GBPUSD	878	−0.054	1.357	−8.206	6.766	−0.515	6.871
CHFUSD	878	0.034	1.477	−11.433	16.785	1.361	25.651
USDGBP	878	0.054	1.357	−6.767	8.203	0.512	6.907
EURGBP	878	0.027	1.169	−7.621	5.351	−0.068	7.095
CHFGBP	878	0.087	1.491	−9.345	16.849	1.444	23.619
GHSUSD	878	−0.306	2.276	−20.493	35.656	3.84	86.102
GHSGBP	878	−0.253	2.706	−21.672	36.595	2.397	48.932

Note: All presented descriptive statistics are for returns as %, i.e. $log(P_t/P_{t-1}) \times 100$.
The values are rounded to 3 decimal places.

Figure 5.2: Daily spot price of USD-denominated currency pairs

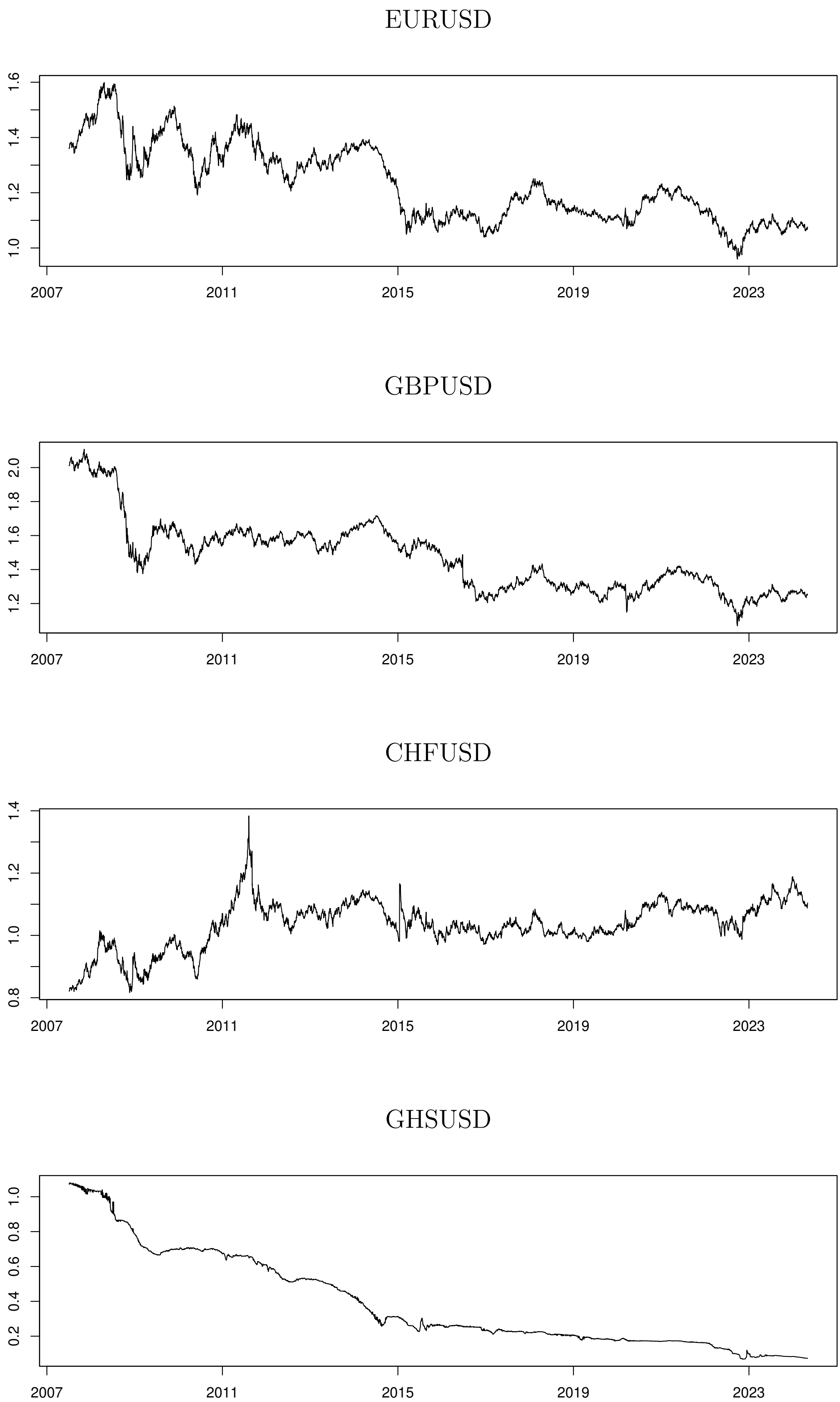
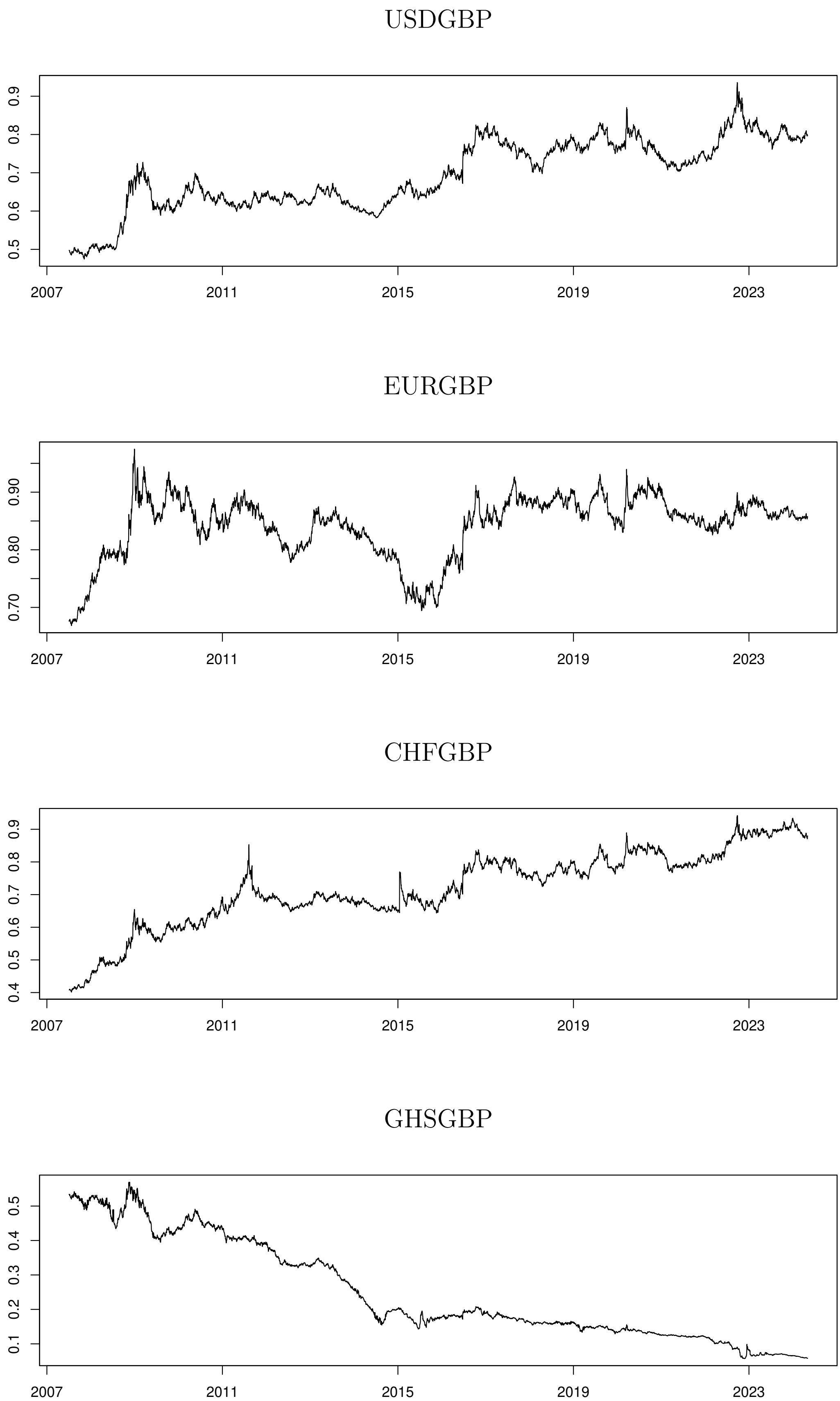


Figure 5.3: Daily spot price of GBP-denominated currency pairs



Descriptive statistics for weekly returns (see Table 5.2) share most qualitative characteristics with their daily data counterparts. Volatility is higher in the case of all weekly series. With few exceptions, minimum and maximum values for weekly returns are higher than those of daily returns. These differences are especially large for cocoa futures contracts and both GHS pairs. Log returns have an additive property, meaning we may express the weekly return as a sum of five daily returns. Consequently, a possible interpretation is that weekly returns will be systematically higher when there is a degree of autocorrelation in daily returns. The degree of autocorrelation in the returns will be examined in Section 5.3, which will provide results of Ljung-Box tests for various lag lengths. Furthermore, weekly returns of GHS currency pairs and cocoa futures are the most volatile and have the largest absolute mean returns.

To conclude the presentation of basic descriptive measures, unconditional correlation matrices of daily and weekly returns have been computed for the full sample of data (see Table 5.3, Table 5.4). The only two highly correlated return series in the data are cocoa futures contracts. US Cocoa is weakly positively correlated with EURUSD and GBPUSD, such a relationship is expected since US Cocoa is denominated in USD. Therefore, if EURUSD and GBPUSD are taken as proxies for the strength of USD, then the appreciation of EUR or GBP (USD depreciation) is expected to partly coincide with the rise in cocoa futures price. In the daily returns correlation matrix, the largest coefficient between currencies and US Cocoa is 0.23 between US Cocoa and GBPUSD. When weekly returns are used, US Cocoa correlates the most with EURUSD, with a correlation coefficient equal to 0.29. The correlation between other currency pairs and US Cocoa is either very weak or nonexistent. London Cocoa correlates very little with currency pairs in general. The only correlation coefficients with 1% statistical significance are those with EURGBP. The coefficient of correlation between London Cocoa and EURGBP is 0.09 when daily returns are used and 0.15 when the coefficients are based on weekly returns.

The correlation structure between cocoa futures contracts and currency pairs is generally weak. However, basic Pearson correlation measure can only provide the most superficial understanding of the relationship between two assets. In order to explore the cross-asset dynamics in greater depth, more sophisticated tools have to be used. First, the correlation between assets may be time-varying. Such a possibility will be explored in Section 6.2 using the DCC-GARCH model. Second, the transmission of information between two return series may flow via channels that cannot be captured by the simple correlation measure. Dynamics of higher conditional moments are one such possibility. The analysis conducted in Chapter 6 focuses on dynamics surrounding the second conditional moment, conditional variance. For such purpose, DCC (see Section 4.3, Section 6.2) and BEKK (see Section 4.4, Section 6.3) models are utilized.

Table 5.3: Correlation matrix for daily returns

	US Cocoa	London Cocoa	EURUSD	GBPUSD	CHFUSD	USDGBP	EURGBP	CHFGBP	GHSUSD
US Cocoa									
London Cocoa	0.88***								
EURUSD	0.21***	0.04**							
GBPUSD	0.23***	-0.04*	0.61***						
CHFUSD	0.12***	0.00	0.67***	0.41***					
USDGBP	-0.23***	0.04*	-0.62***	-1.00***	-0.41***				
EURGBP	-0.04**	0.09***	0.38***	-0.49***	0.25***	0.49***			
CHFGBP	-0.09***	0.03*	0.09***	-0.49***	0.59***	0.49***	0.68***		
GHSUSD	-0.01	-0.02	-0.01	-0.01	0.02	0.01	0.00	0.02	
GHSGBP	-0.12***	0.01	-0.32***	-0.52***	-0.20***	0.52***	0.25***	0.27***	0.84***

Notes: *,** ,*** indicate statistical significance at 10%, 5%, 1% levels. All presented values are Pearson correlation coefficients rounded to 2 decimal places.

Table 5.4: Correlation matrix for weekly returns

	US Cocoa	London Cocoa	EURUSD	GBPUSD	CHFUSD	USDGBP	EURGBP	CHFGBP	GHSUSD
US Cocoa									
London Cocoa	0.90***								
EURUSD	0.29***	0.08*							
GBPUSD	0.27***	-0.05	0.60***						
CHFUSD	0.19***	0.03	0.70***	0.45***					
USDGBP	-0.27***	0.05	-0.60***	-1.00***	-0.45***				
EURGBP	0.01	0.15***	0.39***	-0.50***	0.24***	0.50***			
CHFGBP	-0.05	0.08*	0.14***	-0.47***	0.58***	0.46***	0.69***		
GHSUSD	0.00	-0.02	-0.03	-0.05	-0.01	0.05	0.02	0.03	
GHSGBP	-0.13***	0.01	-0.33***	-0.54***	-0.24***	0.54***	0.27***	0.26***	0.87***

Notes: *,** ,*** indicate statistical significance at 10%, 5%, 1% levels. All presented values are Pearson correlation coefficients rounded to 2 decimal places.

5.3 Statistical Tests

In order to explore the return series in a more sophisticated manner than can be achieved by the basic descriptive statistics presented in Section 5.2, a set of statistical tests is conducted. A standard 5% threshold is used for hypothesis testing, but the outcomes for 10% and 1% levels are also reported in the results. First, we test for the presence of a unit root in every return series. The presence of a unit root would be in conflict with stationarity, the weak form of which is a necessary assumption for the models applied in Chapter 6. Three different tests for unit root are conducted, Augmented Dickey-Fuller (ADF) test by Dickey & Fuller (1979), Phillips-Perron (PP) by Perron (1988); Banerjee *et al.* (1993) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) by Kwiatkowski *et al.* (1992). ADF and PP tests assume the presence of a unit root under the null hypothesis. Meanwhile, the KPSS test assumes stationarity under the null hypothesis.

To explore autocorrelation in the data, Ljung-Box test by Ljung & Box (1978) is carried out. Ljung-Box tests statistic was developed by augmenting Portmenteau statistic by Box & Pierce (1970). The null hypothesis of both assumes that first m autocorrelation coefficients are jointly equal to zero. Therefore, if the null hypothesis is rejected, it indicates that at least one of the autocorrelation coefficients is different from zero. Ljung-Box test was further adapted to test for the effects of conditional heteroskedasticity by McLeod & Li (1983). The test differs from the original Ljung-Box in using r_t^2 in place of r_t. Hence, it tests for the presence of autocorrelation in the squared series of returns. In such a case, we test for a linear dependence in the magnitude of the returns, regardless of the sign and possible presence of volatility clustering in the data. For both autocorrelation tests, lag lengths of 1,5 and 10 are used. A similar test was developed, along with the introduction of the ARCH model by Engle (1982). ARCH-LM test for linear dependence in the series, unlike the previous tests, constructs a linear regression of the past m lags and then conducts a standard F-test of joint significance of m lagged values. ARCH-LM test with two lagged values is used.

Finally, to assess the distributional properties of the returns, Jarque-Bera test by Jarque & Bera (1980) is used to test for the normality of returns.

5.3.1 Tests for Daily Data

First, the described statistical tests are performed for daily data. The values of test statistics, along with indicated statistical significance at 10% (*), 5% (**), and 1% (***) levels, are reported in Table 5.6 and Table 5.5. The null hypothesis of the unit root can be rejected for both the ADF test and PP test for each series. In the case of the KPSS test, the null hypothesis is not rejected for any series. Therefore, based on the results, the assumption of weak stationarity is reasonable. Based on the values of the Jarque-Bera test statistic, the null hypothesis of normality is rejected for every series.

Table 5.5: Unit root and normality tests for daily returns

	Phillips-Perron	KPSS	ADF	Jarque-Bera
US Cocoa	−64.033***	0.289	−15.382***	3,783.060***
London Cocoa	−61.742***	0.310	−14.623***	6,589.189***
EURUSD	−64.311***	0.034	−15.499***	975.624***
GBPUSD	−62.020***	0.063	−15.819***	21,026.760***
CHFUSD	−64.434***	0.063	−16.352***	2,261,930.000***
USDGBP	−62.099***	0.064	−15.811***	20,921.700***
EURGBP	−62.455***	0.122	−16.168***	7,223.222***
CHFGBP	−63.834***	0.153	−16.132***	1,817,946.000***
GHSUSD	−72.137***	0.077	−16.395***	342,776.500***
GHSGBP	−69.145***	0.097	−16.717***	105,956.400***

Notes: *,** ,*** indicate statistical significance at 10%, 5%, 1% levels.
All presented values are test statistics rounded to 3 decimal places.

Based on the Ljung-Box test, no serial correlation is found in US Cocoa return series. In London Cocoa returns, however, there is a significant serial correlation for each selected lag. In the case of the Ljung-Box test for squared returns, a significant serial correlation is present in all lags for both futures contracts. In the case of EURUSD, serial correlation in the returns is found only for the Ljung-Box(10) test. When squared returns are considered, a significant serial correlation is found. For GBPUSD, USDGBP, EURGBP, GHSUSD, and GHSGBP, the null hypothesis of no serial correlation is rejected in every single case for returns as well as for squared returns. Notably, neither CHF currency pairs evince significant serial correlation. The only significant test statistic is Ljung-Box(10) for CHFGBP at 5% significant level. Furthermore, no serial correlation is found in their squared returns. ARCH-LM test rejects the null hypothesis that there are no ARCH effects in each series. Therefore, ARCH-based methods are appropriate tools for the volatility modeling of univariate series.

Table 5.6: Tests of serial correlation for daily returns

	$Q(1)$	$Q(5)$	$Q(10)$	$Q^2(1)$	$Q^2(5)$	$Q^2(10)$	ARCH-LM
US Cocoa	0.214	1.959	9.328	88.956***	665.518***	943.691***	9,915.669***
London Cocoa	9.129***	13.921**	19.502**	133.929***	746.941***	1,170.417***	11,305.080***
EURUSD	0.075	8.687	26.765***	108.835***	517.834***	968.885***	6,074.445***
GBPUSD	6.662***	19.504***	32.659***	129.841***	260.560***	364.562***	17,116.080***
CHFUSD	0.026	1.382	15.266	0.070	1.819	4.407	239,142.900***
USDGBP	6.258**	18.798***	31.882***	126.373***	258.740***	365.045***	17,235.840***
EURGBP	4.647**	13.585**	21.042**	181.036***	310.310***	447.023***	10,731.310***
CHFGBP	0.678	5.054	18.503**	0.447	3.145	8.500	212,721.900***
GHSUSD	54.762***	141.108***	163.242***	687.118***	1,092.841***	1,223.194***	9,112.155***
GHSGBP	19.981***	65.965***	74.682***	672.642***	994.346***	1,127.050***	8,406.508***

Notes: *,**,*** indicate statistical significance at 10%, 5%, 1% levels. All presented values are test statistics rounded to 3 decimal places. $Q(l)$ signifies values of Ljung-Box statistics for l lags. $Q^2(l)$ signifies values of Ljung-Box statistics for l lags using squared returns.

Table 5.7: Tests of serial correlation for weekly returns

	$Q(1)$	$Q(5)$	$Q(10)$	$Q^2(1)$	$Q^2(5)$	$Q^2(10)$	ARCH-LM
US Cocoa	1.400	3.472	9.978	10.573***	97.343***	182.124***	1,847.980***
London Cocoa	5.464**	5.924*	16.659***	22.978	174.835***	321.143***	2,026.953***
EURUSD	0.077	1.767	8.056	26.020***	68.582***	161.574***	1,086.763***
GBPUSD	0.970	13.106**	21.378**	58.409***	199.196***	275.977***	1,424.370***
CHFUSD	3.275*	12.739**	18.497**	0.857	6.657	8.720	10,119.040***
USDGBP	1.055	13.513**	22.019**	60.124***	201.533***	280.527***	1,416.932***
EURGBP	1.441	11.889**	15.571	30.114***	344.539***	478.809***	1,759.520***
CHFGBP	1.471	10.859*	17.976*	0.743	12.571**	14.750	9,322.515***
GHSUSD	4.742**	38.195***	58.772***	14.987***	29.233***	99.350***	14,361.000***
GHSGBP	2.042	27.181***	41.987***	12.092***	30.938***	107.677***	11,907.080***

Notes: *,**,*** indicate statistical significance at 10%, 5%, 1% levels. All presented values are test statistics rounded to 3 decimal places. $Q(l)$ signifies values of Ljung-Box statistics for l lags. $Q^2(l)$ signifies values of Ljung-Box statistics for l lags using squared returns.

5.3.2 Tests for Weekly Data

Table 5.8: Unit root and normality tests for weekly returns

	Phillips-Perron	KPSS	ADF	Jarque-Bera
US Cocoa	−27.561***	0.279	−8.756***	569.448***
London Cocoa	−26.201***	0.340	−8.090***	1,227.830***
EURUSD	−29.850***	0.030	−9.763***	136.865***
GBPUSD	−30.618***	0.088	−8.515***	586.944***
CHFUSD	−31.626***	0.083	−10.235***	19,040.470***
USDGBP	−30.662***	0.088	−8.513***	596.632***
EURGBP	−30.922***	0.150	−10.335***	614.075***
CHFGBP	−31.172***	0.259	−9.481***	15,858.090***
GHSUSD	−27.406***	0.059	−10.702***	254,802.000***
GHSGBP	−28.178***	0.086	−10.805***	78,023.130***

Notes: *,** ,*** indicate statistical significance at 10%, 5%, 1% levels.
All presented values are test statistics rounded to 3 decimal places.

The identical statistical tests that have been conducted for daily returns are conducted for the returns based on the weekly price series. The null hypothesis of the unit root is rejected by ADF and PP tests for every return series. For KPSS, the null hypothesis of level stationary series is not rejected in any case. Therefore, we can assume that the weekly returns behave as weakly stationary series. The results of the Jarque-Bera test show that the null hypothesis of normality for weekly returns is rejected in each case. Results of Ljung-Box tests indicate that both futures contracts have similar autocorrelation structure as in the case of daily returns. The null hypothesis of no serial correlation is rejected for London Cocoa for Ljung-Box(1) and Ljung-Box(10), although only at 10% significance level for Ljung-Box(5). In the case of US Cocoa, no significant serial correlation is found. The Ljung-Box tests for squared returns point to the presence of autocorrelation in squared returns for both futures contracts. When the tests are performed for squared returns, serial correlation is found in every case except for CHF currency pairs. The null hypothesis of no serial correlation is only rejected for Ljung-Box(5) for CHFGBP. Therefore, as in the case of daily returns series, little or no serial correlation in squared returns is found for CHFUSD and CHFGBP. ARCH-LM test results in rejection of the null hypothesis for every weekly return series, which indicates a presence of ARCH-effects. Ljung-Box tests for weekly returns of currency pairs reveal serial correlation patterns that resemble those of daily returns. Generally, the tests indicate that serial correlation becomes weaker when the weekly returns are used.

5.4 Subsample Periods for Study of Time-varying Spillovers

One of the objectives of Chapter 6 is to determine whether the channels of transmission stay constant or change in different periods depending on the general level of volatility in financial markets. In order to explore such phenomena, the data is divided into four subsamples of periods that slightly exceed four years. The choice of such periods is not arbitrary, each is supposed to capture certain fundamental dynamics of the world economy. However, it is necessary to emphasize that the choice of cutoffs between the periods is subject to the author's personal bias and the necessity to obtain subsamples of approximately uniform time periods. To assess the risk environment of individual periods, the CBOE Volatility Index (VIX) daily closing prices are used, and the average value for each period is reported in Table 5.9. The VIX index does not directly relate to commodity or foreign exchange markets. However, it is the most widely used measure of stress in financial markets, with the ability to gauge the overall risk environment with a single measure. Furthermore, the relevance of the VIX for the commodity markets has intensified due to commodity financialization. According to Cheng *et al.* (2015), increases in VIX in times of crisis lead to financial traders reducing their net long positions in agricultural commodities.

The first period corresponds to the time of financial stress and sharp economic downturn caused by the GFC and the European Sovereign Debt Crisis. It is the period with the highest average VIX value (26.94). Therefore, for the purpose of subsample analysis performed in Section 6.3, this period will be regarded as a proxy to test whether spillovers are more extensive in times of great uncertainty in the financial markets.

The second period is characterized by subsiding aftershocks of the crisis and the period when the world economy began to recover. It can be seen that the average value of the VIX index is significantly subsided in comparison with the previous period, decreasing to 16.52.

The third period represents a period in which both the European Union and the United States economy returned to moderate growth. European Crisis was brought to an end, and the environment of low interest rates persisted. Based on the VIX, it is the least volatile period of the four, with the average daily closing VIX value being 14.79.

The last period, commencing in February 2020, may be characterized by a number of global supply and demand shocks. Firstly, the COVID-19 pandemic resulted in the shutdown of the world economy, creating imbalances in aggregate supply and demand that led to the most significant inflation increase in the developed world in the past 40 years, further exacerbated by the Russian invasion of Ukraine in February 2022. Furthermore, to tackle the runaway inflation, central banks abandoned the policy of low interest rates, leading to the United States Government Bond 10-year yield reaching 5% for the first time since 2007. Average VIX attains a higher value (22.32) compared with Period 2 and Period 3, however, it remains well below the level of Period 1.

Table 5.9: Time periods for analysis of time-varying spillovers

	Period duration	*N*	*VIX*
Period 1	2007/7/6 - 2011/9/30	1049	26.94
Period 2	2011/10/3 - 2015/11/30	1038	16.52
Period 3	2015/12/1 - 2020/1/31	1039	14.79
Period 4	2020/2/3 - 2024/5/3	1049	22.32

Source: VIX closing prices were obtained from https://www.cboe.com ; CBOE (2024)

Chapter 6

Empirical Analysis

Empirical analysis of dynamics between cocoa futures and currency pairs is structured into three sections as follows. In the first section (Section 6.1), univariate GARCH(1,1) models are estimated for both cocoa futures return series. Univariate analysis has a dual purpose. First, it serves as a further extension of the descriptive analysis conducted in Section 5.2, where the simple measure of volatility was computed. Second, univariate GARCH(1,1) models effectively enter as inputs into the DCC-GARCH model estimated in the subsequent analysis.

The second section (Section 6.2) of the empirical analysis uses the VAR-DCC-GARCH model to explore the dynamics between assets using DCC parametrization. The time-varying correlation between cocoa futures contracts is explored. Descriptive analysis carried out in Section 5.2 revealed very strong correlation between both cocoa futures contracts and weak or nonexistent correlation between the cocoa contracts and currency pairs. Therefore, the DCC analysis aims to answer whether the same is true when a more sophisticated approach able to capture time-varying dynamics is used.

The third section (Section 6.3) presents the estimation of the VAR-BEKK model that allows for spillovers in returns, shock, and volatility between return series of different assets. The analysis of spillovers is an integral part of the thesis. Full sample analysis is conducted for both daily and weekly data. Such an arrangement is utilized to analyze the spillover effects in two different time frequencies. Additionally, the use of either daily or weekly data requires us to make a trade-off between the robustness of weekly data to nonsynchronous trading and the ability of daily data to capture greater nuance in information transmission. Apart from the full sample analysis, the VAR-BEKK model is estimated for subsample periods (see Section 5.4) to determine whether the degree of spillover between markets varies across different time spans.

The analysis in Section 6.2 and Section 6.3 is organized into three parts. The first part concerns the interrelation between US Cocoa and London Cocoa. The second part concerns dynamics between USD-denominated assets, US Cocoa, EURUSD, GBPUSD, CHFUSD, and GHSUSD. Similarly, the third part explores the relations between GBP-denominated assets, London Cocoa, USDGBP, EURGBP, CHFGBP, and GHSGBP. The outlined structure may be used to provide the following interpretation. Since US Cocoa is an asset denominated in USD and London Cocoa is an asset denominated in GBP, the outlined structure of the models allows us to test for spillover and explore time-varying correlation between the currency and the given futures contract. For example, when the spillover between US Cocoa and EURUSD is being examined, then both may be treated as USD-denominated assets. Therefore, the results of the model may be interpreted as an interrelation between the US Cocoa futures contract and EUR.

6.1 Univariate GARCH Models

Univariate GARCH models for both cocoa futures contracts are estimated in the simplest specification form in which the mean equation for each asset is specified as

$$r_t = \mu + u_t. \tag{6.1}$$

Therefore, μ_t from Equation 4.3 is not modeled as ARMA process, it is plainly estimated as a constant μ. The simplified approach is warranted by the fact that in the multivariate analysis, we employ the VAR model as a mean equation. Therefore, the results of the univariate GARCH models presented here do not directly enter the multivariate models of the subsequent Section 6.2, where VAR specification is used for the mean equation. Instead, GARCH(1,1) is estimated in the simplest form to demonstrate the phenomena of the univariate return series, such as time-varying volatility or persistence of volatility and shocks. Based on the preliminary analysis results in Section 5.3, it is reasonable to assume that the distribution of returns differs from a normal distribution. Both daily and weekly return series exhibit excess kurtosis (see Table 5.1, Table 5.2), which is associated with leptokurtic returns following a distribution more similar to that of Student's t than normal. Therefore, the univariate GARCH(1,1) models are estimated with the assumption of normal as well as Student's t-distribution as described in Section 4.1. Therefore, we may use the value of information criteria (AIC, Bayes Information Criterion (BIC)) and log-likelihood of the fitted models to determine which distributional assumption provides a better model for the univariate series.

Table 6.1: GARCH(1,1) univariate models for cocoa futures

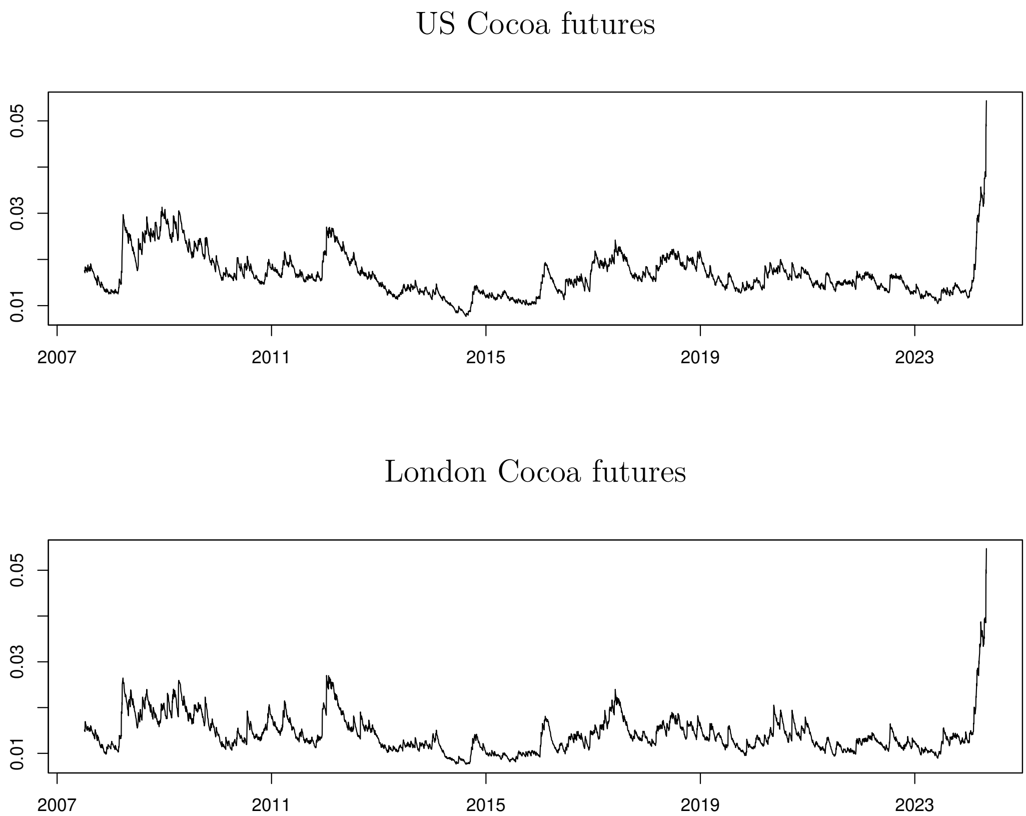
	Daily			
	US Cocoa (norm)	US Cocoa (t)	London Cocoa (norm)	London Cocoa (t)
μ	0.0003(0.0002)	0.0005(0.0002)**	0.0004(0.0002)**	0.0005(0.0002)**
ω	0.0000(0.0000)	0.0000(0.0000)	0.0000(0.0000)	0.0000(0.0000)
α_1	0.0385(0.0019)***	0.0354(0.0019)***	0.0474(0.007)***	0.0445(0.0052)***
β_1	0.9599(0.0017)***	0.9628(0.0016)***	0.9487(0.0075)***	0.9504(0.0057)***
ν		9.3469(1.3979)***		7.0863(0.6956)***
AIC	−5.4119	−5.4294	−5.7421	−5.7751
BIC	−5.4059	−5.4218	−5.736	−5.7676
LogLik	11301.4248	11338.8664	11990.5374	12060.611
	Weekly			
	US Cocoa (norm)	US Cocoa (t)	London Cocoa (norm)	London Cocoa (t)
μ	0.0012(0.0011)	0.0016(0.0011)	0.0019(0.0009)**	0.0019(0.0009)**
ω	0.0000(0.0000)**	0.0000(0.0000)*	0.0000(0.0000)*	0.0000(0.0000)*
α_1	0.1191(0.0239)***	0.0966(0.0241)***	0.1204(0.0233)***	0.1051(0.0239)***
β_1	0.8577(0.0306)***	0.8887(0.0294)***	0.8699(0.0259)***	0.8863(0.0266)***
ν		11.8276(3.9951)***		15.6494(7.0577)**
AIC	−3.7963	−3.8099	−4.095	−4.0996
BIC	−3.7746	−3.7827	−4.0732	−4.0724
LogLik	1670.5828	1677.5644	1801.6957	1804.7274

Notes: *,** ,*** indicate statistical significance at 10%, 5%, 1% levels. All presented values are rounded to 4 decimal places, while the original values are for for computations. *AIC* denotes Akaike Information criterion. *BIC* denotes Bayes Information Criterion. *LogLik* denotes the value of log-likelihood.

The estimated parameters, along with information criteria and the value of log-likelihood, can be found in Table 6.1. GARCH parameters α_1 and β_1 are found to be significant at 1% level in each case. From the high values of β_1, it may be observed that there is a high level of persistence in the conditional variance for both assets. Notably, the persistence is greater in the case of models for daily data. Based on the information criteria and the values of log-likelihood, it can be stated that the model with t-distributed errors performs better than the model that assumes normal distribution. The benefit of the t-distributed errors is more pronounced in the case of daily data. The same is unequivocally true for the weekly returns in the case of US Cocoa. However, the benefit of using t-distributed errors is not definite for the weekly model of London Cocoa. While AIC and log-likelihood slightly favour the t-model, BIC favours the normal model.

Values of conditional volatility $\sqrt{h_t}$ can be extracted from the model as fitted values. Using the models with t-distributed errors, conditional volatility is plotted for both US Cocoa futures and London Cocoa futures. In Figure 6.1, daily conditional volatility fitted values are plotted (for weekly estimates, see Figure A.7).

Figure 6.1: Conditional volatility estimates for cocoa futures



From Figure 6.1, it is apparent that the conditional volatility of cocoa futures varies over time. There has been a significant variation in the values of conditional volatility over the sample period, which signifies the presence of placid and volatile periods. However, the extreme values starting at the beginning of 2024 dwarf all prior developments. Therefore, it can be observed that despite the long-term convergence of conditional volatility to its unconditional value, there is no evident ceiling to values that conditional volatility can attain in the short run.

6.2 VAR-DCC-GARCH Models

This section expands the superficial analysis of asset dynamics into multivariate setting by capitalizing on the VAR-DCC model that allows us to examine cross-asset spillovers in the mean equation and dynamic time-varying correlation. First, the dynamics between London Cocoa Futures and US Cocoa Futures contracts are studied. Next, the US Cocoa is modeled with USD-denominated currency pairs (EURUSD, GBPUSD, CHFUSD, GHSUSD). Lastly, dynamics between London Cocoa futures and GBP-denominated currency pairs (USDGBP, EURGBP, CHFGBP, GHSGBP) are modeled. Both daily and weekly returns are used in this section. Emphasis is placed on the study of conditional correlation between assets. While VAR models are estimated as a component of the VAR-DCC-GARCH model specification, they will not be interpreted in this section. Instead, bivariate VAR models will be examined more closely in Section 6.3 as a device to study mean spillovers.

6.2.1 Model for Cocoa Futures

Deliverable products of both US Cocoa and London Cocoa futures do not differ except for discrepancies of minor character. Therefore, the price action of both futures contracts is expected to be closely linked. This expectation is confirmed by strong unconditional correlation of 0.88 for daily returns (see Table 5.3) and 0.9 for weekly returns (see Table 5.4). In spite of the very strong correlation, there are factors that may cause the trading in both contracts to become less correlated. The exchange rate channel is one such factor. Large swings in GBPUSD will result in a change in the relative value of both contracts. In the efficient market, such opportunity is arbitraged away by market participants almost instantaneously, resulting in the repricing of the futures contracts that was not induced by any new incoming information about the cocoa market per se. Another possible scenario arises from the traditional assumption that London Cocoa is more closely linked to African production due to geographical location and historical ties. Therefore, if relevant news about African production arises, it is reasonable to hypothesize that the price reaction will be initially more concentrated in the London Cocoa and then gradually spill over to US Cocoa.

The results of the VAR-DCC-GARCH model for US and London Cocoa can be found in Table 6.2. Based on the information criteria (AIC, BIC) and the value of log-likelihood, we can see that the model with t-distributed innovations performs better in both daily and weekly data. Therefore, models with t-distributed errors are used to model the dynamic conditional correlation between two futures contracts. VAR model has been used as a mean equation (for VAR results, see Table A.6 for the daily model and Table A.7 for the weekly model), and the required lag length is determined based on the AIC criterion. The lag length was chosen to be 1 for both daily and weekly models. Both the first-stage $(\omega_i, \alpha_{1i}, \beta_{1i}, \nu_i)$ and the second-stage (a, b, ν) parameter estimates are presented. There are only marginal differences between the first-stage estimates in this model and the univariate estimates for both futures contracts (see Table 6.1). The minor discrepancies are caused by the different specifications of the mean equation, the estimation procedure of the second-stage parameters α_1 and β_1 is, however, equivalent.

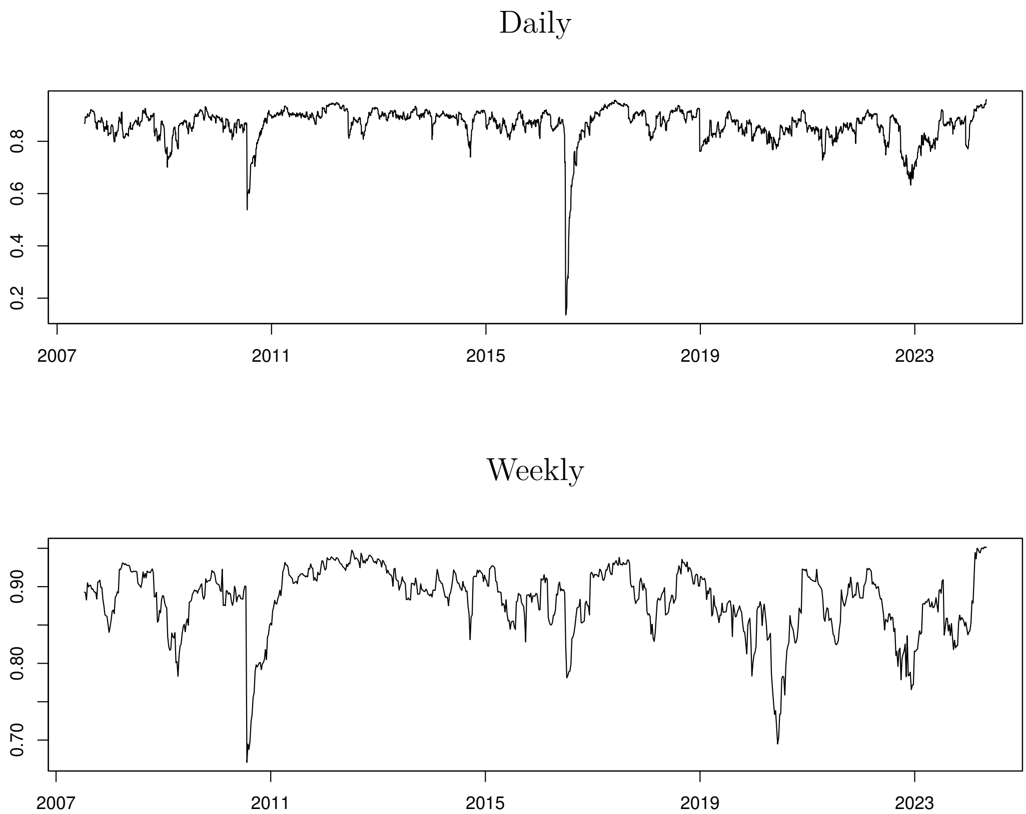
Table 6.2: DCC model for US Cocoa and London Cocoa

	Daily		Weekly	
	DCC(norm)	DCC(t)	DCC(norm)	DCC(t)
$\omega(US)$	0.0000***	0.0000**	0.0000*	0.0000*
$\alpha_1(US)$	0.0388***	0.0361***	0.1203***	0.0948***
$\beta_1(US)$	0.9596***	0.9622***	0.8568***	0.8907***
$\nu(US)$		9.5474***		11.5002***
$\omega(London)$	0.0000	0.0000	0.0000*	0.0000*
$\alpha_1(London)$	0.048***	0.0456***	0.1203***	0.1047***
$\beta_1(London)$	0.948***	0.949***	0.8689***	0.8864***
$\nu(London)$		7.0721***		14.5451***
a	0.0325***	0.0317***	0.0486***	0.0578***
b	0.9538***	0.9583***	0.9222***	0.9106***
$\nu(multi)$		6.1845***		10.0015***
AIC	−12.5909	−12.7451	−9.4586	−9.5234
BIC	−12.5681	−12.7178	−9.377	−9.4255
$LogLik$	26298.5232	26623.4825	4167.3432	4198.7717
$VAR\ lag$	1	1	1	1

Notes: *,** ,*** indicate statistical significance at 10%, 5%, 1% levels. All presented values are rounded to 4 decimal places. AIC denotes Akaike Information criterion. BIC denotes Bayes Information Criterion. $LogLik$ denotes the value of log-likelihood.

From the evolution of conditional correlation (see Figure 6.2), it is apparent that both contracts maintain strong correlation for a vast portion of the time period. However, there are occasions when the relationship may weaken or break down on a temporary basis. For the weekly model, the correlation stays within the narrower band in comparison with the daily model. Two notable local minima of the weekly model are 0.67 on July 23, 2010, and 0.69 on June 12, 2020. In the daily model, the values of conditional correlation show more significant downside potential. The minimum value of the sample period occurred on June 28, 2016, when the conditional correlation bottomed out

Figure 6.2: Conditional correlation between US Cocoa and London Cocoa



at 0.14. This particular episode can be attributed to the sharp decrease in GBPUSD that followed the 2016 United Kingdom European Union membership referendum. Other evident troughs may be found at 0.54 on July 19, 2010, and 0.63 on December 5, 2022. Noteworthy development can be observed at the end of the sample. In the case of both daily and weekly models, both conditional correlation values reached their maximal values for the sample period (0.96 on May 3, 2024, for the daily model and 0.95 on April 19, 2024, for the weekly model). Therefore, while the sharp decrease in correlation appears to be coming from outside of the cocoa market, the rise in correlation at the end of the sample takes place in confluence with unprecedented volatility in both markets that is primarily driven by the fundamentals of the cocoa market.

A simple explanatory analysis is performed for the daily model to assess the influence of volatility on the dynamic conditional correlation between US Cocoa and London Cocoa futures. Six simple linear regression models are estimated with dynamic correlation retrieved from the DCC model as a dependent variable. Measures of volatility are used as independent variables. Conditional volatilites for both futures contracts (see Table 6.1; Figure 6.1) and conditional volatility computed for GBPUSD (see Figure A.10) are used along with the VIX as explanatory variables for the linear regression. GBPUSD is included since it is the currency pair directly linking the USD-denominated US Cocoa futures and GBP-denominated London Cocoa futures. Conditional volatilities are multiplied by 100 to allow for easier interpretation of the results.

From the fitted linear regression (see Table 6.3), it can be seen that all included volatility measures have a statistically significant effect on the time-varying correlation between cocoa futures contracts. When the only independent variables included (Models (1) and (2)) are the conditional volatilities, the effect on the conditional correlation is positive, and the magnitude of the coefficients is of the same order. When both volatilities are included (Model (3)) along with the VIX (Model (4)), the effect of the US Cocoa turns negative, while the effect of London Cocoa remains positive and of large magnitude. Furthermore, we can see that, while statistically significant, the effect of VIX is relatively small, though not negligible (an increase of 10 points in VIX causes a decrease of the correlation by 0.01). It is important to emphasize that the explanatory power of the first four models is fairly limited. The highest value of the Adjusted R^2 is 0.093 for the Model 4. Next, the conditional volatility of the GBPUSD currency pair is considered. Modeling of the interrelations between currency pairs and cocoa futures contracts will be conducted in the subsequent sections. Only GBPUSD is included at this stage as it is the most direct foreign exchange link between the two contracts. First, it is included as a sole independent variable (Model 5). It can be observed that the volatility of the currency pair causes a large decrease in the correlation. Additionally, adjusted R^2 indicates that the explanatory power of the model increased significantly in comparison with the preceding models. Finally, all the volatility measures are included in the Model 6. The effect of $\sqrt{h_{GBPUSD}}$ remains negative, and the magnitude of the coefficient has increased in comparison with Model 5. The effect of the conditional volatilities of the futures contracts was flipped when compared to Models 3 and 4. The effect of the volatility of US Cocoa ($\sqrt{h_{US}}$) has become positive and of a larger magnitude than the effect of the volatility of London Cocoa ($\sqrt{h_L}$), which has turned negative. Moreover, the effect of the VIX remains very limited, although it is now positive. The value of the Adjusted R^2 attains the highest value (0.501). It is necessary to emphasize that this use of linear regression models entails severe limitations, and it should only be considered as an auxiliary device for a better understanding of the results obtained from the DCC model. Taking the aforementioned caveat into account, the most remarkable information that can be extracted from the analysis is the significant negative effect of $\sqrt{h_{GBPUSD}}$ on the correlation between US Cocoa and London Cocoa futures contracts.

Table 6.3: Linear regression model for Dynamic Conditional Correlation and volatility measures

	Dependent variable:					
	Conditional Correlation between cocoa futures contracts R_t					
	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)	(Model 6)
VIX				-0.001^{***}		0.001^{***}
$\sqrt{h_{US}}$	0.025^{***}		-0.047^{***}	-0.013^{**}		0.063^{***}
$\sqrt{h_L}$		0.037^{***}	0.084^{***}	0.056^{***}		-0.013^{**}
$\sqrt{h_{GBPUSD}}$					-0.196^{***}	-0.269^{***}
Constant	0.822^{***}	0.810^{***}	0.821^{***}	0.833^{***}	0.977^{***}	0.906^{***}
Observations	4,172	4,172	4,175	4,172	4,172	4,172
R^2	0.028	0.053	0.068	0.094	0.346	0.501
Adjusted R^2	0.028	0.053	0.067	0.093	0.346	0.501
R.S.E	0.067	0.066	0.065	0.065	0.055	0.048
F Statistic	119.128^{***}	234.223^{***}	151.931^{***}	144.273^{***}	$2{,}207.056^{***}$	$1{,}047.233^{***}$

Notes: *,** ,*** indicate statistical significance at 10%, 5%, 1% levels. All presented values are rounded to 3 decimal places.

6.2.2 Model for US Cocoa Futures

Dynamics between US Cocoa futures and USD-denominated currency pairs (EURUSD, GBPUSD, CHFUSD, GHSUSD) are modeled in this section. The estimation results of the DCC-GARCH model are to be found in Table 6.4. The optimal lag for the VAR model that is used as a mean equation is equal to 3 for daily data and 1 for weekly data (for VAR results, see Table A.8 for the daily model and Table A.10 for the weekly model). When information criteria and the value of log-likelihood are considered, models with t-distributed shocks perform better in both cases. Furthermore, particularly in the case of the daily normal model, there is a large number of statistically insignificant variables that become significant when the model with t-distributed errors is estimated instead. Therefore, conditional correlations from models with t-distribution are used to depict the time-varying correlation between US Cocoa futures and the currencies.

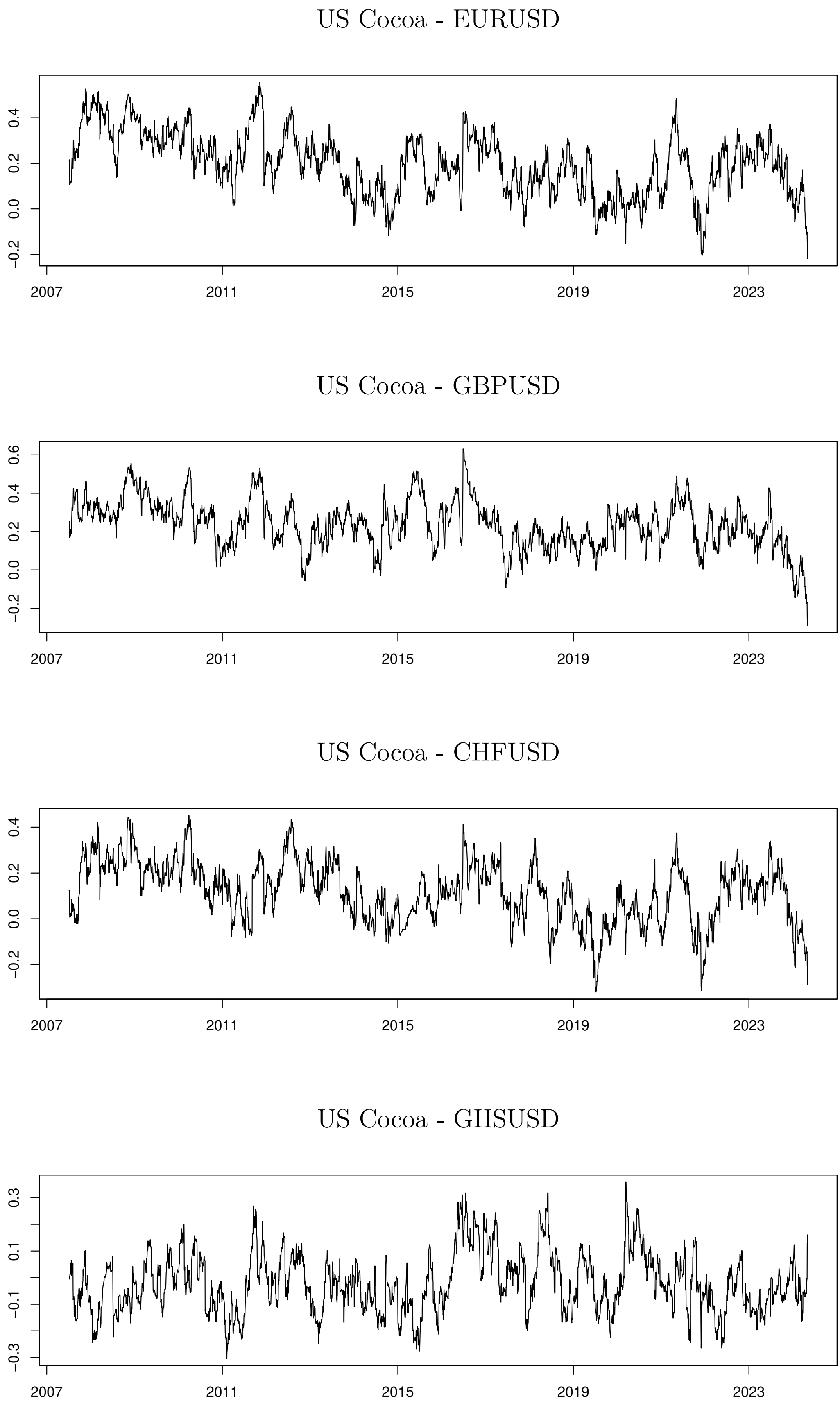
It can be observed that the evolution of conditional correlation in Figure 6.3 largely confirms the conclusion based on the unconditional correlation that the correlation between the cocoa futures and the currencies is weak or nonexistent. The largest unconditional correlation coefficient (see Table 5.3) was 0.23 between US Cocoa and GBPUSD. It can be seen that in comparison with the other pairs, this relation has been slightly more stable, and the value of conditional correlation has remained in the positive area for the vast majority of the sample period, only to deteriorate significantly into negative territory at the end of the sample period.

Table 6.4: DCC model for US Cocoa and currency pairs

	Daily		Weekly	
	DCC(norm)	DCC(t)	DCC(norm)	DCC(t)
$\omega(US)$	0.0000***	0.0000**	0.0000*	0.0000
$\alpha_1(US)$	0.0383***	0.0353***	0.116***	0.0895***
$\beta_1(US)$	0.96***	0.963***	0.8624***	0.8991***
$\nu(US)$		9.3365***		11.1699***
$\omega(EURUSD)$	0.0000	0.0000	0.0000	0.0000
$\alpha_1(EURUSD)$	0.0399***	0.0408***	0.0915***	0.0878***
$\beta_1(EURUSD)$	0.9575***	0.9574***	0.8912***	0.8938***
$\nu(EURUSD)$		10.9891***		15.518**
$\omega(GBPUSD)$	0.0000	0.0000	0.0000	0.0000
$\alpha_1(GBPUSD)$	0.0712	0.0464***	0.1081***	0.1051***
$\beta_1(GBPUSD)$	0.9165***	0.9462***	0.8611***	0.8589***
$\nu(GBPUSD)$		8.0254***		13.9744***
$\omega(CHFUSD)$	0.0000	0.0000	0.0000	0.0000***
$\alpha_1(CHFUSD)$	0.066	0.0408***	0.2192***	0.0998***
$\beta_1(CHFUSD)$	0.9228	0.9503***	0.7511***	0.8493***
$\nu(CHFUSD)$		7.0451***		6.9332***
$\omega(GHSUSD)$	0.0000	0.0000	0.0000	0.0000
$\alpha_1(GHSUSD)$	0.1483***	0.2878***	0.5649***	0.5623***
$\beta_1(GHSUSD)$	0.8507***	0.7112***	0.4341***	0.4367**
$\nu(GHSUSD)$		3.0689***		3.2995
a	0.0162	0.026***	0.0101	0.0368***
b	0.7652	0.9731***	0.7406***	0.9251***
$\nu(multi)$		8.0382***		8.2072***
AIC	−36.3043	−37.4851	−28.752	−29.3297
BIC	−36.1419	−37.3136	−28.4418	−28.9869
$LogLik$	75892.2378	78363.1294	12679.1307	12938.7288
$VAR\ lag$	3	3	1	1

Notes: *,**,*** indicate statistical significance at 10%, 5%, 1% levels. All presented values are rounded to 4 decimal places. AIC denotes Akaike Information criterion. BIC denotes Bayes Information Criterion. $LogLik$ denotes the value of log-likelihood.

Figure 6.3: Daily conditional correlations for US Cocoa and currency pairs



6.2.3 Model for London Cocoa Futures

The last DCC model explores dynamics between London Cocoa futures contract and GBP-denominated currency pairs (USDGBP, EURGBP, CHFGBP, GHSGBP). The model estimation results can be found in Table 6.5. An identical procedure to the prior DCC model is used. VAR model is applied as the specification for the mean equation. The optimal lag for the VAR model is determined based on AIC. In the case of the daily model, the optimal lag is chosen to be 4. Meanwhile, for the weekly model, the optimal lag is selected to be 1 (for VAR results, see Table A.9 for the daily model and Table A.11 for the weekly model). In the same way, as in the case of the model for US Cocoa, the information criteria and log-likelihood value indicate that the DCC model with t-distributed innovations is more appropriate. Also, it is observed that several items that are not significant in normal distribution models for daily and especially for weekly data become statistically significant when t-distributed errors are used.

The unconditional correlation coefficients did not reveal any meaningful level of correlation between the currencies and London Cocoa (see Table 5.3). The evolution of the conditional correlation between the currency pairs and the London Cocoa shows that conclusions derived from the unconditional correlation matrix also translate into the conditional correlation setting. The path of conditional correlations evolves in an erratic manner without an evident structure, and the values fluctuate freely between positive and negative territory.

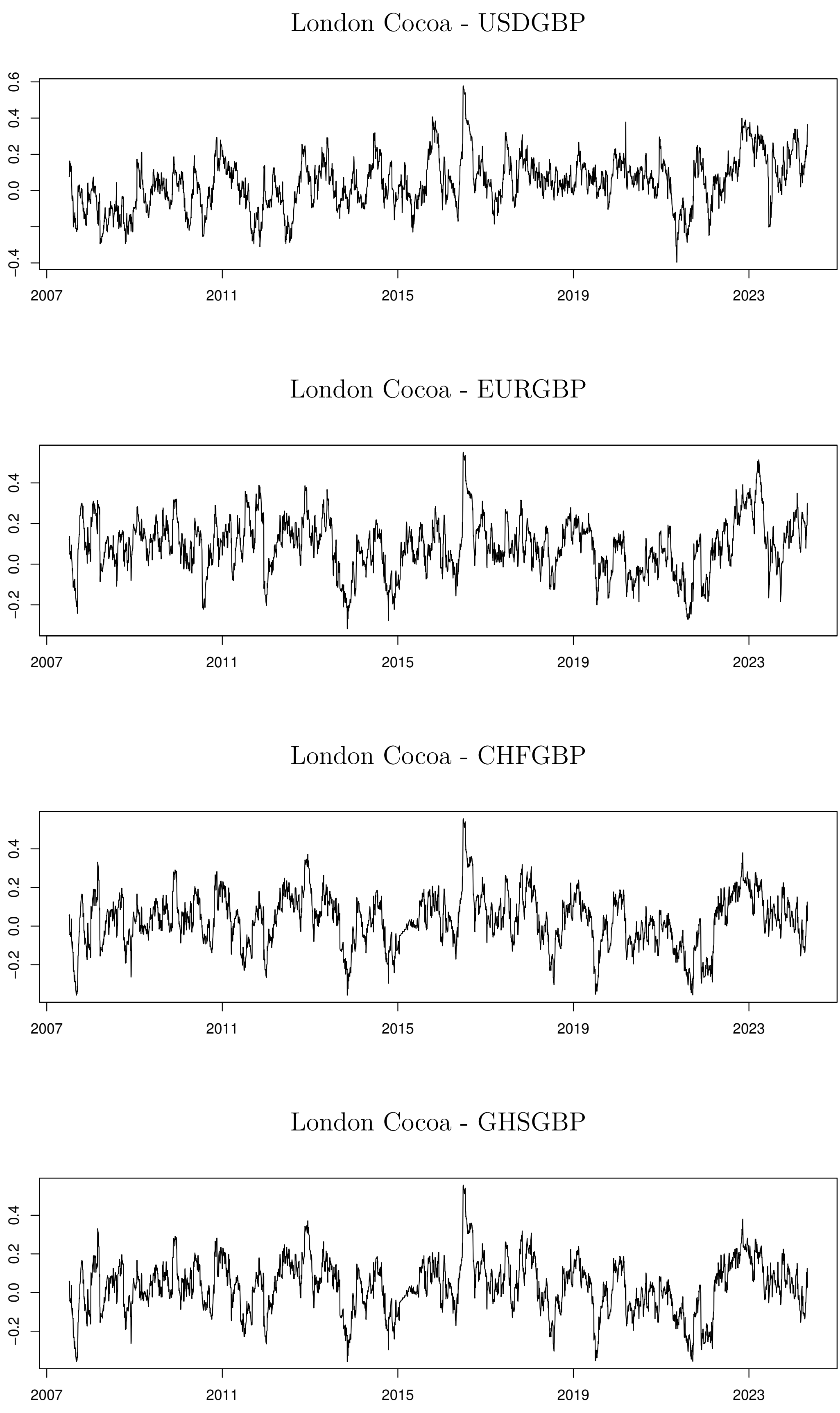
In conclusion, it may be stated that no stable patterns are easily discerned in the conditional correlation between the currencies and both cocoa futures contracts. These results confirm that these assets may be treated as uncorrelated, at least from the long-term perspective. That is in accordance with the lack of shared fundamental drivers for both asset classes. Naturally, the price of a currency pair will be influenced by a wide range of relevant macroeconomic factors. Meanwhile, the price of the cocoa futures will depend predominantly on the cocoa's supply-demand dynamics. However, these findings do not refute that spillovers exist on a more precipitous basis. Such dynamics will be explored in the subsequent section.

Table 6.5: DCC model for London Cocoa and currency pairs

	Daily		Weekly	
	DCC(norm)	DCC(t)	DCC(norm)	DCC(t)
$\omega(London)$	0.0000	0.0000*	0.0000*	0.0000
$\alpha_1(London)$	0.0476***	0.0455***	0.1117***	0.0975***
$\beta_1(London)$	0.9481***	0.9488***	0.8769***	0.8955***
$\nu(London)$		6.854***		12.8733***
$\omega(USDGBP)$	0.0000	0.0000	0.0000	0.0000
$\alpha_1(USDGBP)$	0.0712	0.0491***	0.1087***	0.1057***
$\beta_1(USDGBP)$	0.9166***	0.9431***	0.8612***	0.8588***
$\nu(USDGBP)$		8.0884***		14.4671***
$\omega(EURGBP)$	0.0000	0.0000	0.0000	0.0000
$\alpha_1(EURGBP)$	0.0548***	0.0513***	0.1007**	0.1073***
$\beta_1(EURGBP)$	0.9418***	0.9458***	0.8816***	0.8661***
$\nu(EURGBP)$		7.8962***		12.0553***
$\omega(CHFGBP)$	0.0000	0.0000	0.0000	0.0000**
$\alpha_1(CHFGBP)$	0.081***	0.0802***	0.0869	0.1267***
$\beta_1(CHFGBP)$	0.905***	0.8982***	0.7648***	0.7931***
$\nu(CHFGBP)$		6.3027***		6.2070***
$\omega(GHSGBP)$	0.0000	0.0000**	0.0000	0.0000***
$\alpha_1(GHSGBP)$	0.1272***	0.1588***	0.385**	0.2506***
$\beta_1(GHSGBP)$	0.8703***	0.8125***	0.614***	0.6846***
$\nu(GHSGBP)$		4.887***		4.9974***
a	0.0405***	0.0331***	0.0606	0.0574***
b	0.8737***	0.9653***	0.7992	0.9248***
$\nu(multi)$		7.6288***		7.4285***
AIC	−36.1944	−37.6214	−28.4698	−29.3352
BIC	−35.9941	−37.412	−28.1596	−28.9924
$LogLik$	75687.8348	78672.7708	12555.2468	12941.1538
$VAR\ lag$	4	4	1	1

Notes: *,**,*** indicate statistical significance at 10%, 5%, 1% levels. All presented values are rounded to 4 decimal places. AIC denotes Akaike Information criterion. BIC denotes Bayes Information Criterion. $LogLik$ denotes the value of log-likelihood.

Figure 6.4: Daily conditional correlations for London Cocoa and currency pairs



6.3 VAR-BEKK-GARCH Models

Analysis of spillovers between cocoa futures contracts and currency pairs is conducted in this section. VAR-BEKK model, as described in Section 4.4, is used to explore spillovers in mean, shocks, and volatility. For full sample analysis, estimation is conducted for two data frequencies, daily and weekly. Different data frequencies give insight into two different information transmission channels. The daily frequency model offers a more short-term view, while the weekly model offers a more long-term-oriented perspective. Next, to explore the time-varying nature of the transmission mechanism, subsample analysis is performed. Subsamples were predetermined and described in Section 5.4. In order to preserve sufficiently large sample sizes, only daily data are used for the subsample estimation. Furthermore, in the subsample analysis, it is desirable to focus on precipitous dynamics that may be lost in the weekly data.

6.3.1 Full Sample Analysis

The full sample analysis studies the spillover using daily and weekly returns. The results of the full sample analysis for daily data may be found in Table 6.6, where the results of the bivariate VAR-BEKK models are presented. A concise summary of the presence and direction of spillovers uncovered by the VAR-BEKK model for daily data may be found in Table 6.8. Similarly, the results of the full sample analysis for weekly data may be found in Table 6.7, and the direction of the detected spillovers is indicated in Table 6.9.

It may be observed that there is mean spillover in both frequencies from London to US Cocoa, which can be interpreted as London Cocoa leading US Cocoa in terms of price. Therefore, the informational content of London Cocoa contract has predictive value for US Cocoa. The volatility model uncovers bidirectional spillovers in shocks and volatility. Volatility spillover is present in the daily model, and shock spillover occurs in the model for weekly returns.

In the daily model, US Cocoa receives mean spillover from both EURUSD and GBPUSD, and there is volatility spillover from EURUSD. There is no transmission between US Cocoa and these currencies present in the weekly data. Similarly, spillovers exist between London Cocoa and USDGBP and EURGBP. However, no such transmission may be found in the weekly model.

Spillover between the futures contracts and CHF only occurs in the weekly model. US Cocoa receives mean spillover from CHFUSD, and the spillover of shocks is bidirectional. There is also a shock spillover from CHFGBP to London Cocoa futures contract.

Transmission between GHS and cocoa futures is observed in the case of both contracts and both frequencies. US Cocoa and GHSUSD in the daily model display the most abundant exchange of information with shock spillover from US Cocoa to GHS and bidirectional volatility spillover. Shock spillover from cocoa futures to GHS is present in all four instances where dynamics between futures contracts and GHS are modeled. Therefore, these results indicate significant cross-asset volatility dynamics between cocoa futures contracts and GHS.

The results largely confirm that the spillovers between cocoa futures contracts and currency pairs are limited, but they do exist. The direction of spillovers is predominantly from foreign exchange pairs to futures contracts in the case of global currencies (USD, EUR, GBP, CHF). However, the dynamics differ in the case of GHS. The direction of shock and volatility spillovers between cocoa futures and GHS is either bidirectional or from cocoa to the currency. These findings indicate that cocoa's importance to the Ghanaian economy results in the ability of cocoa futures contracts to influence the volatility of GHS exchange rates.

The number of significant spillover relations between cocoa futures contracts and currency pairs is greater for US Cocoa Futures in both daily and weekly models. Although the difference is not extensive, it is in accordance with US Cocoa being subject to more speculative activity and, therefore, exchanging more spillover with other asset classes. The hypothesis of higher speculative activity in US Cocoa is further supported by higher levels of standard deviation in comparison with London Cocoa for both daily (see Table 5.1) and weekly (see Table 5.2) data. However, it is necessary to emphasize that gauging the amount of speculative activity solely based on the amount of spillover entails significant limitations as it disregards a plethora of other factors.

Table 6.6: Bivariate VAR-BEKK models for daily data

	USC-LC	USC-EURUSD	USC-GBPUSD	USC-CHFUSD	LC-USDGBP	LC-EURGBP	LC-CHFGBP	USC-GHSUSD	LC-GHSGBP
μ_{10}	0.0003	0.0003	0.0003	0.0003	0.0004*	0.0004*	0.0004*	0.0003	0.0004*
μ_{20}	0.0004*	−0.0001	−0.0001	0.0001	0.0001	0.0000	0.0002	−0.0006***	−0.0005**
ϕ_{11}	−0.0804**	−0.0067	−0.0081	0.0037	0.046***	0.0441***	0.0463***	0.0066	0.0458***
ϕ_{12}	0.1159***	0.2012***	0.1848***	0.0761*	0.0527	0.0842*	0.0368	−0.0096	0.0104
ϕ_{13}								0.0065	0.0065
ϕ_{14}								−0.0182	−0.0035
ϕ_{15}								0.0161	0.0148
ϕ_{16}								0.0078	0.0087
ϕ_{21}	−0.0205	0.0068	0.0027	0.0072	−0.0057	0.0002	−0.0013	0.0081	−0.0057
ϕ_{22}	0.0678**	0.0000	0.0382**	0.0002	0.0392**	0.0333	0.0128	−0.1142***	−0.0703***
ϕ_{23}								−0.0041	−0.0062
ϕ_{24}								0.0896***	0.0685***
ϕ_{25}								0.0032	−0.0131
ϕ_{26}								0.1144***	0.0847***
a_{11}	0.1704***	0.1805***	0.1783***	0.1899***	0.196	0.2024***	0.209***	0.1719***	0.1811***
a_{12}	−0.0018	0.0006	−0.0006	−0.0031	0.0012	−0.0053*	−0.009	−0.0201***	0.0054
a_{21}	0.0285	−0.0556*	0.0017	0.0151	0.0557**	0.0136	0.017	0.0156	−0.0071
a_{22}	0.2135***	0.186***	0.2518***	0.199***	0.2467***	0.2165***	0.2139***	0.374***	0.3511***
g_{11}	0.9722***	0.9818***	0.9829***	0.9805***	0.9781***	0.9767***	0.9759***	0.9492***	0.9817***
g_{12}	−0.0104***	0.0000	0.0007	−0.0002	−0.0005	0.0018**	0.001	0.0109***	−0.001
g_{21}	0.01**	0.013**	0.0012	0.0061	−0.0195***	−0.0003	0.0046	0.0078*	0.0033
g_{22}	0.9844***	0.9805***	0.9606***	0.9812***	0.9623***	0.9738***	0.9494	0.9267***	0.9328***

Notes: *,** ,*** indicate statistical significance at 10%, 5%, 1% level. The values of presented parameter estimates are rounded to 4 decimal places. USC represents US Cocoa futures contract. LC represents London Cocoa futures contract. It is necessary to heed the difference in notation of the mean (VAR) equation where parameter ϕ_{12} signifies how the variable 2 affects the variable 1, meanwhile, in the variance (BEKK) equation the parameters a_{12}, g_{12} signify the effect of the variable 1 on the variable 2.

Table 6.7: Bivariate VAR-BEKK models for weekly data

	USC-LC	USC-EURUSD	USC-GBPUSD	USC-CHFUSD	LC-USDGBP	LC-EURGBP	LC-CHFGBP	USC-GHSUSD	LC-GHSGBP
μ_{10}	0.0013	0.0015	0.0014	0.0015	0.0019	0.0019	0.0019	0.0016	0.0021*
μ_{20}	0.0019	−0.0003	−0.0006	0.0003	0.0006	0.0003	0.001*	−0.0032***	−0.0024**
ϕ_{11}	−0.1553**	0.0458	0.0555	0.0565	0.0827**	0.0824**	0.0864**	0.0445	0.0837**
ϕ_{12}	0.2479***	−0.0372	−0.138	−0.1863**	0.0804	0.0347	−0.0576	0.0871	0.0814*
ϕ_{13}								−0.0163	
ϕ_{14}								−0.0456	
ϕ_{15}								−0.0137	
ϕ_{16}								−0.0738	
ϕ_{17}								−0.0121	
ϕ_{18}								0.0226	
ϕ_{21}	−0.073	−0.0072	0.0137	−0.0029	−0.0171	−0.0196*	−0.0183	0.0085	−0.0131
ϕ_{22}	0.1581**	−0.0028	−0.0439	−0.0595*	−0.0324	−0.0316	−0.0374	0.0633*	0.0483
ϕ_{23}								0.0049	
ϕ_{24}								0.1086***	
ϕ_{25}								0.0009	
ϕ_{26}								−0.0477	
ϕ_{27}								−0.0087	
ϕ_{28}								−0.1456***	
a_{11}	0.0284	0.3036***	0.301***	0.2691***	0.3015***	0.3104***	0.3235***	0.2569***	0.2661***
a_{12}	−0.1379***	−0.0082	−0.0032	−0.0266**	−0.0002	−0.0001	−0.0228	−0.0277***	−0.02
a_{21}	0.2969***	0.0358	−0.0207	0.1832**	0.0622	0.1017	0.1553**	0.0288	0.0054
a_{22}	0.4491***	0.2781***	0.3062***	0.4367***	0.3025***	0.2648***	0.2662***	0.6804***	0.648***
g_{11}	0.9614***	0.9338	0.9459***	0.9523***	0.945***	0.9405***	0.9386***	0.9556***	0.9565***
g_{12}	−0.0194	0.0071	0.0029	0.0147*	−0.0013	0.0009	0.0051	0.0069	0.0051
g_{21}	−0.0171	0.0016	−0.062	−0.0473	0.0359	−0.0038	−0.055	−0.0001	0.002
g_{22}	0.9636***	0.9435***	0.9314***	0.8608***	0.9337***	0.952***	0.8749***	0.7358***	0.7549***

Notes: *,** ,*** indicate statistical significance at 10%, 5%, 1% level. The values of presented parameter estimates are rounded to 4 decimal places. USC represents US Cocoa futures contract. LC represents London Cocoa futures contract. It is necessary to heed the difference in notation of the mean (VAR) equation where parameter ϕ_{12} signifies how the variable 2 affects the variable 1, meanwhile, in the variance (BEKK) equation the parameters a_{12}, g_{12} signify the effect of the variable 1 on the variable 2.

Table 6.8: Summary of spillovers in daily data

	Mean Spillover	*Shock Spillover*	*Volatility Spillover*
US Cocoa - London Cocoa	$\leftarrow$	$-$	$\leftrightarrow$
US Cocoa - EURUSD	$\leftarrow$	$-$	$\leftarrow$
US Cocoa - GBPUSD	$\leftarrow$	$-$	$-$
US Cocoa - CHFUSD	$-$	$-$	$-$
US Cocoa - GHSUSD	$-$	$\rightarrow$	$\leftrightarrow$
London Cocoa - USDGBP	$-$	$\leftarrow$	$\leftarrow$
London Cocoa - EURGBP	$-$	$-$	$\rightarrow$
London Cocoa - CHFGBP	$-$	$-$	$-$
London Cocoa - GHSGBP	$-$	$\rightarrow$	$-$

Notes: Indicated spillovers are based on 5% significance level. The arrows " $\leftarrow$ ", " $\rightarrow$ " signify the direction of spillovers, " $-$ " means no significant spillover.

Table 6.9: Summary of spillovers in weekly data

	Mean Spillover	*Shock Spillover*	*Volatility Spillover*
US Cocoa - London Cocoa	$\leftarrow$	$\leftrightarrow$	$-$
US Cocoa - EURUSD	$-$	$-$	$-$
US Cocoa - GBPUSD	$-$	$-$	$-$
US Cocoa - CHFUSD	$\leftarrow$	$\leftrightarrow$	$-$
US Cocoa - GHSUSD	$-$	$\rightarrow$	$-$
London Cocoa - USDGBP	$-$	$-$	$-$
London Cocoa - EURGBP	$-$	$-$	$-$
London Cocoa - CHFGBP	$-$	$\leftarrow$	$-$
London Cocoa - GHSGBP	$-$	$\rightarrow$	$-$

Notes: Indicated spillovers are based on 5% significance level. The arrows " $\leftarrow$ ", " $\rightarrow$ " signify the direction of spillovers, " $-$ " means no significant spillover.

6.3.2 Subsample Analysis

So far, the spillover dynamics between cocoa futures contracts and currency pairs have been assessed using the full sample of data. However, it is reasonable to expect that the degree of interrelation between the assets will differ across different periods. Four subsample periods were defined in Section 5.4 with respect to the macroeconomic and financial fundamentals of the world economy. The detailed estimation results of the VAR-BEKK models for each of the four periods are to be found in Appendix A (see Table A.2, Table A.3, Table A.4, and Table A.5). Findings of significant spillovers (at 5% significance level) and their direction for each period are presented in Table 6.10 (Period 1), Table 6.11 (Period 2), Table 6.12 (Period 3), and Table 6.13 (Period 4).

Spillovers in Period 1 (July 2007 - September 2011) are ubiquitous across all studied relations and vastly more frequent than in any other period (see Table 6.10). The first period represents the GFC and the initial stages of the European Sovereign Debt Crisis, accompanied by economic downturn and severe stress in financial markets. Therefore, the findings confirm that the spillover dynamics become more pronounced in periods of high volatility and financial crisis. Spillover in shocks and volatility is significant between US Cocoa and London Cocoa across all periods, while mean spillover is significant only in Period 1, and it follows the same direction as in the full sample analysis. While the direction of the shock and volatility dynamics between the futures contracts is not entirely uniform, it tends to be either bidirectional or directed from US Cocoa to London Cocoa. The exception is Period 4, where the significant shock spillover is directed from London Cocoa to US Cocoa. Such dynamics are also in accordance with full sample analysis. Therefore, in general, it may be stated that while there is mean spillover from London to US Cocoa, the spillovers in shocks and volatility tend to be either bidirectional or flow in the opposite direction.

Relations between currency pairs and cocoa futures reveal similar patterns in Period 1 as in the full sample analysis. Period 1 (see Table 6.10) is characterized by a high degree of spillover concentrated in both mean and variance equations. The direction of significant mean spillovers is from the currency market to cocoa futures. US Cocoa receives mean spillover from EURUSD and GBPUSD. Meanwhile, London Cocoa receives mean spillover from EURGBP. Shock and volatility spillover from major currencies share similar characteristics with a few notable exceptions. Spillover between CHFUSD and US Cocoa is found to be bidirectional, and there is shock spillover from London Cocoa to EURGBP. In the case of spillover between the futures and GHS, the spillover structure follows a pattern that differs from that of major currencies. Shock and volatility spillovers exist from US Cocoa contracts to GHSUSD. In the case of the channel between GHSGBP and London Cocoa, the shock spillover flows from currency to the futures contract. However, the case of volatility spillovers reveals a bidirectional relation. Moreover, the number of significant spillovers between cocoa futures and currency pairs is larger for US Cocoa Futures, pointing to closer ties of US Cocoa to the financial markets

The degree of spillover between these segments of financial markets was significantly subdued in Period 2 (October 2011 - November 2015) (see Table 6.11). There is both shock and volatility spillover between US Cocoa and London Cocoa. Shock spillover flows from US Cocoa to London Cocoa. The volatility spillover is bidirectional, as in the case of the full sample. Among the currencies, the only spillovers between both futures contracts and GHS remain

Table 6.10: Summary of daily spillovers in Period 1
(July 2007 - September 2011)

	Mean Spillover	*Shock Spillover*	*Volatility Spillover*
US Cocoa - London Cocoa	←	↔	→
US Cocoa - EURUSD	←	←	←
US Cocoa - GBPUSD	←	←	←
US Cocoa - CHFUSD	–	↔	↔
US Cocoa - GHSUSD	–	→	→
London Cocoa - USDGBP	–	←	←
London Cocoa - EURGBP	←	→	–
London Cocoa - CHFGBP	–	←	–
London Cocoa - GHSGBP	–	←	↔

Notes: Indicated spillovers are based on 5% significance level. The arrows " ← ", " → " signify the direction of spillovers, " – " means no significant spillover.

significant. Notably, the direction of the spillover from US Cocoa to GHSUSD remains consistent with Period 1. The relationship between London Cocoa and GHSGBP is weaker, the only significant volatility spillover is from London Cocoa to GHSGBP. The number of spillovers is larger for US Cocoa by a small margin.

Table 6.11: Summary of daily spillovers in Period 2
(October 2011 - November 2015)

	Mean Spillover	*Shock Spillover*	*Volatility Spillover*
US Cocoa - London Cocoa	–	→	↔
US Cocoa - EURUSD	–	–	–
US Cocoa - GBPUSD	–	–	–
US Cocoa - CHFUSD	–	–	–
US Cocoa - GHSUSD	–	→	→
London Cocoa - USDGBP	–	–	–
London Cocoa - EURGBP	–	–	–
London Cocoa - CHFGBP	–	–	–
London Cocoa - GHSGBP	–	–	←

Notes: Indicated spillovers are based on 5% significance level. The arrows " ← ", " → " signify the direction of spillovers, " – " means no significant spillover.

Period 3 (December 2015 - January 2020) displays a higher degree of interconnectedness between US Cocoa and major currency pairs (see Table 6.12). Between US Cocoa and EURUSD, there is a bidirectional spillover in shocks and volatility from US Cocoa to EURUSD. Furthermore, both shock and volatility spillover are significant in the direction from GBPUSD to US Cocoa. Similarly, shock spillover from CHFUSD to US Cocoa is present, and the same holds for mean spillover between these two assets. The spillovers between cocoa futures are significant in shock and volatility, both exhibiting a direction from US Cocoa to London Cocoa. The mean spillover is not significant. Consistent with the previous period, there is no spillover between major currency pairs and London Cocoa. The relation between cocoa and GHS is relatively subdued compared to other periods, and only shock spillover from London Cocoa to GHSGBP is significant. Therefore, the number of significant spillovers for US Cocoa in Period 3 is substantially larger. This phenomenon is consistent with the full sample analysis and previous periods, adding evidence to the notion of US Cocoa being more speculative and more intertwined with other asset classes, currency pairs in this case.

Table 6.12: Summary of daily spillovers in Period 3 (December 2015 - January 2020)

	Mean Spillover	*Shock Spillover*	*Volatility Spillover*
US Cocoa - London Cocoa	−	→	→
US Cocoa - EURUSD	−	↔	→
US Cocoa - GBPUSD	−	←	←
US Cocoa - CHFUSD	←	←	−
US Cocoa - GHSUSD	−	−	−
London Cocoa - USDGBP	−	−	−
London Cocoa - EURGBP	−	−	−
London Cocoa - CHFGBP	−	−	−
London Cocoa - GHSGBP	−	→	−

Notes: Indicated spillovers are based on 5% significance level. The arrows " ← ", " → " signify the direction of spillovers, " − " means no significant spillover.

Spillovers between cocoa contracts in both shock and volatility are significant in Period 4 (February 2020 - May 2024) (see Table 6.13). Shock spillover is present in the direction from London Cocoa to US Cocoa, and volatility spillover is significant in both directions. Relations between currencies and cocoa futures were weak in general. The only mean spillover that was found to be statistically significant was from London Cocoa to CHFUSD. The only significant dynamics uncovered by the variance model relate to cocoa futures and GHS, where significant volatility spillover is found from GHSUSD to US Cocoa, and significant shock spillover exists from London Cocoa to GHSUSD. Therefore, this period is an exception in terms of London Cocoa displaying more spillover dynamics with currency pairs than US Cocoa, although the difference is not substantial as the overall extent of spillovers in Period 4 was very limited.

Table 6.13: Summary of daily spillovers in Period 4 (February 2020 - May 2024)

	Mean Spillover	*Shock Spillover*	*Volatility Spillover*
US Cocoa - London Cocoa	–	←	↔
US Cocoa - EURUSD	–	–	–
US Cocoa - GBPUSD	–	–	–
US Cocoa - CHFUSD	–	–	–
US Cocoa - GHSUSD	–	–	←
London Cocoa - USDGBP	–	–	–
London Cocoa - EURGBP	–	–	–
London Cocoa - CHFGBP	→	–	–
London Cocoa - GHSGBP	–	→	–

Notes: Indicated spillovers are based on 5% significance level. The arrows " ← ", " → " signify the direction of spillovers, " – " means no significant spillover.

Chapter 7

Conclusion

The analysis conducted in this thesis explores the volatility dynamics of cocoa futures contracts and their interrelation with foreign exchange markets for the sample period spanning from July 2007 to May 2024. The interdependence between the assets is studied from time different perspectives, and various methodological tools within the GARCH framework are employed. Cocoa futures contracts traded on the ICE US (US Cocoa) and ICE Europe (London Cocoa) are both considered. Global currency pairs selected for the analysis are USD, EUR, GBP, and CHF. Furthermore, GHS is included in the analysis as a currency of Ghana, a cocoa-dependent country.

The univariate GARCH models confirm that the level of conditional volatility varies significantly over time, and the values attained in the first half of 2024 are unprecedented for the whole sample period.

The level of conditional correlation between US Cocoa and London cocoa futures contracts extracted from the DCC-GARCH model remains very high during the majority of the sample period for both daily and weekly models. However, it has been shown that certain occasions do exist when the level of dynamic correlation decreases significantly for a short period of time. One source of decreasing correlations uncovered by the analysis of the daily model is the conditional volatility of the GBPUSD currency pair, which highlights the relevance of the exchange rate risk for the cocoa futures contracts.

Over the sample period, cocoa futures contracts evince only little or no unconditional correlation with currency pairs. DCC analysis for both US and London Cocoa confirms such assessment as no apparent correlation structure arises between cocoa futures and the respective currency pairs.

Analysis of spillovers in mean, shock, and volatility is conducted by estimating the VAR-BEKK-GARCH model. The mean equation represented by the VAR model reveals the direction of the mean spillover from London Cocoa to US Cocoa futures. Therefore, it confirms that London Cocoa tends to lead the US counterpart in price. The spillovers in volatility and shocks between cocoa futures contracts are bidirectional, which is in accordance with the previous study of Jumah & Kunst (2001). In terms of the spillovers between cocoa futures and global currency pairs, most detected spillovers are directed from currencies to cocoa futures. In contrast with the major currencies, GHS displays spillover dynamics that flow either from cocoa futures to GHS or in both directions. These dynamics hint that developments occurring in the cocoa futures market have a significant effect on the GHS exchange rates. Furthermore, the results show that this transmission unfolds primarily via the shock spillover channel. A larger number of significant spillovers is uncovered for US Cocoa than London Cocoa, providing some evidence that more speculative activity is concentrated in this contract and that US Cocoa is likely more intertwined with currency markets.

Subsample analysis reveals that the spillovers are substantially more extensive in the period of high volatility and stress in financial markets. Such findings confirm the previous studies examining the effect of financialization of the commodity futures asset class. Furthermore, apart from certain consistent patterns (e.g., the presence of shock and volatility spillover between cocoa futures contracts), the presence and directionality of the spillover dynamics differ across the four periods. More spillover dynamics between cocoa futures and currency pairs are found in US Cocoa than in London Cocoa for three of the four periods. Similar to the full sample analysis, such findings indicate moderately greater interconnectedness of US Cocoa with the currency markets when compared to London Cocoa.

Several avenues for future research hold the prospect of expanding on our findings and further exploring the studied dynamics using different methodological frameworks. The spillover index framework by Diebold & Yilmaz (2009; 2012) is a natural pathway for further exploration of interconnectedness between cocoa futures contracts and the currency-cocoa futures channel. The study of time-varying correlation in Section 6.2 demands further attention. The absence of apparent correlation structures emerging between cocoa futures contracts and currency pairs in our analysis does not necessarily prove that such structures are entirely nonexistent in reality. The DCC model was applied over a relatively long period, during which, as we argued, significant structural changes stemming from commodity financialization continued to unfold in the markets. The conditional correlation in the DCC model tends to be too susceptible to local dynamics, and the persistence may be overstated in the presence of structural breaks (Silvennoinen & Thorp 2013). Double Smooth Transition Conditional Correlation (DSTCC) model by Silvennoinen & Teräsvirta (2015) may remedy such issues as it allows for switching between different regimes governed either by time or by financial indicators such as VIX (Silvennoinen & Thorp 2013). Furthermore, the spillover analysis in Section 6.3 could be replicated with the application of a wavelet-based VAR-BEKK model as in Liu *et al.* (2017), which allows for analysis of spillovers across different frequency dimensions in a more sophisticated manner than one applied in this thesis.

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Appendix A

Appendix A

Table A.1: Supply and Demand of cocoa beans per season (000s MT)

Crop year	Gross crop	Grindings	Stocks	Surplus/Deficit	Stock/Grindings(%)
2008/09	3592	3557	1557	19	43.8
2009/10	3634	3737	1418	-139	37.9
2010/11	4309	393	1746	328	44.3
2011/12	4095	3972	1828	82	46.0
2012/13	3943	4180	1552	-276	37.1
2013/14	4370	4335	1543	-9	35.6
2014/15	4252	4152	1600	57	38.5
2015/16	3994	4133	1421	-179	34.4
2016/17	4768	4391	1750	329	39.9
2017/18	4647	4576	1775	25	38.8
2018/19	4811	4742	1796	21	37.9
2019/20	4752	4685	1815	19	38.7
2020/21	5245	4949	2059	224	41.6
2021/22	4826	4994	1843	-216	36.9
2022/23	4996	5020	1769	-74	35.2
2023/24 est.	4449	4779	1395	-374	29.2

Source: https://www.icco.org/statistics/; ICCO (2024)

Table A.2: VAR-BEKK model for Period 1 (2007/7/6 - 2011/9/30)

	USC-LC	USC-EURUSD	USC-GBPUSD	USC-CHFUSD	LC-USDGBP	LC-EURGBP	LC-CHFGBP	USC-GHSUSD	LC-GHSGBP
μ_{10}	0.0002	0.0003	0.0003	0.0002	0.0005	0.0004	0.0004	0.0002	0.0004
μ_{20}	0.0004	0.0000	−0.0002	0.0003	0.0002	0.0002	0.0004	−0.0007***	−0.0003
ϕ_{11}	−0.1913***	−0.0727**	−0.0662**	−0.0362	0.0204	0.012	0.0192	−0.0247	0.019
ϕ_{12}	0.2349***	0.3901***	0.3284***	0.13*	0.012	0.1821**	0.0712	−0.1399	−0.0269
ϕ_{13}								0.0437	0.0442
ϕ_{14}								−0.0893	0.0166
ϕ_{21}	−0.0832*	0.0014	−0.0076	0.012	0.0045	0.0089	0.0151	−0.0003	0.0068
ϕ_{22}	0.1067*	0.0243	0.0586*	−0.0146	0.0488	0.0608*	0.016	−0.4007***	−0.127***
ϕ_{23}								−0.0229**	−0.0274
ϕ_{24}								−0.2456***	−0.0754**
a_{11}	0.0000	0.2048***	0.2166***	0.1312***	0.1507***	0.2474***	0.3151***	0.1742***	0.0971***
a_{12}	−0.1618***	0.003	−0.0121	0.0248***	−0.012	−0.0345***	−0.0251	0.0138**	−0.0175
a_{21}	0.1655***	0.2226***	0.2759***	−0.154**	0.1248***	0.1419*	0.1619**	0.0676	0.0801**
a_{22}	0.2621***	0.1766***	0.1801***	0.2378***	0.215***	0.2258***	0.3102***	0.3908***	0.2484***
g_{11}	1.0002***	0.902***	0.8976***	0.9851***	0.981***	0.8959***	0.6433***	0.8796***	0.9906***
g_{12}	0.023***	0.0067	0.0193*	−0.0082	0.0043	0.0187*	−0.0549*	0.0234**	0.0111***
g_{21}	−0.0188	−0.0544**	−0.0603**	0.089***	−0.0437***	−0.0381	−0.0245	−0.035	−0.039***
g_{22}	0.9584***	0.98***	0.9712***	0.952***	0.9712***	0.967***	0.9428***	0.9161***	0.9657***

Notes: *,**,*** indicate statistical significance at 10%, 5%, 1% level. The values of presented parameter estimates are rounded to 4 decimal places. USC represents US Cocoa futures contract. LC represents London Cocoa futures contract. It is necessary to heed the difference in notation of the mean (VAR) equation where parameter ϕ_{12} signifies how the variable 2 affects the variable 1, meanwhile, in the variance (BEKK) equation the parameters a_{12}, g_{12} signify the effect of the variable 1 on the variable 2.

Table A.3: VAR-BEKK model for Period 2 (2011/10/3 - 2015/11/30)

	USC-LC	USC-EURUSD	USC-GBPUSD	USC-CHFUSD	LC-USDGBP	LC-EURGBP	LC-CHFGBP	USC-GHSUSD	LC-GHSGBP
μ_{10}	0.0002	0.0002	0.0002	0.0002	0.0003	0.0003	0.0003	0.0002	0.0003
μ_{20}	0.0003	−0.0002	0.0000	−0.0001	0.0000	−0.0002	−0.0001	−0.0009**	−0.0007*
ϕ_{11}	0.0388	0.0568*	0.0504	0.0573*	0.0606*	0.0617**	0.0609**	0.0588*	0.0589*
ϕ_{12}	0.0197	−0.0112	0.0487	−0.0223	0.0806	−0.0375	−0.0094	0.0616	0.0473
ϕ_{13}	−0.0721		−0.033					−0.0256	−0.0539*
ϕ_{14}	0.0621		0.1024					−0.0078	−0.0037
ϕ_{15}	0.1359*		−0.0053					0.002	−0.0285
ϕ_{16}	−0.1659*		0.0834					0.013	−0.0006
ϕ_{17}	−0.0021		−0.134***					−0.1229***	−0.1073***
ϕ_{18}	−0.1411*		0.1331					−0.0119	−0.0184
ϕ_{21}	0.1083	0.0117	0.0103	0.0106	−0.0042	−0.0046	−0.006	−0.0051	0.0178
ϕ_{22}	−0.0487	−0.0406	−0.0369	−0.0169	−0.029	−0.0105	−0.011	−0.1888***	−0.1096***
ϕ_{23}	−0.0548		0.0094					0.0103	−0.0067
ϕ_{24}	0.0001		0.0186					0.0214	0.0107
ϕ_{25}	0.1513**		0.0108					0.0095	−0.0117
ϕ_{26}	−0.1895**		−0.0291					0.1106***	0.1342***
ϕ_{27}	−0.0245		0.0005					0.0039	0.0069
ϕ_{28}	−0.0801		−0.0228					0.0086	0.0093
a_{11}	0.1746***	0.1756***	0.178***	0.1912***	0.2008***	0.1921***	0.2382***	0.191***	0.1797***
a_{12}	0.085**	−0.011	0.0027	−0.0064	−0.0022	−0.01	−0.0115	0.0326***	−0.0091
a_{21}	0.0172	0.0425	0.0714	0.0262	−0.0163	−0.0262	−0.0124	−0.0186	−0.021
a_{22}	0.1223***	0.1964***	0.1673***	0.0627	0.1701***	0.2175***	0.0634	0.4631***	0.3674***
g_{11}	0.948***	0.981***	0.9804***	0.9782***	0.9763***	0.9785***	0.965***	0.9621***	0.9819***
g_{12}	−0.0438***	0.0027	−0.0005	0.0084	0.0001	0.0022	0.0024	−0.0141**	0.0002
g_{21}	0.0363***	−0.0077	−0.0072	0.002	−0.0013	0.0124	0.0822	0.0014	0.0106**
g_{22}	1.019***	0.9771***	0.9803***	0.8903***	0.98***	0.9686***	0.8799***	0.8867***	0.9275***

Notes: *,** ,*** indicate statistical significance at 10%, 5%, 1% level. The values of presented parameter estimates are rounded to 4 decimal places. USC represents US Cocoa futures contract. LC represents London Cocoa futures contract. It is necessary to heed the difference in notation of the mean (VAR) equation where parameter ϕ_{12} signifies how the variable 2 affects the variable 1, meanwhile, in the variance (BEKK) equation the parameters a_{12}, g_{12} signify the effect of the variable 1 on the variable 2.

Table A.4: VAR-BEKK model for Period 3 (2015/12/1 - 2020/1/31)

	USC-LC	USC-EURUSD	USC-GBPUSD	USC-CHFUSD	LC-USDGBP	LC-EURGBP	LC-CHFGBP	USC-GHSUSD	LC-GHSGBP
μ_{10}	−0.0002	−0.0002	−0.0002	−0.0002	−0.0001	−0.0001	−0.0001	−0.0002	−0.0001
μ_{20}	−0.0001	0.0000	−0.0001	0.0001	0.0001	0.0002	0.0002	−0.0004	−0.0002
ϕ_{11}	−0.0683	−0.0379	−0.0405	−0.0362	−0.0108	−0.0116	−0.0106	−0.0311	−0.0088
ϕ_{12}	0.0507	0.1748	0.1249	0.2497**	0.0838	0.1001	0.0933	0.0175	0.0313
ϕ_{21}	−0.037	0.0148*	0.0038	0.0038	−0.0019	0.0124	0.0017	0.0279*	0.0292
ϕ_{22}	0.0314	−0.0524*	0.0168	0.0027	0.0182	0.0317	0.0279	−0.3821***	−0.2721***
a_{11}	0.1091	0.1486***	0.1268***	0.1811***	0.1701***	0.1718***	0.1641***	0.1109***	0.1618***
a_{12}	−0.1915***	0.0368***	−0.0121	0.0283*	0.0001	0.005	0.0253	−0.0178*	0.0809***
a_{21}	0.0797	0.4707***	0.1723**	0.4813***	0.0251	0.0404	0.0305	−0.0339	−0.0162
a_{22}	0.3808***	0.1076***	0.3763***	0.1822***	0.3669***	0.2885***	0.3776***	0.4002***	0.3977***
g_{11}	1.0164***	0.9192***	0.9865***	0.9361***	0.9743***	0.9719***	0.976***	0.9891***	0.9747***
g_{12}	0.148***	−0.0312***	0.0008	−0.0237*	0.0025	0.0015	−0.0061	0.0007	−0.0126
g_{21}	−0.0462	−0.079	−0.0882**	−0.3412*	0.0078	0.0051	0.0063	0.0078	−0.0032
g_{22}	0.8099***	0.958***	0.879***	0.8297***	0.8755***	0.9379***	0.8872***	0.906***	0.895***

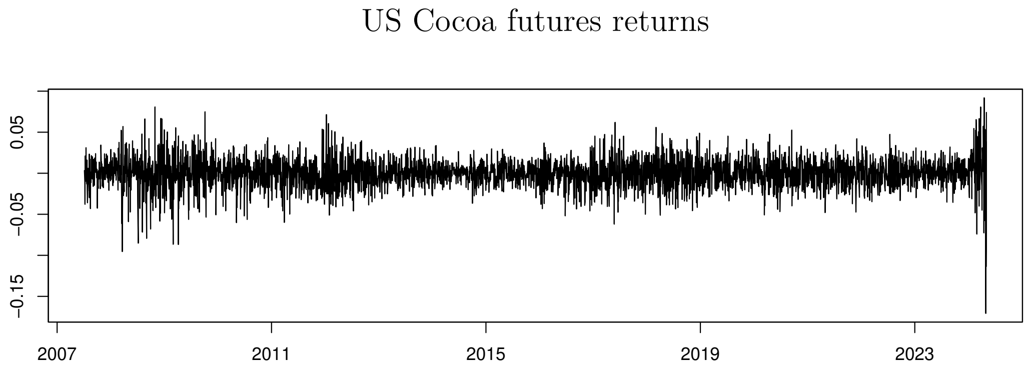
Notes: *,** ,*** indicate statistical significance at 10%, 5%, 1% level. The values of presented parameter estimates are rounded to 4 decimal places. USC represents US Cocoa futures contract. LC represents London Cocoa futures contract. It is necessary to heed the difference in notation of the mean (VAR) equation where parameter ϕ_{12} signifies how the variable 2 affects the variable 1, meanwhile, in the variance (BEKK) equation the parameters a_{12}, g_{12} signify the effect of the variable 1 on the variable 2.

Table A.5: VAR-BEKK model for Period 4 (2020/2/3 - 2024/5/3)

	USC-LC	USC-EURUSD	USC-GBPUSD	USC-CHFUSD	LC-USDGBP	LC-EURGBP	LC-CHFGBP	USC-GHSUSD	LC-GHSGBP
μ_{10}	0.001*	0.001*	0.001*	0.001*	0.001**	0.001**	0.0008*	0.0009	0.0009*
μ_{20}	0.001**	0.0000	0.0000	0.0001	0.0000	0.0000	0.0002	−0.0006	−0.0006
ϕ_{11}	0.0319	0.0438	0.0394	0.0466	0.1013***	0.1037***	0.1008***	0.0468	0.1001***
ϕ_{12}	0.019	0.1342	0.1798*	0.066	0.0573	0.0025	−0.0175	−0.0401	−0.0145
ϕ_{13}							−0.0114	−0.0085	−0.0102
ϕ_{14}							−0.1015	−0.0304	−0.052
ϕ_{15}							0.0306	0.0309	0.0294
ϕ_{16}							0.0792	0.0232	0.0291
ϕ_{17}							0.0927***		0.0936***
ϕ_{18}							0.0396		0.0738**
ϕ_{21}	0.0498	0.001	0.0081	0.0025	−0.0193*	−0.0151*	−0.0164*	0.0103	−0.0507*
ϕ_{22}	0.0548	0.0342	0.0825***	0.0693**	0.0915***	0.009	0.0251	0.1001***	0.0878***
ϕ_{23}							−0.0025	0.01	0.0232
ϕ_{24}							−0.0283	0.1559***	0.1555***
ϕ_{25}							−0.0121	0.0049	−0.019
ϕ_{26}							0.0568*	0.1109***	0.1078***
ϕ_{27}							−0.0215**		−0.0166
ϕ_{28}							−0.027		−0.056*
a_{11}	0.0717	0.2178***	0.1992***	0.2008***	0.2247***	0.2991***	0.2377***	0.1505***	0.1901***
a_{12}	−0.0827*	0.0029	0.0039	0.0177*	−0.0042	−0.005	−0.0062	0.006	−0.014
a_{21}	0.2023***	−0.1101	−0.0244	0.0467	0.0744	0.0374	0.0618	0.0344	0.0067
a_{22}	0.4142***	0.1909***	0.2865***	0.3621***	0.2825***	0.1937***	0.2269***	0.397***	0.5405***
g_{11}	1.0081***	0.9747***	0.9797***	0.9768***	0.9734***	0.9452***	0.9698***	0.9159***	0.9805***
g_{12}	0.0395**	−0.0013	−0.0016	−0.01*	0.0025	0.0023*	0.0033	−0.0049	0.0076
g_{21}	−0.0504**	0.0236	−0.0022	−0.0698	−0.0208	−0.0035	−0.0199	0.0321**	−0.0021
g_{22}	0.8887***	0.9756***	0.9399***	0.8128***	0.9393***	0.9789***	0.9613***	0.9188***	0.8414***

Notes: *,** ,*** indicate statistical significance at 10%, 5%, 1% level. The values of presented parameter estimates are rounded to 4 decimal places. USC represents US Cocoa futures contract. LC represents London Cocoa futures contract. It is necessary to heed the difference in notation of the mean (VAR) equation where parameter ϕ_{12} signifies how the variable 2 affects the variable 1, meanwhile, in the variance (BEKK) equation the parameters a_{12}, g_{12} signify the effect of the variable 1 on the variable 2.

Figure A.1: Daily returns of cocoa futures contracts



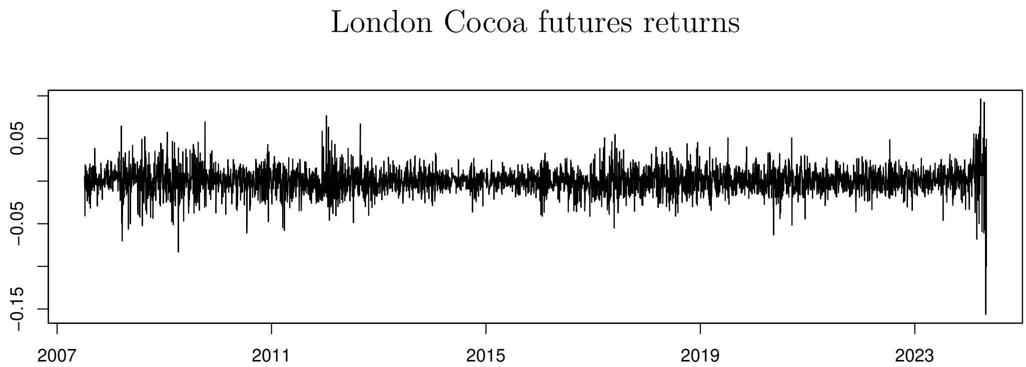


Figure A.2: Weekly returns of cocoa futures contracts

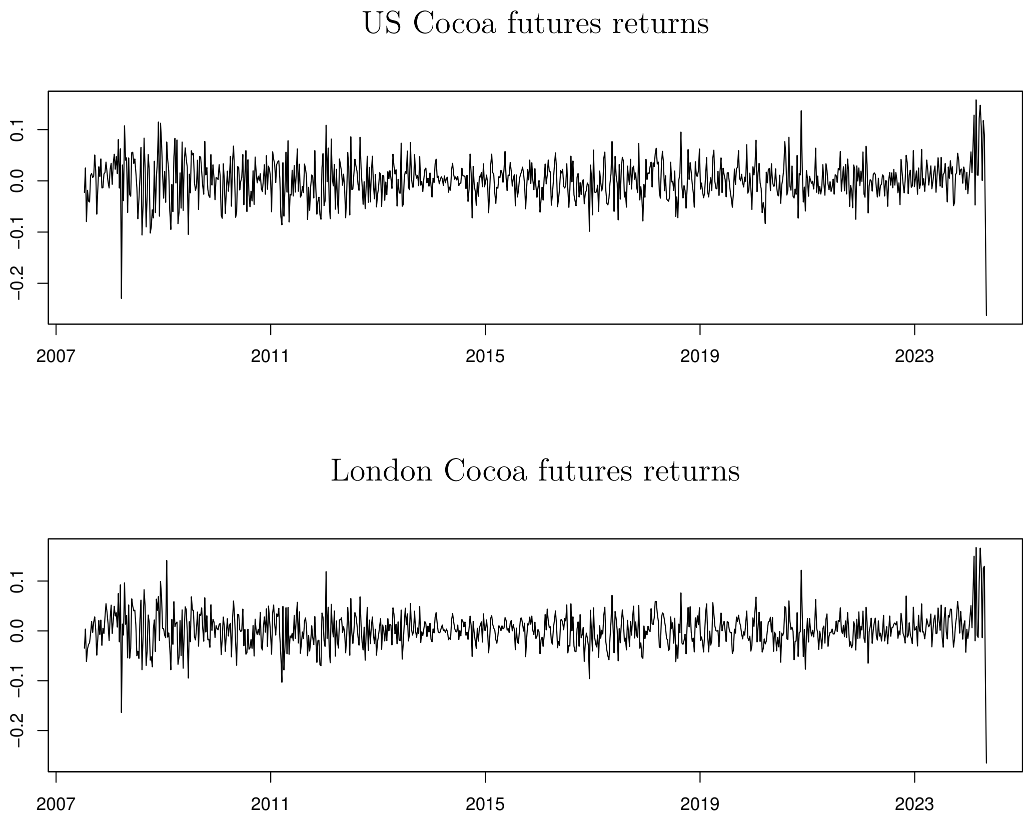


Figure A.3: Daily returns of USD-denominated currency pairs

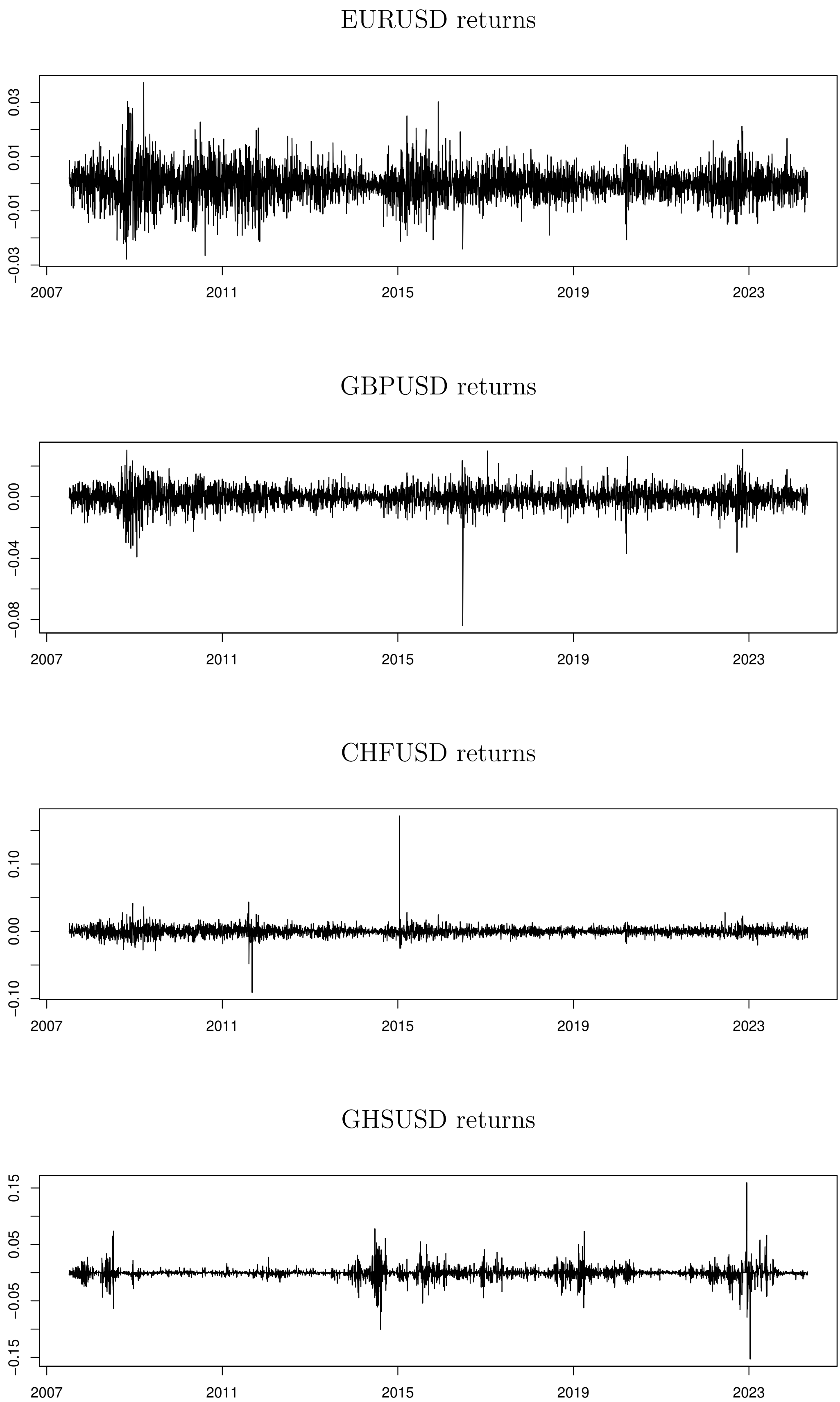


Figure A.4: Weekly returns of USD-denominated currency pairs

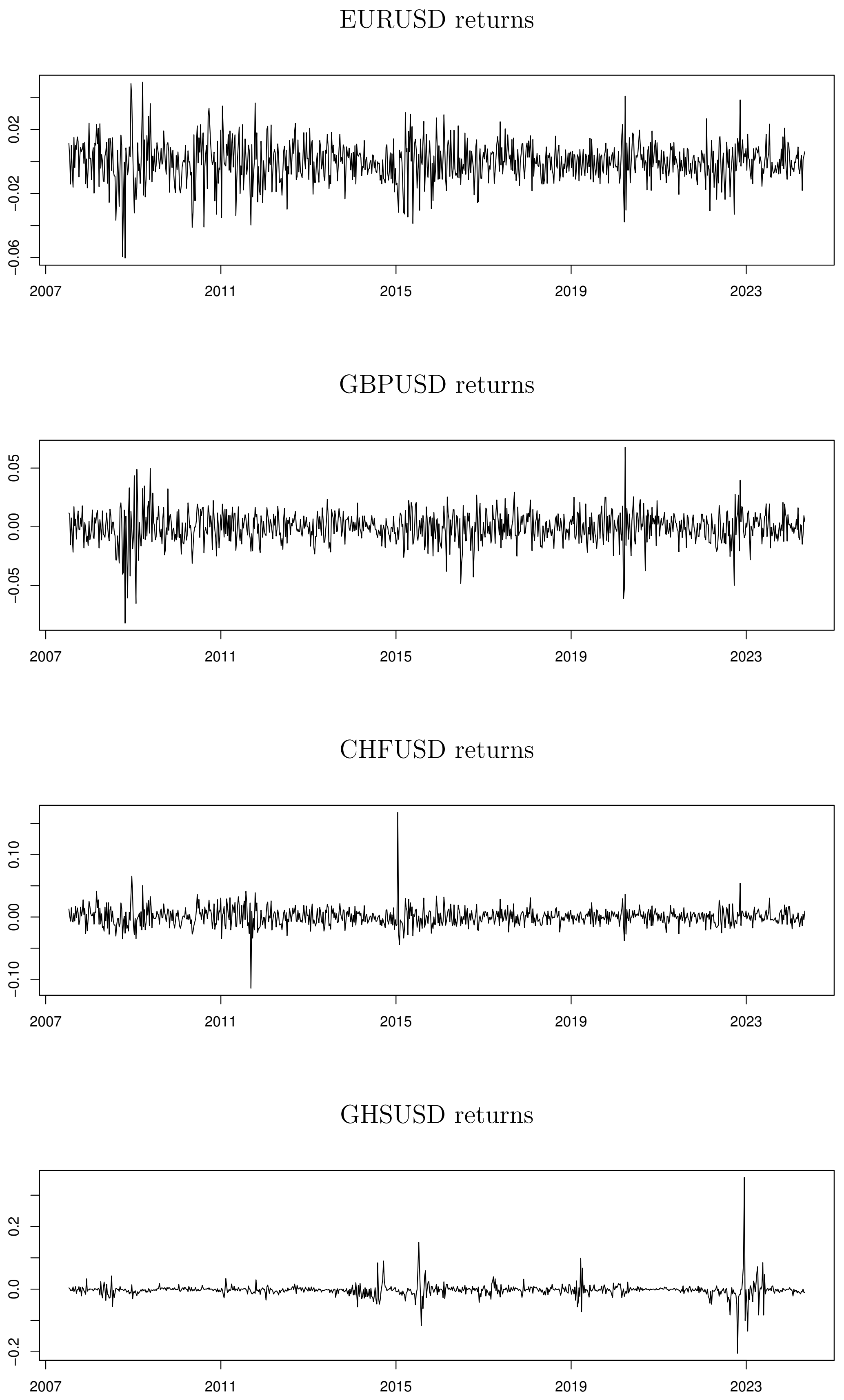


Figure A.5: Daily returns of GBP-denominated currency pairs

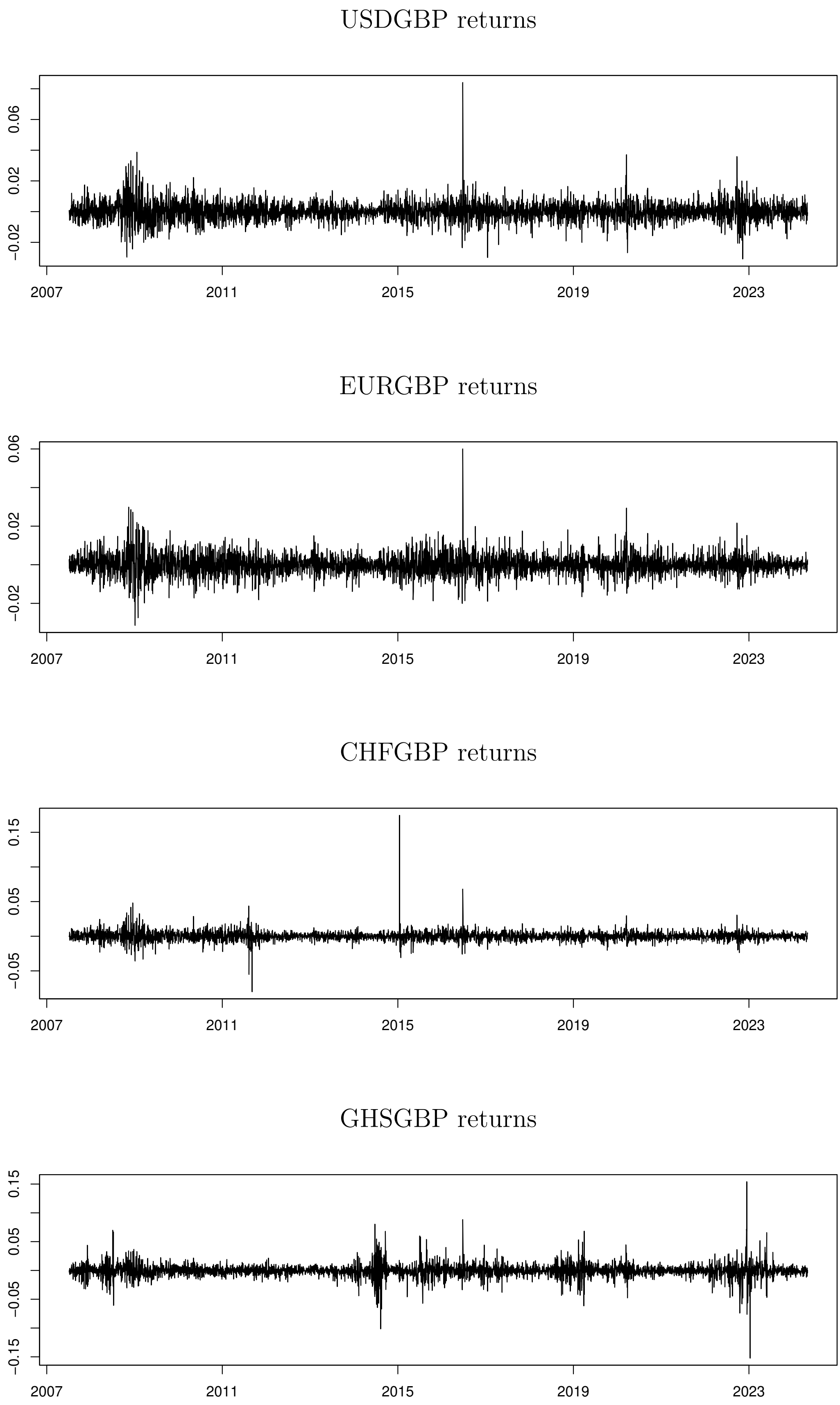
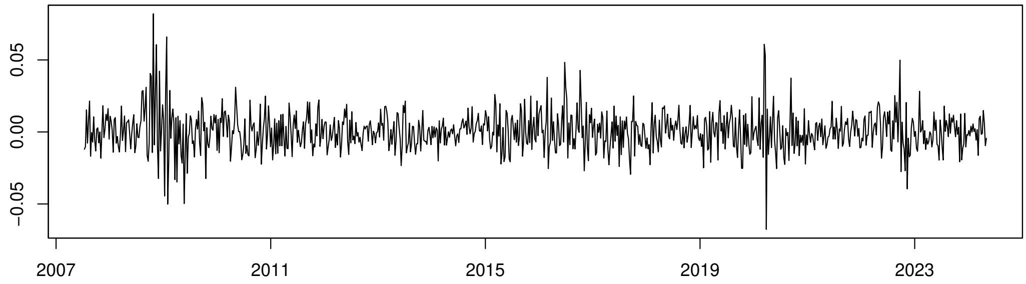
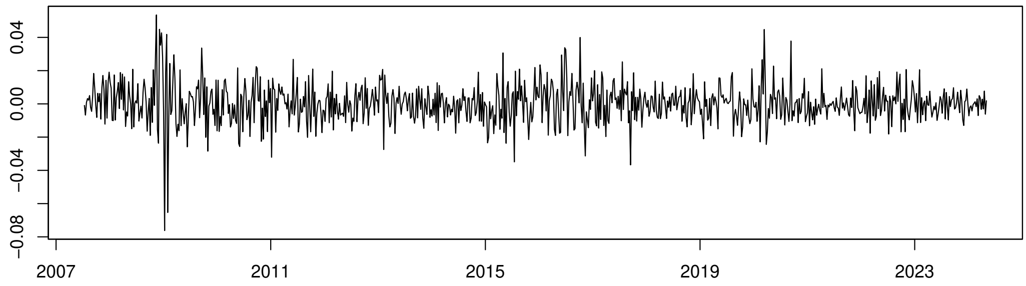


Figure A.6: Weekly returns of GBP-denominated currency pairs

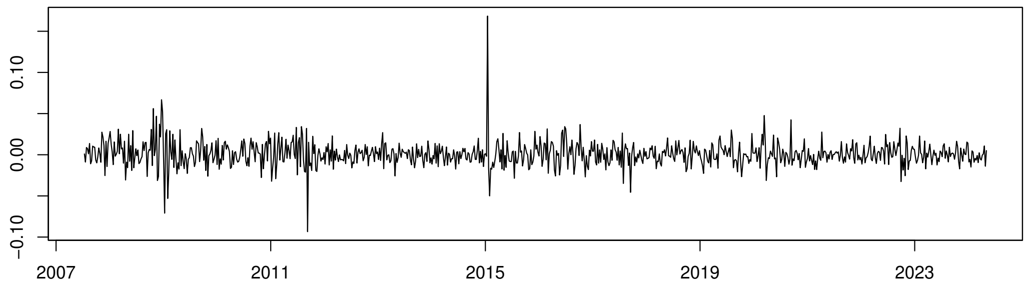
USDGBP returns



EURGBP returns



CHFGBP returns



GHSGBP returns

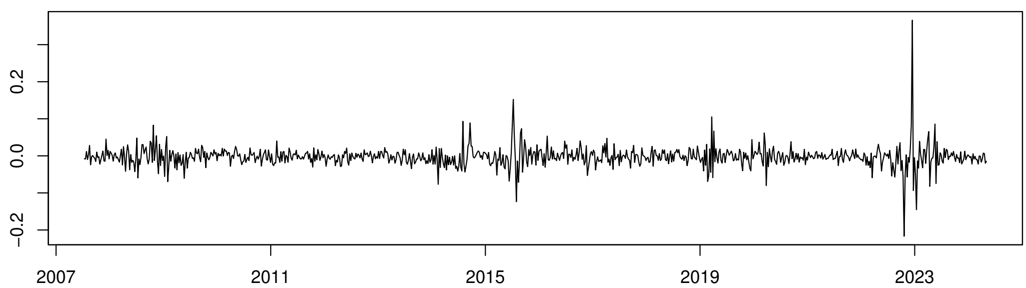
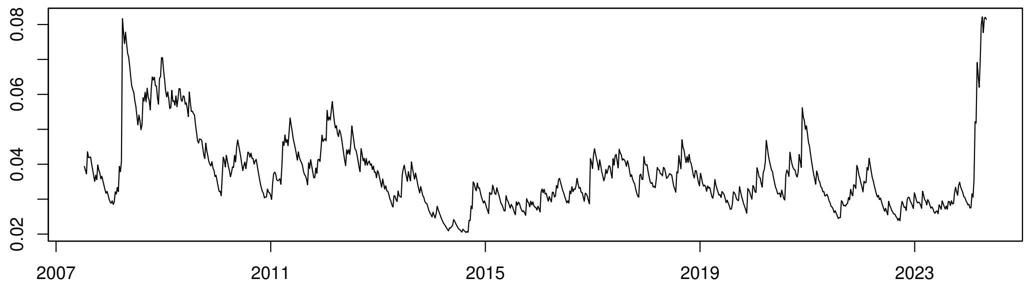


Figure A.7: Weekly conditional volatility estimates for cocoa futures

US Cocoa futures



London Cocoa futures

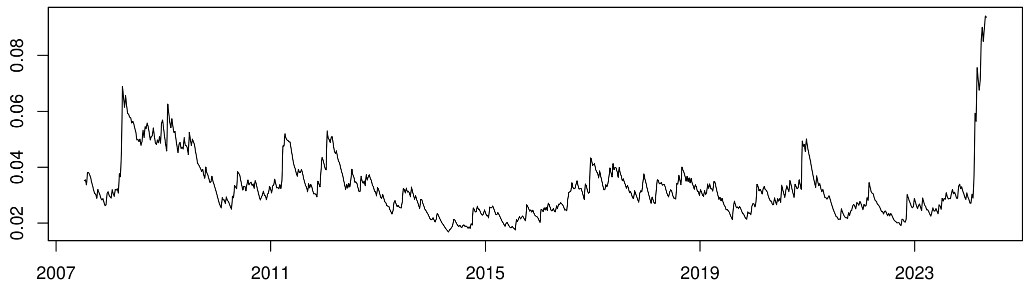
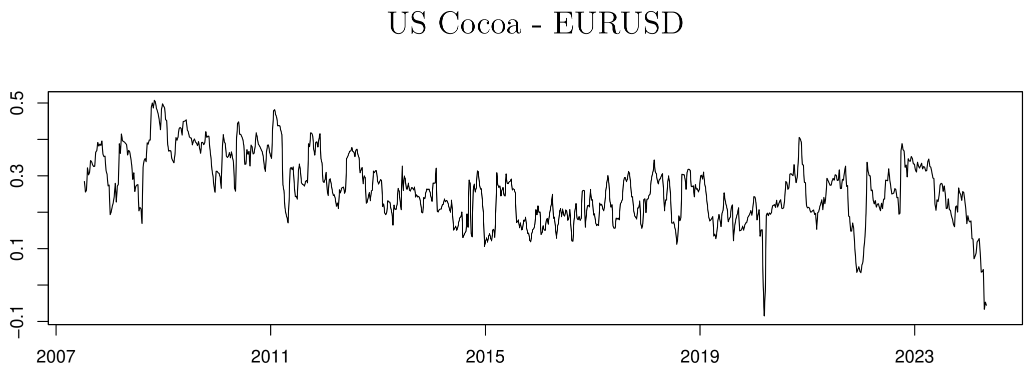
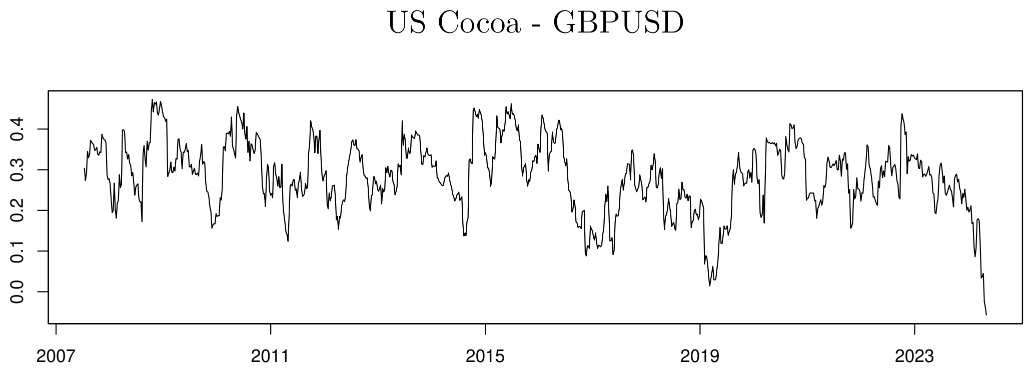
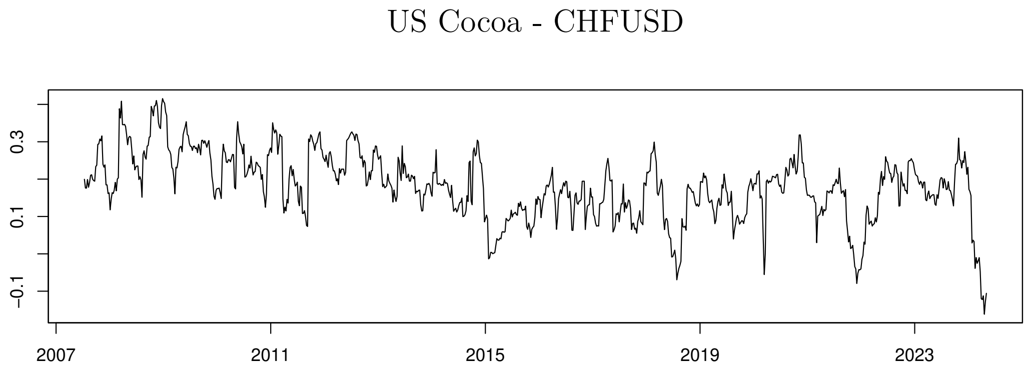


Figure A.8: Weekly conditional correlations for US Cocoa and currency pairs







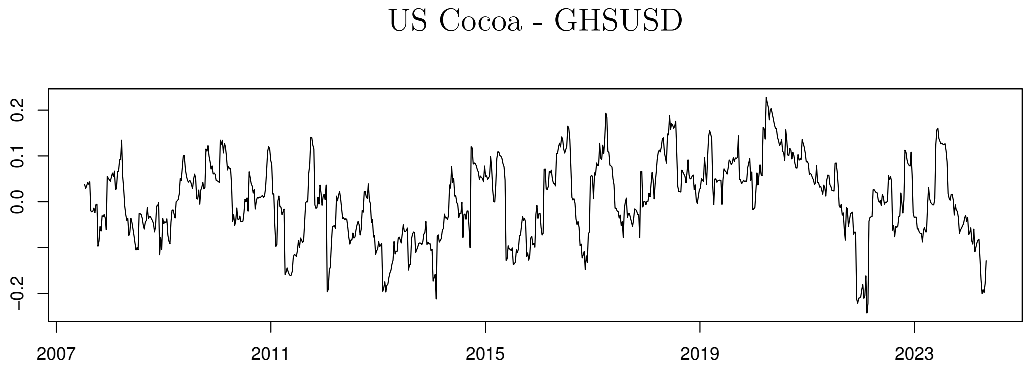
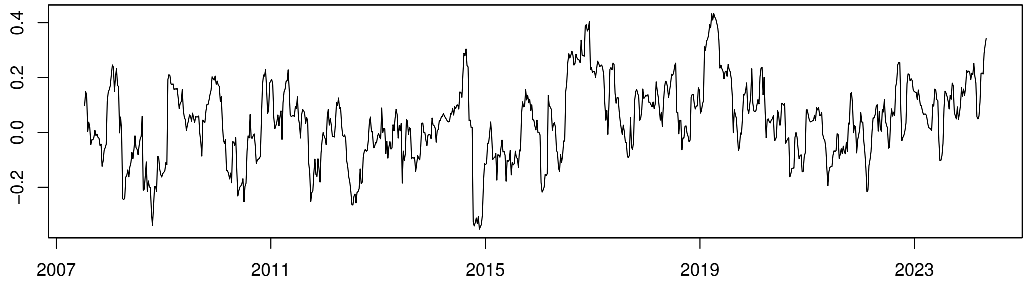
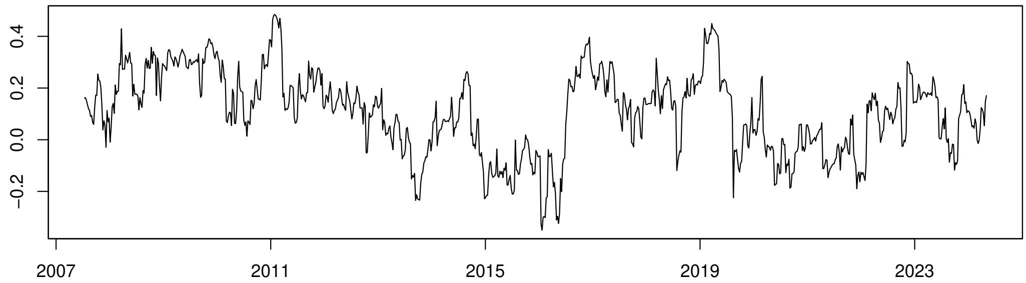


Figure A.9: Weekly conditional correlations for London Cocoa and currency pairs

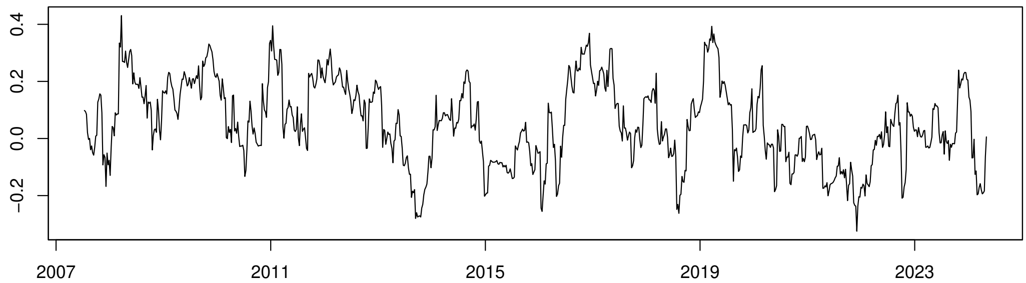
London Cocoa - USDGBP



London Cocoa - EURGBP



London Cocoa - CHFGBP



London Cocoa - GHSGBP

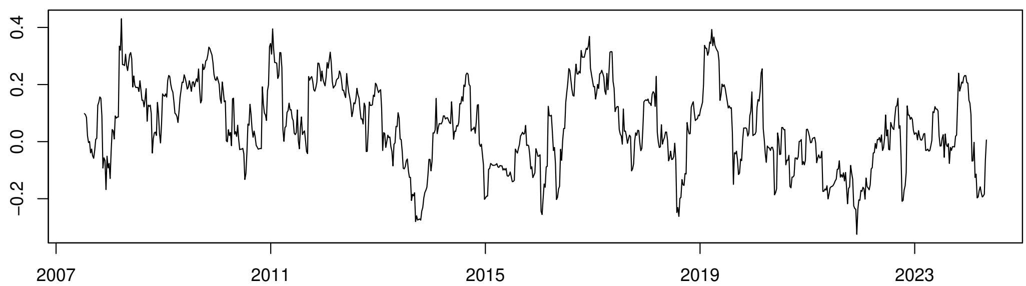


Figure A.10: Conditional volatility estimates for GBPUSD

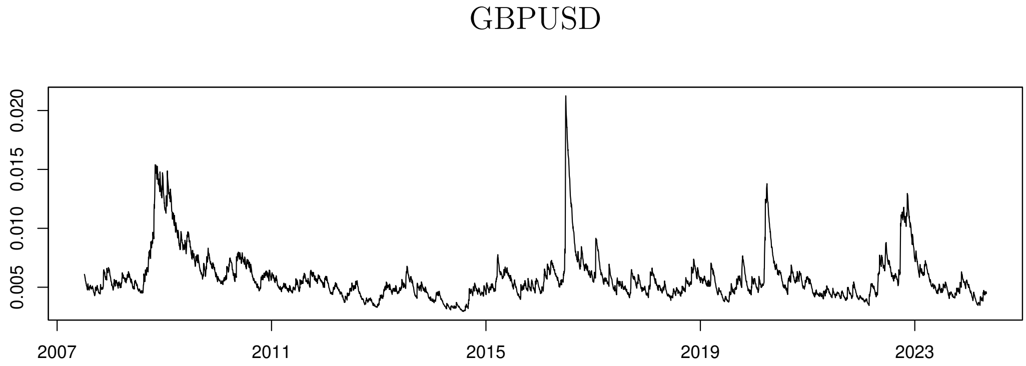


Table A.6: VAR results for daily VAR-DCC-GARCH model for cocoa futures

	USC_{t-1}	LC_{t-1}	μ_i
USC_t	-0.0804^{**}	0.1159^{***}	0.0003
LC_t	-0.0205	0.0678^{**}	0.0004^{*}

Notes: VAR results are presented in the cross table of variables and their lagged values. *,**,*** indicate statistical significance at 10%, 5%, 1% level. The values of presented parameter estimates are rounded to 4 decimal places. USC stands for US Cocoa futures, LC stands for London Cocoa futures, μ stands for a constant in the VAR model.

Table A.7: VAR results for weekly VAR-DCC-GARCH model for cocoa futures

	USC_{t-1}	LC_{t-1}	μ_i
USC_t	-0.1553^{**}	0.2479^{***}	0.0013
LC_t	-0.073	0.1581^{**}	0.0019

Notes: VAR results are presented in the cross table of variables and their lagged values. *,**,*** indicate statistical significance at 10%, 5%, 1% level. The values of presented parameter estimates are rounded to 4 decimal places. USC stands for US Cocoa futures, LC stands for London Cocoa futures, μ stands for a constant in the VAR model.

Table A.8: VAR results for daily VAR-DCC-GARCH model for US Cocoa futures and currency pairs

	USC_{t-1}	$EURUSD_{t-1}$	$GBPUSD_{t-1}$	$CHFUSD_{t-1}$	$GHSUSD_{t-1}$	USC_{t-2}	$EURUSD_{t-2}$	$GBPUSD_{t-2}$
USC_t	−0.0114	0.1845**	0.1111**	−0.0693	−0.0072	0.0079	−0.0287	−0.0198
$EURUSD_t$	0.0066	0.0204	−0.0001	−0.0277	−0.0141	0.0041	−0.0264	0.0096
$GBPUSD_t$	0.0029	−0.0035	0.0501**	−0.0236	−0.0124	0.0066	0.0212	−0.0272
$CHFUSD_t$	0.0047	0.0051	0.0321	−0.0142	−0.0209**	0.0052	−0.0129	0.0067
$GHSUSD_t$	0.0052	−0.0077	0.0508	−0.0128	−0.1134***	−0.0023	0.029	−0.0272

	$CHFUSD_{t-2}$	$GHSUSD_{t-2}$	USC_{t-3}	$EURUSD_{t-3}$	$GBPUSD_{t-3}$	$CHFUSD_{t-3}$	$GHSUSD_{t-3}$	μ_i
USC_t	0.0219	−0.0162	0.0163	0.0348	−0.0031	−0.0604	0.0102	0.0003
$EURUSD_t$	0.018	−0.0054	0.0075	−0.0502**	0.0035	0.0204	0.0094	−0.0001
$GBPUSD_t$	−0.0018	−0.0118	0.0038	−0.03	−0.0115	0.0062	−0.0069	−0.0001
$CHFUSD_t$	0.0172	0.0007	0.0051	−0.0448	0.0084	0.0098	0.0079	0.0001
$GHSUSD_t$	−0.0272	0.0901***	0.0041	−0.0555	0.0278	0.0145	0.114***	−0.0006

Notes: VAR results are presented in the cross table of variables and their lagged values. *,** ,*** indicate statistical significance at 10%, 5%, 1% level. The values of presented parameter estimates are rounded to 4 decimal places. USC stands for US Cocoa futures, LC stands for London Cocoa futures, μ stands for a constant in the VAR model.

Table A.9: VAR results for daily VAR-DCC-GARCH model for London Cocoa futures and currency pairs

	LC_{t-1}	$USDGBP_{t-1}$	$EURGBP_{t-1}$	$CHFGBP_{t-1}$	$GHSGBP_{t-1}$	LC_{t-2}	$USDGBP_{t-2}$
LC_t	0.0432***	0.041	0.0815	−0.0187	−0.0099	0.0069	0.0441
$USDGBP_t$	−0.0051	0.013	0.0018	0.0244	0.0121	−0.006	−0.0116
$EURGBP_t$	0.0007	0.0334*	0.0185	−0.0022	−0.003	−0.0027	−0.0163
$CHFGBP_t$	−0.0012	0.0054	0.0104	0.0091	−0.0091	0.001	−0.0298
$GHSGBP_t$	−0.0062	0.0793**	−0.0008	0.0191	−0.0986***	−0.0033	−0.0535

	$EURGBP_{t-2}$	$CHFGBP_{t-2}$	$GHSGBP_{t-2}$	LC_{t-3}	$USDGBP_{t-3}$	$EURGBP_{t-3}$	$CHFGBP_{t-3}$
LC_t	−0.0192	−0.0021	−0.018	0.0142	−0.0046	−0.0024	−0.0289
$USDGBP_t$	−0.0213	0.0015	0.0108	−0.0054	−0.0377*	0.029	-0.0061
$EURGBP_t$	−0.0457**	0.0213	0.0053	0.0043	−0.0292*	−0.0223	0.0148
$CHFGBP_t$	−0.0363	0.0211	0.0122	−0.0011	−0.0254	−0.0189	0.0035
$GHSGBP_t$	0.001	−0.0325	0.0855***	−0.009	−0.1392***	−0.0203	−0.0048

	$GHSGBP_{t-3}$	LC_{t-4}	$USDGBP_{t-4}$	$EURGBP_{t-4}$	$CHFGBP_{t-4}$	$GHSGBP_{t-4}$	μ_i
LC_t	0.0171	0.0129	0.0411	0.0771	−0.0543	0.0365	0.0004*
$USDGBP_t$	0.0074	0.0009	0.0183	−0.0838***	0.0412**	0.0024	0.0001
$EURGBP_t$	0.0191**	−0.0016	0.0051	0.0271	−0.0439***	0.0039	0.0001
$CHFGBP_t$	0.0164	−0.005	−0.006	0.0149	−0.0109	0.0029	0.0002
$GHSGBP_t$	0.1308***	0.0033	−0.0432	−0.1274***	0.059	0.0339*	−0.0004**

Notes: VAR results are presented in the cross table of variables and their lagged values. *,** ,*** indicate statistical significance at 10%, 5%, 1% level. The values of presented parameter estimates are rounded to 4 decimal places. USC stands for US Cocoa futures, LC stands for London Cocoa futures, μ stands for a constant in the VAR model.

Table A.10: VAR results for weekly VAR-DCC-GARCH model for US Cocoa futures and currency pairs

	USC_{t-1}	$EURUSD_{t-1}$	$GBPUSD_{t-1}$	$CHFUSD_{t-1}$	$GHSUSD_{t-1}$	μ_i
USC_t	0.0500	0.3061*	−0.1538	−0.3024**	0.0717	0.0018
$EURUSD_t$	−0.0082	0.1058**	0.0121	−0.1427***	−0.0023	−0.0002
$GBPUSD_t$	0.0123	0.0975*	−0.0523	−0.0979**	−0.0249	−0.0006
$CHFUSD_t$	−0.0133	0.2038***	−0.0143	−0.1707***	0.0058	0.0005
$GHSUSD_t$	0.0120	−0.0482	0.0519	0.0412	0.0746**	−0.0029***

Notes: VAR results are presented in the cross table of variables and their lagged values. *,**,*** indicate statistical significance at 10%, 5%, 1% level. The values of presented parameter estimates are rounded to 4 decimal places. USC stands for US Cocoa futures, LC stands for London Cocoa futures, μ stands for a constant in the VAR model.

Table A.11: VAR results for weekly VAR-DCC-GARCH model for London Cocoa futures and currency pairs

	LC_{t-1}	$USDGBP_{t-1}$	$EURGBP_{t-1}$	$CHFGBP_{t-1}$	$GHSGBP_{t-1}$	μ_i
LC_t	0.0831**	0.0254	0.1166	−0.1709	0.0853	0.0022*
$USDGBP_t$	−0.0152	−0.0673	−0.0869	0.0901**	0.0240	0.0006
$EURGBP_t$	−0.0199*	−0.0297	0.0141	−0.0484	0.0226	0.0004
$CHFGBP_t$	−0.0214	−0.0757	0.1111*	−0.0789*	0.0296	0.0011**
$GHSGBP_t$	−0.0074	−0.1989**	−0.1268	0.1283	0.0988**	−0.0022**

Notes: VAR results are presented in the cross table of variables and their lagged values. *,**,*** indicate statistical significance at 10%, 5%, 1% level. The values of presented parameter estimates are rounded to 4 decimal places. USC stands for US Cocoa futures, LC stands for London Cocoa futures, μ stands for a constant in the VAR model.

Appendix B

Materials for Replication of Econometric Analysis

The original R code used to conduct the econometric analysis along with a brief commentary may be accessed at the author's GitHub repository at `https://github.com/MatyasSvehla/cocoa-currency-spillover.git`.