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„Analysing the effect of Hungary's dependence on Russian energy on the exchange rate volatility of the Hungarian Forint using ARCH-analysis"

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ABSTRACT

Russian energy dependence in the Central European region is an interesting field of analysis, especially since the start of the Russian-Ukrainian conflict in 2022, which has exposed the entire European Union – especially V4 countries – to energy supply uncertainty. While there has been extensive research investigating exchange rate volatility of CE currencies and their relationship with oil, no study has attempted to investigate the effect of Russian energy dependence on national currencies. The aim of the current thesis is to provide a detailed inspection of this relationship for, the Hungarian forint, the Polish zloty, and the Czech koruna, with the British pound as a Western European benchmark currency. Using the DCC-GARCH(1,1) framework and the Diebold-Yilmaz volatility spillover index following the work of Kočenda and Moravcová (Kočenda – Moravcová, 2019), the thesis investigates the co-movements and directional spillovers between the currencies, Henry Hub gas prices, Brent crude oil prices, and the Russian rouble for the time period 2004-2022. Results indicate weak exposure of Central European exchange rates to global commodity prices and the rouble's exchange rate. The thesis also highlights the increased exposure of the forint and the zloty to Russia-related commodity news compared to the Czech koruna and the British pound.

ZUSAMMENFASSUNG

Die russische Energieabhängigkeit in der mitteleuropäischen Region ist ein interessantes Analysefeld, insbesondere seit dem Beginn des russisch-ukrainischen Konflikts im Jahr 2022, der die gesamte Europäische Union - insbesondere die V4-Länder - einer Energieversorgungsunsicherheit ausgesetzt hat. Während die Wechselkursvolatilität der Währungen der mittel- und osteuropäischen Länder und ihre Beziehung zum Erdöl bereits ausgiebig erforscht wurde, hat bisher keine Studie versucht, die Auswirkungen der russischen Energieabhängigkeit auf die nationalen Währungen zu untersuchen. Ziel der vorliegenden Arbeit ist eine detaillierte Untersuchung dieser Beziehung für den ungarischen Forint, den polnischen Zloty und die tschechische Krone, wobei das britische Pfund als westeuropäische Referenzwährung dient. Unter Verwendung des DCC-GARCH(1,1)-Rahmens und des Diebold-Yilmaz-Volatilitäts-Spillover-Index in Anlehnung an die Arbeit von Kočenda und Moravcová (Kočenda - Moravcová, 2019) werden in dieser Arbeit die Ko-Bewegungen und direktionalen Spillovers zwischen den Währungen, den Henry Hub-Gaspreisen, den Brent-Rohölpreisen und dem russischen Rubel für den Zeitraum 2004-2022 untersucht. Die Ergebnisse deuten auf eine schwache Abhängigkeit der mitteleuropäischen Wechselkurse von den globalen Rohstoffpreisen und dem Wechselkurs des Rubels hin. Die These unterstreicht auch, dass der Forint und der Zloty im Vergleich zur tschechischen Krone und zum britischen Pfund stärker von russlandbezogenen Rohstoffnachrichten abhängen.

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1. Introduction

Exchange rate movements of a currency against another is a crucial factor in the analysis of any economy. Exchange rate volatility influences every part of the economy, including international trade, investor decisions, central bank intervention, and economic activity in general (Kočenda – Moravcová, 2019). Moderating exchange rate volatility has been a particularly important yet difficult task for the countries of the Central European (CE) region upon joining the European Union (EU), as these countries face a trade-off between economic stability and flexibility in their exchange rate regimes (Fidrmuc – Horváth, 2008).

The exchange rate movements of the Hungarian forint (HUF) against the Euro (EUR) have become an interesting topic to analyse, especially since the start of the Russian-Ukrainian conflict in early 2022. Shortly after the announcement of the conflict, the forint faced a fast-paced depreciation against the euro which peaked at a staggering 432.94 HUF on 13 October 2022 (MNB (2023)), an all-time low point in the history of forint. Despite the war heavily affecting the entirety of EU, Hungary's case is interesting as the country has historically been heavily dependent on Russian gas and crude oil imports (Ámon – Deák, 2015, Bayat – Nazlioglu – Kayhan, 2015, Horváthová – Dobbins, 2019). Moreover, following decades of heavy anti-Russian politics, the Orbán-government finally turned towards the East again in the early 2010s and has ever since put an increasing amount of importance on Russian economic relationships, especially in the energy sector (Ámon – Deák, 2015).

While the case of Hungary is particularly interesting, extending the scope of the research to other countries within the region with similar economic background (Dangerfield, 2014, Bauerová, 2018, Čihovská – Hudec, 2018, Etl, 2019) and exposure to Russian primary energy sources (Binhack - Tichý, 2012, Sharples, 2012, Misik, 2016, Siddi, 2019, Antosiewicz et al., 2022, Strzelecki, 2022) might provide further insight into understanding the relationship between Russian energy dependence and exchange rate volatility. The extension of the scope can be further justified by the fact that so far, almost none of the V4 countries (except for Slovakia) have joined the European Exchange Rate Mechanism (ERM II). Therefore, the use of their own national currencies results in significant exposure of national currencies to global market movements. Hence, conducting the analysis on the Polish zloty and the Czech koruna is a reasonable decision.

The analysis on how the Russian energy dependence of the Hungarian economy – and the economies of other V4 countries that still use their own currencies – affects the exchange rate volatility of national currencies is of great interest, especially since there has not yet been extensive literature on examining such a relationship. The thesis aims to study this relationship using different univariate and multivariate versions of the Generalised Autoregressive Conditional Heteroskedasticity (GARCH) framework for the observation period between 1 January 2004 and 31 December 2022. The analysis is performed in multiple steps: in the first step, univariate GARCH(1,1) model specifications are developed to uncover the individual volatility structure of the four exchange rates of interest. Then, exposure to commodity markets and the Russian ruble's exchange rate volatility is measured by fitting a DCC-GARCH(1,1) model to all four exchange rates with the control variables, along with the time-varying conditional covariances across variables. Finally, to uncover directional effects, the Diebold-Yilmaz volatility spillover index is derived for the four models.

To measure the potential effect of the Russian aspect of energy dependence, modelling is also performed on the British pound. The British currency was chosen due to the fact that while Russia plays a pivotal role in the British energy mix (ONS, 2024), it is by far not the most important supplier of the United Kingdom, thereby allowing for the assumption of no significant Russian effect. Furthermore, the United Kingdom can be considered a comparable currency as during the observation period, the United Kingdom was still part of the European Union, while it never joined ERM II.

The thesis aims to evolve according to the following structure. Section 2 presents an extensive literature review of the monetary and macro-economic environment of V4 countries, political and economic relationships between V4 countries and Russia, Hungary's, Poland's and the Czech Republic's dependence on Russian energy sources, as well as a meticulous outlook to previous econometric time series analyses performed on exchange rate volatility, both inside and outside of the CE region. Section 3 provides a detailed description of the scope of the thesis and the data and methodology applied. Section 4 displays the results of the analysis, along with the evaluation of the research questions and the limitations faced during the modelling process. Finally, Section 5 concludes the thesis.

2. Review of existing literature

2.1.Western integration of V4 countries

Following the collapse of the communist bloc in Eastern Europe in 1989, countries of the Central European region found themselves in a difficult position as they needed to integrate their infant democratic systems and crisis economies into the Western economic world. Not only were their democratic systems in their infant stages, but due to former socialist economic structures, all successor countries suffered heavily from building market economies from scratch (Etl, 2019). Due to the common historical heritage and similar level of economic and social development across the region (Čihovská – Hudec, 2018), cooperation between the three post-socialist countries in Central Europe – Czechoslovakia, Poland, and Hungary – began immediately to facilitate the integration into the European Union and NATO. V3 countries realised that by not competing against each other for European development funds and for foreign capital but instead by coordinating national and regional interests and step up for them together, EU integration could be achieved more efficiently (Dangerfield, 2014, Bauerová, 2018, Etl, 2019). Despite some setbacks experienced following the split of Czechoslovakia into the Czech Republic and Slovakia in the 1990s, the so-called V4 cooperation proved to be effective as all four countries successfully helped each other into becoming EU member states starting from 1 May 2004, as part of the largest enlargement wave in EU history (Bauerová, 2018). NATO-membership was also successfully achieved by all countries in 1999. Furthermore, members have also been relatively successful at converging to the EU economic standards in terms of GDP and GNI, although the extent of convergence varies across members depending on their economic baseline, as well as their openness to EU reforms and the European single market (Čihovská – Hudec, 2018).

Following the success of European integration, it was questionable whether the cooperation between V4 countries would continue as the alliance had achieved its primary goals (Dangerfield, 2014, Bauerová, 2018, Etl, 2019). However, in 2004, Visegrád leaders confirmed the continuation of the alliance by defining V4 as a flexible policy platform on which Central European countries can discuss their interests regarding EU policies, and form interest-based coalitions on a European level accordingly. In terms of strategic visions, four directions were identified that have also been the cornerstone of the V4 alliance ever since: cooperation with other V4 countries, cooperation with the EU, cooperation with other NATO allies, and cooperation with third-party countries, especially neighbour countries from the former communist bloc and the Western Balkans (Dangerfield, 2014). As part of this long-term action plan, V4 cooperation focuses in particular on issues related to the EU's enlargement and neighbourhood policy, defence and military activities, the economic convergence of the CE region to Western European standards, and energy policies of various sorts. Strategic goals for the upcoming period are decided on bi-annual Visegrád summits with the participation of members' prime ministers and senior government officials. These summits also allow members to pre-negotiate any EU policies in which the group wishes to form common interests (Visegrád Group, 2023).

Effective regional cooperation has enabled V4 to become one of the largest and most influential regional alliances within the European Union. This has not only been enabled by the fact that the Visegrád countries own about 12.5% of the EU population, but also by the power of the unified representation of shared CE interests on various platforms (Etl, 2019).

Countries have the opportunity to represent both previously negotiated stances and their own national interests not only during regular EU summits, but also through rotating EU presidencies (Bauerová, 2018). So far, all four countries have been effective in exerting their influence related to national and regional interests during their respective periods of presidency. The Czech EU presidency in early 2009 focused on enabling EU-wide energy security, strongly protecting the unified interests of the V4 as all four members are heavily dependent on Russian energy imports, especially in the light of the Russian gas crisis at the beginning of the year. Energy policy was also a predominant agenda point during the Hungarian presidency in the first half of 2011. Being completely dependent on foreign energy sources, Hungary was heavily campaigning for the establishment of a better gas pipeline system in the CE region, both to ensure continuous flows of Russian gas, but also to create alternative routes in case of geopolitical disturbances, thereby reducing dependence from the Russian Federation (Bauerová, 2018). Poland's presidency in the second half of 2011 continued to represent CE interests regarding energy security, whereas it also concentrated on other pressing matters at the time, such as increased border protection in light of military turbulences in the Middle East, as well as speeding up the convergence of new member states through the reallocation of EU funds, some of the largest beneficiaries of which are Poland and Hungary (Etl, 2019, Bauerová, 2018, European Parliament, 2023). Both these issues were areas of common interests of the V4 group, emphasising the influence of its alliance on EU-level decision-making.

Despite the potential to influence EU-level decision making by lobbying for common interests, the V4 cooperation is far from being a unified platform. As each member country faces its own unique economic and political issues, once individual interests and group interests collide, countries tend to pursue their own agendas, disrupting some of the negotiating power of the alliance. These ruptures usually show in terms of strategic policy issues, such as funding, energy security, and defence. For instance, Hungary has been particularly strict regarding energy policy due to its significant exposure to Russian energy sources. On many occasions, Hungary openly abandoned not only V4 stances, but also EU-wide practices by pursuing and tightening relationships with the Russian Federation, even during crisis periods (Bauerová, 2018, Etl, 2019, Spike, 2023). Similarly, Slovakia tends to operate differently from the rest of the group as it frequently prefers to align its interests and political agenda more with the EU guidelines rather than V4 directives. This was represented very visibly both by the fact that so far, Slovakia is the only V4 member country using euro as its official currency, as well as the heavy pro-European agenda of the Slovakian presidency in 2016, going against many V4 lobbies (Bauerová, 2018). Despite national conflicts regarding specific issues, V4 cooperation is still one of the strongest regional bonds within the European Union, supporting not only the interest of newer member states with a less significant voice, but also their economic convergence and integration into the Western world.

Considering the shared historical heritage and the economic coherence of the V4 region, it seems plausible to extend the analysis performed on Hungary's national currency also to the other countries within the region. The exception will be Slovakia as it has been part of the Eurozone since 1 January 2009.

2.2.Exchange rate regimes of the selected countries

2.2.1. Exchange Rate Mechanism

The Exchange Rate Mechanism (ERM II) set up starting with 1 January 1999 is one of the most significant policy measures of the European Union towards a monetary union. The aim of the mechanism is to keep the single market resilient by limiting the damages arising from exchange rate fluctuations, as well as to prepare member states with local currencies for the adoption of the euro (Stančik, 2006, European Commission, 2023b).

ERM II is part of the convergence criteria for any member state wishing to join the eurozone upon becoming a member of the EU. Participation is not mandatory for member states, however, if a country wishes to adopt the euro, it must first fulfil the requirements as set by ERM II for at least two consecutive years before the currency change can be considered (European Commission, 2023b).

The main criterion of the mechanism is that the exchange rate of the local currency against the euro must be kept within a ±15% fluctuation band. This ensures the relative stability of the local currency and consequently, protects the economic stability of the European single market. In case of extremities, both the European Central Bank and the local national bank are allowed to influence exchange rates through open-market operations to restrict fluctuation within the target fluctuation band. For a country to be eligible for the introduction of the euro, stability of the local currency must be maintained for at least two years without long periods of excessive appreciation/ depreciation (European Commission, 2023b).

2.2.2. Exchange rate regime of Hungary

Starting in 2008, Hungary adopted a managed floating exchange rate regime, replacing the previously used currency peg against the euro. Under the floating rate system, the Hungarian National Bank (Magyar Nemzeti Bank/ MNB) allows the forint to react freely to market forces, including supply and demand dynamics on forex markets, international trade, and exogenous global factors. Albeit very limited, central bank intervention is sometimes used to smooth out extremities or to support the realisation of specific policy measures (MNB, 2023b). Despite having a floating exchange rate regime – which is one of the requirements of ERM II – Hungary is not part of this initiative as it is not planning the introduction of the common currency for the foreseeable future (European Commission, 2023c).

As part of its monetary policy, MNB aims to achieve and maintain price stability within the Hungarian economy, usually through the above-mentioned monetary interventions performed through open-market operations (MNB, 2023d). Inflation targeting and the resulting exchange rate stability are not only national interests but also an EU requirement for all member states, especially those that are still awaiting the realisation of the appropriate monetary and macroeconomic conditions for the introduction of the euro (European Commission, 2023c).

As depicted in Figure 1, the Hungarian forint is particularly sensitive to sudden changes in the global economic environment, especially during times of uncertainty. In 2022, due to the ongoing inflation crisis resulting from the geopolitical conflicts in Ukraine, MNB had to intervene numerous times, usually raising the risk-free interest rate to smooth out inflation (24.5% at the end of 2022 (MNB, 2022ab)) and the fast depreciation of the forint on forex markets (MNB, 2023a). The series of MNB interventions started almost immediately after the outbreak of the military conflict: on 22nd February 2022, MNB raised the original base rate of 2.9% to 3.4%. This was followed by further 100 basis point-increases in March and April. As interventions seemed to be insufficient to tame rising inflation and the depreciation of the currency, MNB intervened twice in June, raising the base rate further to 5.9% and 7.75%, respectively. As even these measures were to be inadequate, two additional base rate increases were necessary in July, pushing it up to 10.75%. Nevertheless, even after the increase in August, the forint continued to depreciate, eventually triggering a last intervention that pushed up the base rate by an additional 125 basis points, to 13% in September 2023. (MNB, 2022b). Despite the forint reaching an all-time low point, 432.112 HUF against the euro in early October 2023, MNB decided not to intervene any further as it expected disinflation to start by the start of 2023, and carry over to the consecutive two years. This projection proved to be valid: after peaking at 25.7% in January 2023, inflation slowly started decreasing, reaching 21.5% in May, hence allowing for increased interest rate stability (MNB, 2023c).

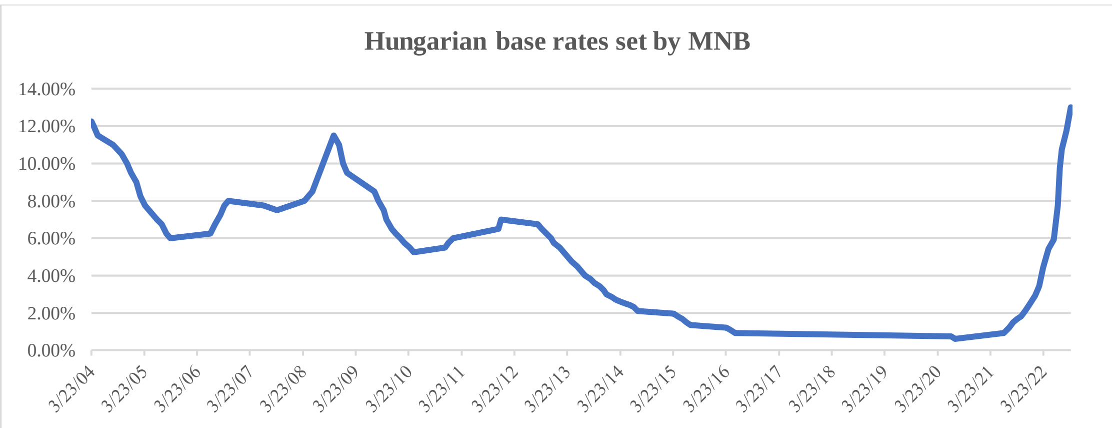


Figure 1: Hungarian base rates set by MNB. (source: MNB, 2023a)

From the Hungarian perspective, the conflict is a sensitive topic as the Hungarian economy is heavily dependent on foreign energy imports, the majority of which is sourced from Russia in the form of oil and oil products, natural gas, and – especially in recent years – nuclear energy (Ámon –Deák, 2015). Thus, it could be expected that any issue in the area with an economic impact would shake the resilience of both the real economy and the monetary sphere, as experiences following the Crimean annexation in 2014 already indicated (Ámon – Deák, 2015).

2.2.3. Exchange rate regimes of Poland and the Czech Republic

The system regarding exchange rate in Poland is similar to the Hungarian regime. Poland is also not a participant of the common Exchange Rate Mechanism as the introduction of the euro instead of the Polish zloty is not part of the immediate monetary strategy of the Polish National Bank (European Commission, 2023d). Nevertheless, NBP aims at introducing the euro as soon as all convergence criteria are met, and the Polish economy is deemed ready for the implementation (European Commission, 2023d). Regarding monetary policy, Poland has also been operating under the floating exchange rate regime since 1999, as a preliminary step to prepare the country for joining ERM II (Gadomski, 2019, NBP, 2022, NBP, 2023b). Just like the Hungarian National Bank, NBP also aims at diversifying various market risks through a diversified and liquid foreign reserve portfolio, as well as through open-market operations and inflation targeting (NBP, 2022, NBP, 2023ab). As a reaction to international macroeconomic and political uncertainties, NBP raised the base rate numerous times throughout 2022, albeit not as drastically or frequently as MNB did. The base rate was finally fixed at 6.75% in September 2022 which has been unchanged ever since (NBP, 2023c).

The Czech Republic also shows the above-mentioned features of the other Central European countries. Even though the adoption of a floating exchange rate system was successfully implemented in 2003, as well as the increasing openness of the Czech economy towards the West, ČNB is not planning to join the Exchange Rate Mechanism or introduce the euro in the foreseeable period (ČNB, 2007, ČNB, 2023a, European Commission, 2023a). Like its partner countries in the region, open market transactions and inflation targeting are ČNB’s most used tools to maintain price stability and limit exchange rate volatility. ČNB controls inflation very systematically, aiming to keep an annual 2% inflation target. Base rate modifications are also regularly discussed every year, thereby providing a stable framework for monetary and macroprudential policy (ČNB, 2023b). This stringent methodology provided the Czech economy with a secure macroprudential environment even during the global uncertainties in 2022, as ČNB only had to intervene four times regarding the base rate, keeping it at a relatively stable 7% from June 2022 onwards (ČNB, 2022).

2.3.Relationships between the EU and Russia in the energy sector

Despite having a dichotomous and mutually suspicious political relationship with Russia following the events of the 20th century, European countries remain highly dependent to Russian energy imports even in the 21st century (Siddi, 2019). Regarding the total energy mix of the European Union, Russia remains by far the biggest partner, covering almost 50% of the total natural gas imports of the European Union (Eurostat, 2023a). The EU's dependence on Russian sources became even more significant after the 2004 EU enlargement wave as the entire Central European region has an almost exclusive dependence on Russian natural gas and oil imports (Siddi, 2019). On the other hand, the European Union is also a strategic economic partner for Russia since energy exports to the region constitute about 75-80% of Russia's export revenues on a yearly basis (Binhack – Tichý, 2012).

Due to the interdependence, both parties are heavily exposed to sudden disruptions in flows. This became even more pronounced during the 2006 and 2009 gas price disputes between Russia and Ukraine which resulted in suspended natural gas flows to the entirety of the European Union for almost three weeks, necessitating strong cooperation in the CE region which was completely cut off from energy sources (Binhack – Tichý, 2012). As shown in Figure 2, conflicts in Ukraine and Belarus are of particular concern for the EU as a significant share of raw materials are flowing through the pipelines via these two countries, such as the Soyuz, Bratstvo, Yamal-Europe gas pipelines, and the Druzhba crude oil pipeline (Janíček et al., 2010, Sharples, 2012, Siddi, 2019, Antosiewicz et al., 2022). Due to the panic caused by the gas crises, the EU quickly realised the need for the diversification of its suppliers, as well as the need for a single energy policy and energy market, which was echoed as one of the main points of the Lisbon Treaty and the Third Energy Package (Binhack – Tichý, 2012, Sharples, 2012).

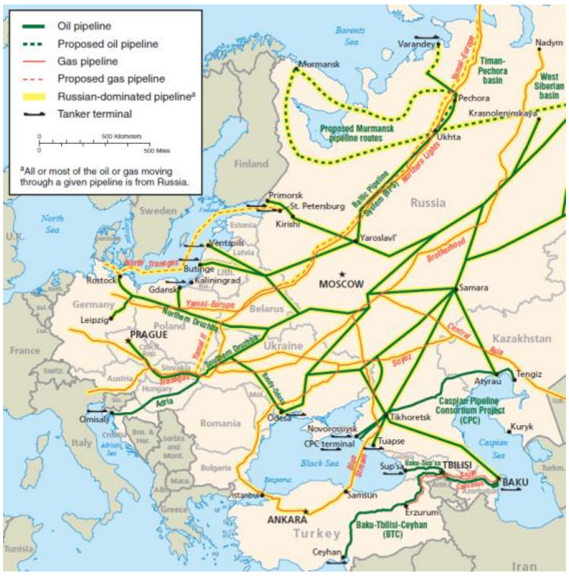


Figure 2: Russian natural gas and oil pipelines towards Europe. (source: Janíček et al., 2010)

Nevertheless, as of today, there is no single energy market across the European Union, and energy negotiations continue to happen in the shape of bilateral agreements between member states and external suppliers. Lacking a common legislation, amongst political turbulences surrounding the war in Ukraine, the EU finds itself in a difficult position as diversification of imports would be very costly and difficult to achieve without a common framework (Siddi, 2019, Antosiewicz et al., 2022). Since Russia continues to be the only viable solution for permanent and relatively stable gas and oil imports, the EU continues to be cooperative with Russia in terms of energy policy. To balance out the geopolitical risk concerning Ukraine and Belarus, many initiatives have been implemented to build diverse pipeline systems circumventing these two countries and ensure smooth flows to Western European countries, such as the Nord Stream and Nord Stream 2 projects (Siddi, 2019).

Due to the geographical proximity and the strategic importance of Ukraine in terms of gas imports, the EU has sanctioned Russia many times in the last decade to enforce a diplomatic resolution between the two countries. Following the outbreak of the military conflict in early 2022, the EU adopted strict and unprecedented sanctions against Russia, heavily impacting international macroeconomic and financial activities. As part of the sanctioning packages, the Union prohibits the import of all seaborne crude oil arriving from Russian territories, with the exception for pipeline imports in case of countries that, due to their dependent situation, cannot substitute Russian crude oil with other market alternatives (Council of the European Union, 2023). In terms of natural gas imports, however, no such sanctions can be made due to the member states' dependency on Russian sources.

2.4.Hungary's relationship with Russia and Russian energy dependence

Following the fall of the socialist bloc in 1989, Hungary tried to separate itself from Russia both politically and economically as it started a swift process of democratisation and Western integration, a part of which was joining the European Union in 2004. Since 2014, however, Prime Minister Viktor Orbán and the ruling conservative party Fidesz decided to give up long-term reservations against Russia and have been continuously strengthening relationships with the East, both politically and economically (Ámon – Deák, 2015). While Russian presence in the Hungarian economy is very limited on the exports and investment side, the influence is very substantial on the imports side of the energy sector. This dependence Russia is also the source of many conflicts on the EU level, especially since the beginning of the war in Ukraine. Hungarian Prime Minister Orbán condemned Russian actions only reluctantly, claiming that Hungary must stay politically cautious and level-headed due to its exposure to Russian energy imports (Reuters, 2022).

2.4.1. Foreign Direct Investment

In terms of investments, Russia has never been significant in the Hungarian economy. There have been only a handful of events in the past 30 years when Russian FDI reached significant share in the Hungarian economy, mostly related to energy imports. Russian investors have also been somewhat present in the banking (via OTP Bank, ÁÉB, and Sberbank) and metallurgical (via ISD Dunaferr) sectors, but their presence has never been significant either, especially due to continuous sanctioning by the European Union midst of the ongoing Ukrainian conflicts (Weiner, 2015).

The largest part of Russian FDI has been concentrated in the energy sector (Weiner, 2015). Most of these deals were related to either acquisition deals between (1) the states directly, (2) between state-owned corporations (such as the attempt of Gazprom to take over petrochemical plants TVK and BorsodChem, as well as Surgutneftegaz's accession to majority shareholder position in Hungarian oil giant MOL (Weiner, 2015)), or (3) were directly related to the Rakhimkulov family's deals (who were wealthy

Russian investors holding significant shares in major Hungarian corporations and representing Russian interests until the early 2010s (Weiner, 2015, Weiner, 2017)). The most recent deal that is noteworthy to mention in terms of Russian FDI is the planned lifecycle extension of the Paks nuclear power plant (Paks II project) which is expected to be started in 2024 (Paks II Zrt., 2023).

It is important to mention, however, that measuring Russian FDI is a difficult task: Hungarian and Russian statistics regarding investments differ significantly which is due to the fact that a significant share of direct investments is cascaded, meaning that they arrive to the destination country indirectly by being rerouted to third countries. This serves the purpose of hiding the nationality of the true owners as joint-stock companies are not required to disclose their ownership structures (Weiner, 2015).

2.4.2. Russian energy imports

Russian economic influence is mostly visible in terms of energy imports. Due to the lack of natural resources, the country is very dependent on foreign energy supplies. Much like other countries in the Central European region, Russia has historically been the only viable trading partner in terms of crude oil and natural gas, due to (1) the proximity of these countries to Russian pipelines, (2) the lack of natural resources available locally that could cover national energy demand, and (3) the lack of alternatives in terms of contracting price (Sharples, 2012, Bayat et al., 2015).

2.4.2.1. Natural gas and oil

Natural gas is the single biggest source of Hungarian energy supply, amounting to 30% of domestic energy consumption (KSH, 2023). In 2022, Hungary imported 10.8 million cubic meters of natural gas (Eurostat, 2023a), out of which 95% was directly from Russia (Eurostat, 2023b). Most of natural gas and oil imports arrive through pipelines connecting to the Soyuz and Bratstvo pipelines coming through Ukraine (ENTSOG, 2023). Hence, peace in Ukraine is an imperative prerequisite for Hungary's energy security as sudden disruptions in the network might lead to severe outages in the country's energy supply. Since gas trade deals are defined in terms of long-term import contracts (LTCs) (Weiner, 2015), import prices are relatively fixed regardless of the contracted amount (Ámon – Deák, 2015).

Much like for other countries in the Central European region (Sharples, 2012), Russian energy remains the cheapest source to fulfil Hungarian energy demand: Western hub alternatives – despite potentially being cheaper than Russian sources – lose their price advantage due to long transit routes and consequently, higher transit costs, as Hungary does not have short-range, direct access to Western pipelines. Likewise, while local hubs may offer more favourable prices, they can supply energy in a less liquid way, exposing the Hungarian side to significant supplying risk. In recent years, there have been several attempts jointly by MOL and MVM from the Hungarian side and Gazprom from the Russian side for the establishment of underground gas storage facilities and direct gas pipelines between the two countries. This would have deepened investment relations even further while exposing the Hungarian energy system even more to Russian supplies. However, all planned projects were unsuccessful either due to abandonment on the Russian end or due to financing constraints on the Hungarian end, and none of the planned facilities were realised. This significantly limited Russian investment alternatives as Russian investors did not manage to gain control over the entire gas supply chain in Hungary (Weiner, 2015).

Regarding crude oil imports, Hungary is just as dependent on its foreign partners than in the case of natural gas. Only in 2022, the country imported 9.72 million tonnes of crude oil and petroleum products into its energy mix next (Eurostat, 2024), which added up to 89% of the total crude oil consumption (OECD, 2020a, KSH, 2024b). In this regard, Russia again is the leading trading partner, even though Hungarian exposure to Russian imports has been decreasing in recent years (IEA, 2022). Much like the rest of the CE region, crude oil is imported mostly through the Druzhba pipeline system flowing through Slovakia and Ukraine, while on the Adria pipeline, the share of Middle Eastern imports is also increasing (IEA, 2022).

2.4.2.2.Nuclear energy

As Hungary does not have a lot of space for considering alternatives or – due to the political agenda – is unwilling to reach out towards sustainable sources – and is dependent on Eastern gas and oil trades, discourse and conditions continue to be Russian-dominated, with negotiations being secretive, non-transparent, and politically heavily biased (Ámon – Deák, 2015, Horváthová – Dobbins, 2019). The most recent example of how the strengthening political relationships affect trade deals in terms of Russian energy is the above-mentioned extension of the Paks nuclear power plant with two additional nuclear blocks, the planning phase of which is expected to start in 2024. The contractor for the new units is Rosatom, the Russian state-owned nuclear company. Furthermore, the EUR 10 billion credit line (which constitutes almost 10 percent of the Hungarian GDP) for the implementation of the lifetime-extension project will also be provided by Russia, with very unfavourable contracting terms for the Hungarian end: In case of a delay in payments over 180 days on the Hungarian side, the Russian party is entitled to enforce the repayment of the entire unpaid portion of the credit line in a lump sum (Ámon – Deák, 2015). Paks II is expected to be a game-changer in the Hungarian energy landscape, with the estimated capacity to provide more than 50 percent of the country's electricity demand (MVM Zrt., 2023). On the other hand, the extension deepens the energy dependence between Hungary and Russia even further, especially since there has not been any other supplier alternative considered besides Rosatom during the negotiation phase (Ámon – Deák, 2015).

2.5.Russian energy dependence and Russian relationships in the Czech Republic and Poland

2.5.1. Poland

Poland's relationship with Russia is very ambiguous, mostly due to the negative historical experiences with the Soviet Union, as well as constant worries about Russia utilising its position as an energy superpower to exert political influence in Europe (Sharples, 2012, Siddi, 2019). Hence, any sort of political or economic relationship, let that be on a national or on an EU-level, brings around heavy resistance from the Polish side. Nevertheless, much like other Central European countries, Poland continues to be dependent on Russia for natural resources, especially on coal and crude oil, albeit – due to its own natural resources and direct access to trading alternatives – to a much lesser extent than other countries in the CE region (Antosiewicz et al., 2022).

As a large portion of Poland's energy mix consists of coal (mostly used in industrial production and in the residential sector), the country is in an active trading relationship with Russia regarding coal as well, importing around 35% of its energy mix from Russia: total oil imports account for 76% of domestic consumption, while this ratio for natural gas is 46% (Antosiewicz et al., 2022). However, historically antagonistic views materialised in coal trade as well following the outbreak of the conflict in Ukraine in early 2022. Complying with EU sanctions against Russia, coal imports from Russian territory were permanently halted, with imports expected to be eliminated. This is not expected to put Poland under a significant pressure as domestic production must be able to substitute for the loss of imports (Sharples, 2012). Moreover, complying with EU regulation regarding the reduction of the use of coal, in the medium and long run, Poland is expected to gradually eliminate coal from its energy mix and replace it with alternative sources, such as natural gas, nuclear energy, and renewable sources (Sharples, 2012, Antosiewicz et al., 2022).

Up until the sudden halt and consequent termination of the long-term gas contract with Russia in early 2022 (Strzelecki, 2022), Poland received natural gas through the Yamal-Europe pipeline and crude oil through the Druzhba pipeline via Belarus (Sharples, 2012, Antosiewicz et al., 2022). As the pipeline continues to Western Europe, Poland has the capacity to generate additional revenues in the form of transit costs (Sharples, 2012). This was one of the reasons why Polish sentiments towards the agreement on the Nord Stream 2 projects were antagonistic as the Polish government believed it to be a threat to Poland's energy security and strategic relevance due to the circumvention of the transmitting Polish pipeline system. Furthermore, Polish representatives continuously expressed their concerns about the potential impact of the new pipeline on the situation regarding Ukraine, which would have endangered the energy security of the entire Central European region (Siddi, 2019). Nevertheless, the breach in the LTC with Russia in early 2022 is not expected to cause catastrophic economic damages to Poland due to the country's immense stockpiles and its diversification possibilities to start importing natural gas from Norway through the Baltic pipeline. Poland is also able to import Russian gas indirectly via Germany by reverse flows in the Jamal pipeline (Antosiewicz et al., 2022, Strzelecki, 2022).

As a result of diversification among gas suppliers, as well as Poland's own potential to increase coal and shale gas production, the country is most exposed to Russia in terms of crude oil imports. Should Russia sabotage import flows, Poland would mostly be affected by the corresponding costs of substituting oil from other sources at significantly higher market prices (Antosiewicz et al., 2022), even though the country maintains strategic oil reserves on the Baltic coastline to draw upon in case of short-term disturbances (Sharples, 2012). Yet, in the long run, thanks to its geographical situation, Poland has direct access to alternative sources of crude oil (Antosiewicz et al., 2022).

The diversification possibility and the strategic location of Poland makes the country one of the biggest energy hubs in the European Union, especially for the Central European region (Antosiewicz et al., 2022). A more comprehensive European energy security cooperation can secure Poland's position in the CE region as the new regional energy supplier since the country has the capacity to redistribute significant amounts of sources to more import-dependent countries in Central Europe (Sharples, 2012).

2.5.2. Czech Republic

Similarly to other countries in the Central European region, the energy influence of Russia in the Czech Republic is also strong, even though to a lesser extent that that of Hungary. The country receives about 40% of its total energy mix from Russian sources (Binhack - Tichý, 2012).

In terms of crude oil, despite moderate Czech oil production in Southern Moravia, Russia has a singular monopolistic import position, as all alternative routes are connected to geopolitically unstable Middle Eastern countries. Oil imports are transported mostly through the Druzhba and Ingolstadt–Kralupy–Litvínov pipelines, through which the Czech Republic is also capable of forwarding crude oil to Western European countries, thereby profiting on transit costs (Binhack - Tichý, 2012, Misik, 2016).

When it comes to natural gas, the Czech Republic is almost totally dependent on foreign supplies as it has no natural gas resources of its own (Binhack - Tichý, 2012). However, due to a significantly critical and cautious approach towards the Russian Federation (Misik, 2016), the country has achieved significant diversification from exclusively Russian imports in the 1990s by signing long-term contracts with Norway (Binhack - Tichý, 2012, Misik, 2016). Yet, Russian imports still make up for most natural gas flows coming into Czech territories, with this ratio making up near 100% of Czech imports, exclusively through the Soyuz and Bratstvo pipelines (Eurostat, 2023b).

Despite its huge exposure to Russian flows, the Czech Republic has the means to effectively protect itself from the negative consequences of short-term gas outages. Through connecting pipelines, the country can ensure transmitting gas to other EU member states in the region, which also serves as a safety net for the country in case of sudden disturbances. The Czech Republic was able to successfully manage shortages and help other Central European countries during the 2009 gas halt by enabling reverse flows through the pipelines and consequently, ensuring supplies to the region. Furthermore, underlying gas storage facilities can also provide backups for the short run should Russia sabotage the signed LTCs (Binhack - Tichý, 2012). Due to its strategic position, much like Poland, the Czech Republic holds significant interests in stability in Belarus and Ukraine, and has been, consequently, one of the most proactive EU member states to promote diversification, the construction of new circumventing pipelines, and energy security discourses (Binhack - Tichý, 2012, Misik, 2016).

2.6.Exchange rate volatility of the selected CE countries

Studying exchange rate volatility in the countries of the CE region is a topic of particular interest: First, exchange rate stability is a crucial requirement of EU membership and overall economic stability (Stančik, 2006). Furthermore, Hau's hypothesis (Hau, 2002) – that smaller, open economies are subject to lower levels of exchange rate volatility – is a hypothesis worthy of further investigation (Schnabl, 2007, Bubák et al., 2011). Additionally, resemblance in the EU integration paths and the similar legacy of the countries allow for an informative comparison of exchange rate volatility measures in the CE region.

2.6.1. Exchange rate co-movements and volatility spillovers

A particularly well-researched topic is exchange rate co-movements and volatility spillovers between local currencies of the region.

Bubák et al. (Bubák et al, 2011) study the volatility transmission effect between the Czech koruna, the Polish zloty, and the Hungarian forint together with the U.S. dollar as a benchmark value, to get a general overview on the magnitude of shock transmissions in the CE region. For the analysis, they use a non-parametric, modified version of a HAR-GARCH model with high frequency data combined with a DCC-MGARCH model – as proposed by Engle (Engle, 2002) – to assess the extent of overall volatility transmission mechanism. Finally, they evaluate the magnitude of this mechanism by the Diebold Yilmaz spillover index, a metric based on generalised autoregressive variance decomposition. They document the existence of substantial spillover effects within the region, highlighting that the examined currencies follow different patterns of volatility transmission. They find that the EUR/HUF rate is unique as it showed little responsiveness to exchange rate shocks to the other three currencies prior to the global financial crisis, mainly due to strict exchange rate monitoring. As a conclusion, they derive that while during increased market uncertainty, there is more substantial spillover, especially on the short-term market reaction component, the main determinant of exchange rate volatility continues to be each currency's own rate legacy (Bubák et al., 2011).

In another study, Kočenda and Moravcová (Kočenda – Moravcová, 2019) use a simple DCC-GARCH model to analyse the time-varying co-movements of the Hungarian forint, the Czech koruna, and the Polish zloty against the euro and the EUR/USD rate, as these countries are considered advanced new EU-members with high investment attractiveness. They use the obtained time-varying conditional correlations to (a) construct hedge ratios with the optimal portfolio weights, and (b) investigate the effects of volatility spillovers among the currencies over time using again the Diebold Yilmaz spillover index. Over the observation window, they find that all three currencies move homogenously when considered against the euro. When examined against the EUR/USD movement, the currencies move homogenously when examined mutually until the global financial crisis but tend to follow different evolution during and past the crisis period. In terms of volatility spillovers, they determine that the Hungarian forint suffered the most during the global financial crisis, mostly due to fast depreciation that pushed up the overall retail debt burden of Swiss franc-denominated mortgages. In general, they emphasise that while cross-rate effects are important, the main determinant of exchange rate volatility remains the own-currency volatility for each of the investigated currencies, hence, diversification can be best achieved when each currency is individually considered in the hedging portfolio (Kočenda – Moravcová, 2019).

2.6.2. Determinants of individual exchange rate dynamics across the CE region

Exchange rate volatility is also often researched in terms of individual components, whereby each currency's evolution over time is investigated separately, allowing for the analysis of heterogeneity across research subjects.

Considering the entire EMU periphery region, Schnabl (Schnabl, 2007) tests the hypothesis whether flexibility in exchange regimes fosters economic growth more efficiently than fixed regimes, using GLS panel estimation. He argues that flexible exchange rate policy allows for better absorption of asymmetric macroeconomic shocks as it lets the economy adjust through market-based price adjustments, while in fixed exchange rate regimes, such adjustments must be carried out through relative price changes, impacting economic growth negatively. He concludes that members of the Emerging Europe region – mostly CE countries that have recently joined the European Union – have already achieved significant economic growth directly through reaching overall exchange rate stability, generally due to the implementation of flexible exchange rates with moderate levels of inflation targeting (Schnabl, 2007).

Stančik (Stančik, 2006) tightens the scope to only six Central European countries that were in the process of EU integration at the time: the Czech Republic, Hungary, Latvia, Poland, Slovakia, and Slovenia. Furthermore, he restricts the observation period to the years preceding the integration in order to gain an appropriate insight into the convergence of national currencies towards monetary standards. He experiments with different lag specifications of a TARCH(p,q) model, considering individual exchange rate volatilities as the dependent variables and each country's economic openness, news effects, and exchange rate regimes as exogenous variables. As the regressors are not directly measurable, these vectors are previously estimated in separate steps, the proxies of which are then used in the modelling stage. Interestingly, for Hungary and for the Czech Republic, the analysis concludes the openness proxy to be statistically insignificant, meaning that the exchange rate volatility of the forint and the koruna are not influenced by changes in macroeconomic integration. Another interesting result is that in the case of Hungary, loosening exchange rate criteria from the previous 2.25% crawling peg to the EU-standard 15% fluctuation band resulted in significant and permanent increases in exchange rate volatility as exchange rates are more exposed to changes in international supply and demand. In terms of the effect of news, Stančik finds that the effect of news on exchange rate volatility is significant in almost all countries in the region, albeit the nature of the news is not significant in determining the magnitude of such volatility changes (Stančik, 2006). These conclusions provide further support for the relevance of the current thesis.

Fidrmuc and Horváth (Fidrmuc – Horváth, 2008) examine the dynamics of daily exchange rates of five CEE countries using GARCH(1,1) and TARCH(1,1) models. They restrict their attention to the Czech Republic, Poland, Hungary, Slovakia and Romania, newly joined EU member states that have implemented inflation targeting to ensure monetary stability and thus, comply with EU membership requirements. The focus of the study is testing whether exchange rate mismanagement – i.e., times when predefined implicit target bands within which the local currency is allowed to move against the euro were overstepped – increases exchange rate volatility. This supports the hypothesis of Schnabl (Schnabl, 2007) that inflation targeting is associated with lower economic growth potential. They find evidence for increasing exchange rate volatility when approaching the edges of the implicit target band – especially in the appreciation domain in case of TARCH models – which they consider a sign of low exchange rate credibility. They hence derive evidence that exchange rates in these countries do not act as external shock absorbers. Furthermore, they highlight Hungary and Poland as the two countries where the impact of deviations is the largest and most persistent (Fidrmuc – Horváth, 2008).

2.6.3. The effect of oil price dynamics on exchange rate movements

Finally, there is a growing literature focusing on the interaction between energy prices and exchange rate movements, albeit thus far, research is mostly concentrated around the effect of oil price movements only.

Bayat et al. (Bayat et al., 2015) examine the relationship between oil price changes and exchange rate movements separately for the Polish, Czech, and Hungarian currencies – CE countries with relatively large oil dependence and with flexible exchange rate regimes – using linear and non-linear Granger causality, causality-in-variance, and frequency domain causality tests. As the relationship between exchange rate movements and oil prices is more bi-directional in nature (Krugman, 1980, Bloomberg – Harris, 1995), they find it meaningful to not only test for one-one causality, but also for frequency domain causality, thereby delving deeper into the bilateralism of the relationship. Their results confirm the need for such analysis as neither the linear causality test, nor the GARCH(1,1) model (causality-in-variance test) show any statistically significant relationship between the examined variables. They only find significant bi-directional relationships when running the frequency domain causality test, for which the results are only substantial in the case of the Czech Republic and Poland. There is no causation linkage between the exchange rate of the Hungarian forint and international oil prices for either test methodology, even though Hungary's dependence on foreign energy sources is much higher than that of the Czech Republic and Poland. The researchers attribute this result to the fact that changing from a fixed exchange rate to a floating one might effectively reduce the exchange rate exposure to exogenous macroeconomic shocks (Bayat et al., 2015).

Following a different research scope, nevertheless providing valuable insights into the nature of such relationship, Rautava (Rautava, 2002) conducts a detailed analysis regressing Russian fiscal revenues and GDP on oil prices and on exchange rate movements to uncover the exposure of the Russian economy to its oil trade. His research question arises from the contradictory hypothesis in existing literature regarding Russia's dependence on its raw materials trade – while many argue that the annual 150 million tons of crude oil exports create a great exposure to market risk for the Russian economy, others claim the country's economy is resilient enough to be able to handle such market movements. To investigate this contradiction in research, he applies the vector autoregressive (VAR) model embedded into a cointegration framework. He finds that in the long-run model, there is a significant causality between Russian fiscal revenues and changes in oil prices and exchange rates. Regarding the short-run analysis, he discovers several interesting causal relationships. He concludes that oil price changes heavily affect fiscal revenues even in the short run, both directly and indirectly, while changes in GDP – which are influenced by oil price movements – have a statistically significant impact on exchange rates, which in turn will shift fiscal revenues. In conclusion, he finds evidence for the significant role of oil trade on Russian economic performance, however, he emphasises that such exposure can be balanced out by opposite changes in exchange rates (Rautava, 2002).

In a similar manner, Hegerty (Hegerty, 2015) approaches the relationship between oil prices and exchange rates from a different perspective. He conducts a multivariate GARCH analysis on macroeconomic indicators – exchange rate movements among them – and oil prices in eight countries from the CEE region to test whether there exists an oil price volatility spillover effect on macroeconomic variables, such as interest rate volatility, economic output, exchange rate volatility, and inflation. He concludes that in all cases except for Ukraine, there exists a negative correlation between oil prices and exchange rate volatility, implying that in times of turbulence in the oil market, exchange rates are exposed to less volatility. He furthermore discovers statistically significant correlation between the inflation rate – which is significantly correlated with oil price volatility – and exchange rate volatility in the case of Hungary (Hegerty, 2015), indicating that it might be interesting to use inflation measures as an exogenous regressor when analysing the exchange rate volatility of the Hungarian forint.

3. Data and methodology

3.1.Research objectives

Based on the literature review presented above, there is extensive literature analysing the exchange rate volatility of the local currencies in the Central European region, especially in the case of Hungary, Poland, and the Czech Republic. Furthermore, there are many macroeconomic studies conducted that explore different aspects of Russian energy dependence on certain aspects of the Hungarian economy. However, there has been no detailed analysis that would investigate the direct effect of Russian energy dependence on the national currency's exchange rate volatility. This gap in academic research is understandable as exchange rate movement is a complex process that is influenced by several monetary, macroeconomic, and non-economic factors.

Upon reviewing the existing research, the current thesis aims to provide insight into the previously identified research gap by answering the following research questions:

Research question 1: *How does the dependence of the Hungarian economy on Russian energy imports affect the Forint-Euro exchange rate volatility?*

Research question 2: *How do Russian energy import dependencies affect the exchange rate volatilities of the other two national currencies – the Czech koruna and the Polish zloty – within the CE region?*

3.2.Modelling

The thesis aims to investigate the relationship between CE exchange rate movements and Russian energy dependence by applying different versions of General Autoregressive Conditional Heteroskedasticity (GARCH) models following the previous works of Bubák et al. (Bubák et al., 2011), Hegerty (Hegerty, 2015), and Kočenda and Moravcová (Kočenda – Moravcová, 2019).

GARCH-type modelling was selected as the main methodology to be followed by the current thesis due to its several advantages in terms of modelling time-varying volatility. As the national currencies of the V4 region are susceptible to shocks caused by market forces as discussed in Section 2, GARCH-models are a plausible fit to capture the existence of volatility clusters and the effects of long-term persistence of volatility shocks. Furthermore, GARCH-models provide a more adaptable framework than ARCH-models by leveraging a more flexible lag structure, utilizing lagged conditional variances as well. This corresponds to some sort of adaptive learning mechanism (Bollersev, 1986). Finally, the dynamic conditional correlation (DCC) extension of GARCH models allows for the deep examination of the correlation between the time-varying volatility structure of different time series, thereby providing a complex framework to analyze the set of variables in a system. Parsimony and flexibility allow DCC-GARCH models to be superior to simple correlation analysis in terms of complex time series (Kočenda – Moravcová, 2019), while these same characteristics prevent the model from being as complex as standard multivariate versions (Engle, 2002).

As DCC-GARCH model versions do not allow for the measurement of directional effects of variables, the thesis aims to uncover the extent of Russian energy dependence by performing a comparative analysis for the Russia-specific component of the analysis on the British pound as well. The United Kingdom was chosen as a basis for comparison as it is a comparable country against V4 countries in terms of its energy mix (ONS, 2024) and the use of its own national currency despite being an EU member state until 2021 (EUR-Lex, 2024). However, despite relying strongly on primary energy imports, the United Kingdom is not particularly exposed to Russia-originated energy sources due to its diversification opportunities. In fact, according to the Office for National Statistics (ONS, 2024), Russia plays a non-pivotal role in the UK's energy suppliers as it is only the 4th largest supplier behind Norway, Qatar, and the United States. Therefore, the United Kingdom was deemed an appropriate fit to test the extent of exposure of V4 countries' national currencies against the Russia-related aspects of energy dependence.

The comparative analysis included performing the same modelling process on the British pound sterling as for the other three variables of interest, after which the model outputs were analysed in parallel according to the same criteria. This allowed for the recognition of patterns in each time series, and the detection of patterns that might be related to Russian energy dependence.

3.3.Data

The scope of the analysis was restricted to the V4 region where euro introduction has not yet been implemented. Hence, the research considered national currencies used in Hungary, the Czech Republic, and Poland, and excluded Slovakia. Additionally, for the comparative analysis, the British pound sterling was also used.

To create a proxy by which the effects of Russian energy dependence on exchange rate volatility could be tested and quantified, global gas prices and oil prices were used, alongside with daily euro-rouble exchange rate pairs.

3.3.1. Daily exchange rates

For the analysis, data was collected for the three CE countries – Hungary, Poland, and the Czech Republic – , and the United Kingdom. The country selection regarding the V4 countries is common in literature (Schnabl, 2007, Fidrmuc – Horváth, 2008, Bubák – Kočenda – Žikes, 2011, Bayat – Nazlioglu – Kayhan, 2015, Hegerty, 2015, Horváthová – Dobbins, 2019, Kočenda – Moravcová, 2019) due to the similar historical background, post-socialist development, and EU-integration path discussed in Chapter 2. Furthermore, as mentioned previously, none of these countries have joined the European Monetary Union (EMU), allowing for a deep and detailed analysis on their national currency movements against the euro.

The exchange rate data was obtained from each national bank's database (Magyar Nemzeti Bank/ MNB, 2023e, Česká Národní Banka/ ČNB, 2023c, Naradowy Bank Polski/ NBP, 2023d, Bank of England, 2024).

3.3.2. Regressors

As there is no quantitative statistical measure existing in literature for Russian energy dependence, this thesis aims to explore the relationship by inspecting dynamic conditional correlation patterns of daily Russian rouble exchange rates against the euro, daily global gas prices, and daily global crude oil prices. To assess the magnitude of the Russia-related component of energy dependence across the region, modelling was also extended to the case of the British pound to obtain benchmark data for Western Europe.

Russian rouble-euro exchange rate pairs were obtained from the exchange rate database of the Central Bank of the Russian Federation (Центральный банк Российской Федерации, CBR, 2023). Daily Euro Brent spot prices (denominated in U.S. dollars) and Henry Hub Natural Gas spot prices (denominated in U.S. dollars) were collected from the U.S. Energy Information Association's website (EIA, 2023a, EIA, 2023b), and then converted to euros using the official USD-EUR exchange rates published by the Federal Reserve System (Fed, 2023).

3.3.3. Observation period

As a common guideline, the research covers the period between 1st January 2004 and 31st December 2022. As the starting date, the year in which all three countries joined the European Union was selected. The end date was selected in a way to accurately capture both the potential short- and long-term effects of the ongoing geopolitical conflict between Ukraine and Russia starting in early 2022. Excluding country-specific national holidays and other general European holidays for which central banks do not provide data and market data for the macroeconomic indicators were not available, the entire sample on which the modelling was performed consists of 3112 observations.

As the focus of the current thesis is to evaluate general volatility clustering and volatility persistence in the data, the analysis does not concern itself with a special effect caused by crisis periods or economic booms. Hence, structural breaks were not accounted for in the modelling process, in order to avoid overcomplications of model specifications.

3.4.Data analysis

Following the derivation of descriptive statistics, preliminary testing on the raw data, and the appropriate data transformation, the analysis was performed in 4 stages to examine the co-movement from different aspects. The data cleansing was performed in Python, while for modelling, R was used. For the evaluation of regression and test outputs, a confidence interval of 95% (i.e. a 5% significance level) was applied, considering the size of the samples.

3.4.1. Data transformation

After the derivation of descriptive statistics, each of the seven variables were transformed into daily returns to ensure the stationarity condition for modelling. The calculation of daily exchange rate and commodity price returns is shown in Equation 1.

$$r_{i,t} = \frac{p_{i,t} - p_{i,t-1}}{p_{i,t-1}}$$

Equation 1: Calculation of daily exchange rate and regressor price returns. (source: own construction)

3.4.2. Testing for ARCH and GARCH effects

To validate the use of ARCH-type modelling, testing the return series for the presence of ARCH and GARCH effects was necessary. Testing was performed in two phases.

In the first step, the ACF and PACF correlograms for each exchange rate return series was derived and analysed, allowing for the detection of underlying autocorrelation within the mean structure of the data sets.

In the second step, an optimal-lag ARMA(p,q) model was fit for each of the seven variables of interest to obtain their respective residuals. The residuals were then used to derive the ACF and PACF correlograms again, this time both for the original standardised residuals, as well as for the standardised squared residuals. This method allowed not only for the detection of remaining autocorrelation patterns in the residual series themselves, but also in the squared residuals, signalling the presence of ARCH and GARCH effects. Additionally, based on the ARMA(p,q) residuals, two additional tests were performed to validate ARCH-type modelling: the ARCH tests tested the standardised squared residuals under the null hypothesis of i.i.d. distribution (i.e., white noise), while the ARCH-LM test proposed by Engle (Engle, 1982) fits a linear regression on the squared residuals to test the model's significance, under the null hypothesis of no ARCH effects.

3.4.3. Univariate GARCH(1,1) models

As the initial step, three univariate GARCH(1,1) models were developed separately for each of the three national currencies: standard GARCH(1,1) (Equation 2), as proposed by Bollersev (Bollersev, 1986), as well as EGARCH(1,1) by Nelson and Cao (Nelson – Cao, 1992) (Equation 3), and GJR-GARCH(1,1) by Glosten, Jagannathan and Runkle (Glosten et al., 1993) (Equation 4), in order to account for the non-normality of the sample.

$$\sigma_t^2 = \omega + \alpha_1 e_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Equation 2: Variance equation of standard GARCH(1,1) model (source: Bollersev, 1986).

$$\log(\sigma_t^2) = \omega + \alpha_1 e_{t-1} + \gamma_1(|e_{t-1}| - \mathbb{E}|e_{t-1}|) + \beta_1 \log(\sigma_{t-1}^2)$$

Equation 3: Variance equation of EGARCH(1,1) model. (source: Nelson – Cao, 1992)

$$\sigma_t^2 = \omega + \alpha_1 e_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 I_{\{e_{t-1}^2 > 0\}} e_{t-1}^2$$

Equation 4: Variance equation of GJR-GARCH(1,1) model. (source: Glosten et al., 1993)

Model outputs were then evaluated according to the magnitude and significance of the optimal regression parameters, stationarity, and persistence conditions. The results of the weighted Ljung-Box tests performed both on standardised residuals and standardised squared residuals were inspected to detect any additional autocorrelations and ARCH-effects in the residuals that were left untreated by the model specifications. Finally, the adjusted Pearson goodness-of-fit test was also run to check whether the null hypothesis – that the empirical sample follows the same distribution as the theoretical sample (in this case, a standard normal distribution) – holds in the given models.

The model variations were then compared to each other based on the Akaike Information Criterion (AIC), the Bayes-Schwarz Information Criterion (BIC), and the Hannan-Quinn Criterion (HQC) to find the best model fit for each currency. Additionally, each model version was tested for four forecasting performance metrics – the Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) – to determine the best model variation in terms of forecasting accuracy for all four variables of interest.

3.4.4. DCC-GARCH(1,1) models

To assess the evolution of time-varying volatilities and correlations between the different dimensions considered in modelling during the observation period, the Dynamic Conditional Correlation model proposed by Engle (Engle, 2002) were applied (as shown in Equation 5), further considering the inputs of the study of Kočenda and Moravcová (Kočenda – Moravcová, 2019):

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t$$
$$\mathbf{D}_t = \mathrm{diag}\left(h_{iit}^{\frac{1}{2}}, \ldots, h_{NNt}^{\frac{1}{2}}\right)'$$
$$\mathbf{R}_t = \mathrm{diag}\left(q_{iit}^{-\frac{1}{2}}, \ldots, q_{NNt}^{-\frac{1}{2}}\right) \mathbf{Q}_t \mathrm{diag}\left(q_{iit}^{-\frac{1}{2}}, \ldots, q_{NNt}^{-\frac{1}{2}}\right) \text{ or } \rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{ij,t}}}$$

where h_{iit} can be defined as a univariate GARCH process,

$\mathbf{Q}_t = (q_{ij,t}) = (1 - \alpha - \beta)\overline{\mathbf{Q}} + \alpha \mathbf{e}_{t-1}\mathbf{e}'_{t-1} + \beta \mathbf{Q}_{t-1}$ is the $(N \times N)$ symmetric definite matrix,

$\mathbf{e}_t = (e_{1t}, e_{2t}, \ldots, e_{Nt})$ is the $N \times 1$ vector of standardised residuals,

$\overline{\mathbf{Q}}$ is the $(N \times N)$ vector of the unconditional variance of $\mathbf{e}_t$, and

α and β are non-negative scalar parameters that satisfy the stationarity condition $\alpha + \beta < 1$.

Equation 5: Composition of the conditional covariance matrix used in DCC-GARCH estimation (source: Kočenda – Moravcová, 2019)

The model was developed for each of the four currencies separately, using daily euro-rouble exchange rate returns, daily gas price returns, and daily oil price returns as regressors in the system. This variable selection allows for the examination of the conditional correlation patterns across the individual variables.

During the analysis, model outputs were interpreted according to the magnitude and statistical significance of the optimal parameters, in alignment with the interpretation process of the GARCH(1,1) models.

This model specification also allowed for the investigation of the co-movements between individual variables and their joint co-movements, i.e., the given currency's exposure to the global primary energy market and the movements in the Russian rouble's exchange rate. Moreover, the derivation of conditional correlation measures allowed for the visual detection of constant and time-varying dynamics across the different variables included in the model specifications.

To assess the magnitude of the Russia-related component of energy dependence, model outputs were evaluated against the results of the comparative analysis performed on the pound.

3.4.5. Diebold-Yilmaz Index

In the final step of modelling, the Diebold-Yilmaz spillover index was developed, following the work of Diebold and Yilmaz (Diebold – Yilmaz, 2009, Diebold – Yilmaz, 2012), and Kočenda and Moravcová (Kočenda – Moravcová, 2019).

This stage in the analysis aimed at calculating the magnitude of direct spillovers between currencies and the developed macroeconomic variables, in order to gain a deeper understanding about the nature of the relationships beyond simple correlation analysis.

4. Research results

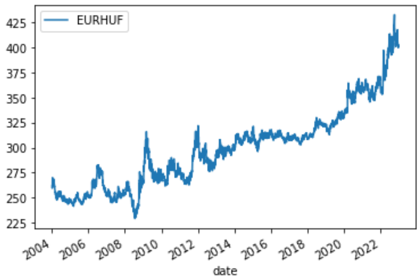
4.1.Descriptive statistics

4.1.1. Daily exchange rates and daily returns

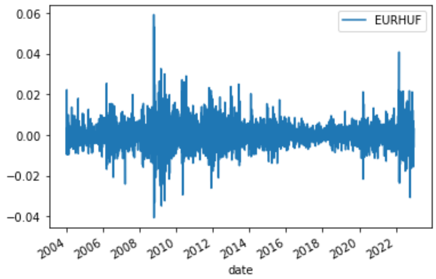
As a first step, each of the four exchange rates of interest was plotted to obtain a visual overview of movement patterns. As the graphs show, all of the currencies behave differently over the observation period. In case of the forint, there is a strong pattern of continuous depreciation against the euro, especially around times of international uncertainty, such as the global financial crisis, or the recent Ukrainian war. When looking at the zloty and the koruna, such a pattern is harder to observe. The zloty showed heavy appreciation until the global financial crisis but has been depreciating against the euro ever since the structural break in 2009. The koruna also appreciated initially but following the two significant shifts in pattern in 2007, there has been no consistent trajectory in the currency’s behaviour. As for the British pound, there is an observable depreciation against the euro between 2008 and 2010, during the time of the global financial crisis, followed by a volatile period of appreciation until 2016, when it was announced that the United Kingdom would leave the European Union. Finally, this was followed by a period of depreciation again, and relative stagnation from 2018 onwards. Furthermore, when considering the Augmented Dickey-Fuller (ADF) test to analyse the stationarity of the four original time series, the p-values for the forint (p-value = 0.9737), the zloty (p-value = 0.0652), and the pound (p-value = 0.5827) were high enough to conclude that their movements are non-stationary processes. For the koruna (p-value = 0.0464), the ADF test concluded a slightly stationary process. Considering these results, it was plausible to convert the exchange rates to a format in which all of the time series are stationary.

Hence, exchange rates were converted to exchange rate returns (as shown in Equation 1), by calculating the percentage change between two consecutive trading days.

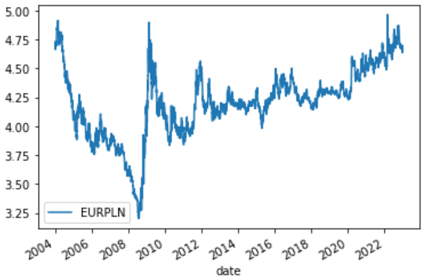
Running the ADF test again for the transformed time series, all four variables turned out to be stationary (p-value for forint returns = 3.304E-23, p-value for zloty returns = 1.9941E-23, p-value for koruna returns = 0, p-value for pound returns = 1.0392E-25). These results were also visible when plotting currency returns against the untransformed return series. The plots of the original exchange rates and their transformed daily returns are shown on Figure 3. Daily prices and returns regarding natural gas prices, Brent prices, and EUR/RUB exchange rates are summarised in Appendix 1.



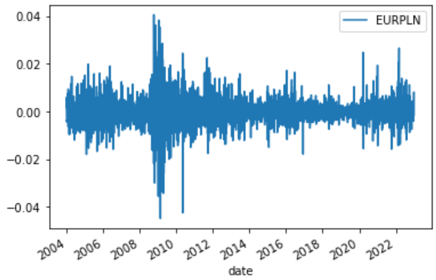
Daily closing exchange rates - EUR/HUF



Daily exchange rate returns – EUR/HUF

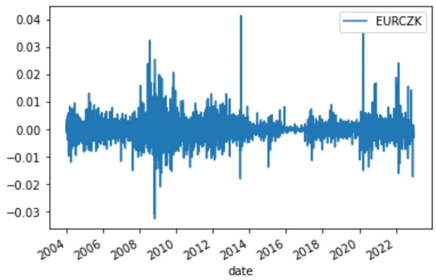


Daily closing exchange rates - EUR/PLN

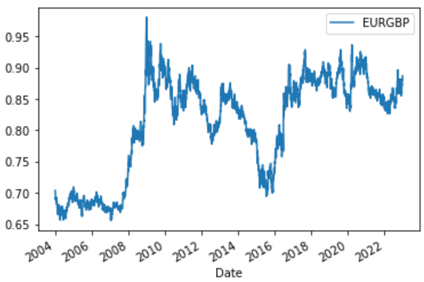


Daily exchange rate returns – EUR/PLN

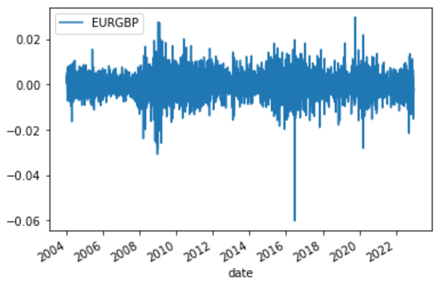
Daily closing exchange rates - EUR/CZK



Daily exchange rate returns – EUR/CZK



Daily closing exchange rates - EUR/GBP



Daily exchange rate returns – EUR/GBP

Figure 3: Daily closing exchange rates and exchange rate returns. (sources: MNB (2023e), NBP (2023), CNB (2023c), BoE (2024))

After the transformation, descriptive statistics for all four exchange rate return series were derived, the results of which are detailed in Table 1. While the mean is very close to zero in all four cases, there is slight deviation across countries regarding the sign of the mean return: while returns of the forint and the zloty tend to be on average positive, koruna and pound returns are on average negative. This indicates that on average, there is an observable depreciation in the forint's and zloty's purchasing power against the euro, while the koruna and the pound tend to appreciate slightly.

	EURHUF	EURPLN	EURCZK	EURGBP
mean	0.000106	0.000013	-0.000056	-0.000035
std	0.0058	0.0053	0.0035	0.005170
min	-0.0408	-0.0449	-0.0326	-0.060204
25%	-0.0026	-0.0025	-0.0014	-0.002816
50%	-0.0001	-0.0001	0.0000	0.000087
75%	0.0027	0.0022	0.0012	0.002839
max	0.0593	0.0406	0.0413	0.029752
kurtosis	8.1987	8.7827	15.3426	6.3326
skewness	0.4986	0.3527	0.7506	-0.4631
Jarque-Bera statistic	13493.9380	15499.6804	47255.6432	8172.0749
Jarque-Bera p-value	0.0000	0.0000	0.0000	0.0000

Table 1: Summary of descriptive statistics. (source: own calculations)

4.1.2. Normality of the sample

To assess the distribution properties of the return datasets, skewness and kurtosis measures were calculated, which are also included in Table 1. Based on the obtained results, the returns of CE currencies all exhibit high levels of kurtosis with significant positive skewness, indicating non-normal, leptokurtic distribution of the samples (EUR/HUF: K = 8.1987, S = 0.4985, EUR/PLN: K = 8.7826, S = 0.3527, EUR/CZK: K = 15.3426, S = 0.7506). EUR/GBP returns also followed a non-normal distribution, but in this case, high kurtosis (K = 6.3326) was accompanied by negative skewness (S = -0.4631).

Additionally, to further check for distribution properties of the samples, the Jarque-Bera normality test was also performed. As the test returned a p-value of zero in all four cases, the assumption of normality was rejected, confirming the non-normality of the four samples.

Figure 4 also provides a visualisation of the distribution properties of the four exchange rate return series.

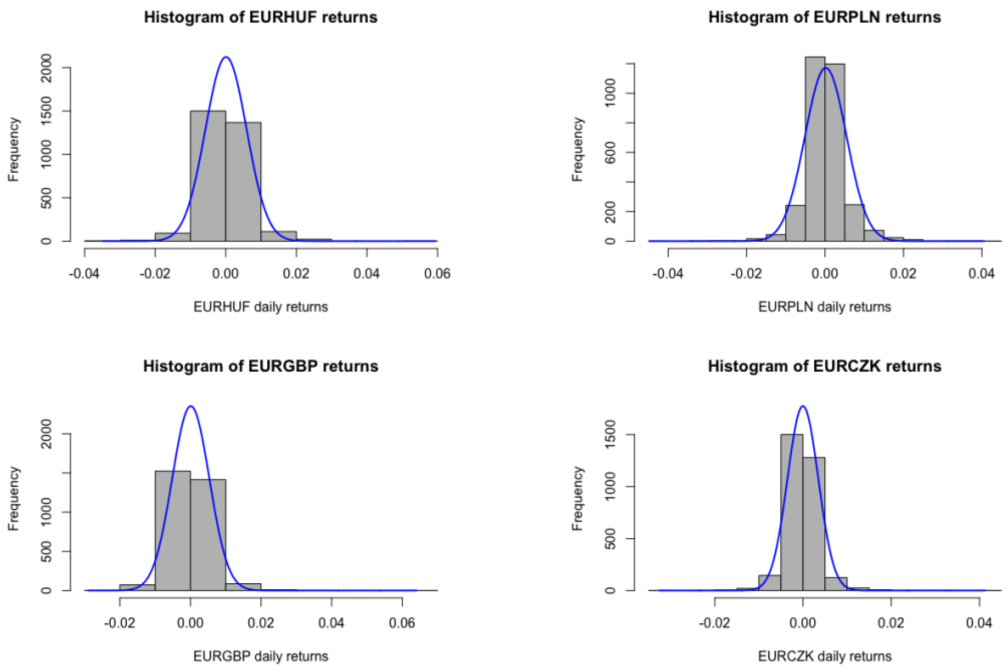


Figure 4: Histograms of daily exchange rate returns. (source: own calculations)

4.1.3. Analysis of correlation coefficients

Finally, Pearson correlation coefficients were derived for all variables to assess their contemporaneous co-movements before moving on to a dynamic framework. Correlation coefficients are summarised in Table 2.

Aligning with previous expectations, as well as with related literature discussed in Section 2, Central European exchange rate returns exhibit significant positive correlations, this phenomenon being especially strong for EUR/HUF and EUR/PLN. This is a plausible finding considering the similar economic performance and foreign relationships of these countries, as well as the close cooperation among V4 countries, as explained in Section 2.

The summary also highlights some disparity across the exchange rates in terms of correlation with the rouble: while the forint and the zloty exhibit positive correlation with the Russian currency, the koruna and the pound are slightly negatively correlated with the rouble. This result is a further proof that countries which have strong economic ties with Russia in terms of primary energy are more exposed to positive exchange rate co-movements than those countries that can diversify their economic relations.

In the negative domain, the largest negative correlation can be seen between Brent oil returns and Central European exchange rate returns, which is a surprising result.

Negative correlation between oil importing countries and global oil prices originates from the fact that an upward shift in oil prices causes markets to be flooded with U.S. dollar, causing a devaluation in its exchange rate, which in turn causes an appreciation in the currencies of oil importing countries.

Finally, in terms of gas prices, the forint, the zloty, and the British pound are again negatively correlated, while correlation is positive for the koruna. This finding aligns with previous conclusions about the correlation with oil prices. The only outlier here is the koruna, indicating that this currency is positively affected by increases in oil prices. However, this effect is barely significant as correlation with gas is very close to zero.

Pearson correlation coefficients

	EURHUF	**EURPLN**	**EURCZK**	**brent_returns**	**EURRUB**	**gas_returns**	**EURGBP**
EURHUF	1.0000	0.6183	0.2133	-0.0576	0.0027	-0.0201	-0.0034
EURPLN	0.6183	1.0000	0.2230	-0.0558	0.0022	-0.0075	0.0264
EURCZK	0.2133	0.2230	1.0000	-0.0479	-0.0314	0.0019	-0.0289
brent_returns	-0.0576	-0.0558	-0.0479	1.0000	0.0194	0.0815	-0.0204
EURRUB	0.0027	0.0022	-0.0314	0.0194	1.0000	0.0201	-0.0290
gas_returns	-0.0201	-0.0075	0.0019	0.0815	0.0201	1.0000	-0.0302
EURGBP	-0.0034	0.0264	-0.0289	-0.0204	-0.0290	-0.0302	1.0000

Table 2: Pearson correlation coefficients. (source: own calculations)

4.1.4. Testing for autocorrelation, and ARCH and GARCH effects

To prepare the datasets for modelling, autocorrelation and partial autocorrelation patterns were analysed for each time series, which are shown in Figure 5. For the assessment, a 5% significance level was applied in all cases.

When considering regular returns, ACF and PACF were inconclusive. Based on the ACF plots, it can be inferred that for EUR/HUF returns the 14th 15th, and 27th lags, for EUR/PLN returns the 2nd, 14th, 15th, and 29th lags were statistically significant. For EUR/CZK returns, no lags were strongly autocorrelated, and for EUR/GBP returns only the 3rd lag was significant. In terms of ACF in the regressor series, EUR/RUB returns showed autocorrelation at the 1st, 6th, 7th, and 21st lags, Brent returns were significantly autocorrelated only at the 1st lag, and gas returns were significantly autocorrelated at the 2nd and 4th lags.

In terms of PACF values, EUR/HUF returns exhibited significant value at the 14th lag, EUR/PLN returns exhibited significant values at the 1st, 14th, 15th, 23rd, and 29th lags, EUR/CZK returns showed significant partial autocorrelation at the 11th, 32nd and 33rd lags, while EUR/GBP returns exhibited significant value only at the 2nd lag. EUR/RUB returns were partially autocorrelated at the 1st, 3rd, 6th, and 21st lags, Brent returns exhibited significant values at the 1st, 6th, and 9th lags, and gas returns were significantly partially autocorrelated at the 2nd and 4th lags.

As results indicate, the white noise property is not satisfied for all variables equally: some of them also exhibit statistically significant autocorrelation and partial autocorrelation early on in the lag structure, indicating the presence of AR and MA effects that must be taken into account.

To ensure the white noise property for the underlying variables, all seven variables were fitted with an optimal-lag ARMA(p,q) model specification, based on which ARCH and GARCH effects were tested. The results of the ARMA(p,q) specifications are shown in Appendix 2. After the model specifications have been determined, outputs were used to calculate the regression residuals and the squared residuals. To check the white noise property of the residual series, ACF and PACF correlograms were developed.

Results of these analyses confirm that residuals already fulfil the white noise property necessary for ARCH-type modelling, as depicted in Appendix 2. In terms of ACF, EUR/HUF and EUR/PLN residuals exhibit significant autocorrelation only from the 14th lag onwards, while EUR/CZK and EUR/GBP residuals do not show particularly strong autocorrelation in any of the lags. As for the regressors, EUR/RUB residuals exhibited statistically significant autocorrelation only at the 21st lag, while this effect was noteworthy from the 6th lag onwards for Brent residuals, and at none of the lags for gas return residuals. In terms of PACF values on residuals, CE residuals did not show signs of autocorrelations up until the 12th lag, while EUR/GBP residuals were not significant at any of the lags. As for the regressors, EUR/RUB residuals exhibited significant partial autocorrelation only at the 21st lag, Brent residuals were significantly partially autocorrelated only from the 6th lag onwards again, while gas residuals were not partially autocorrelated.

The presence of ARCH and GARCH effects were tested through three different methods: first, ACF and PACF correlograms were derived and assessed for the squared residuals at 5% significance level. The obtained results are visualised in Figure 6.

When inspecting ACF values, EUR/HUF squared residuals are strongly autocorrelated up to the 21st lag, while for EUR/PLN squared residuals, this pattern is visible up to the 35th lag. EUR/CZK squared residuals exhibit significant autocorrelation up to the first five lags, having occasional spikes in higher-order lags as well. EUR/GBP squared returns are significantly autocorrelated at the 1st, 2nd, 4th, 9th, and 16th lags, while EUR/RUB squared returns are significantly autocorrelated up to the 10th lag. In terms of commodities, Brent squared residuals exhibit significant autocorrelation up to the 8th lag, while autocorrelation in gas squared returns vanishes after the 5th lag. These results indicate that there is a strong ARCH-effect in all seven variables, justifying the use of ARCH-models.

Based on the PACF derived for the squared residuals, the presence of GARCH effects was also shown. EUR/HUF squared returns exhibit significant partial autocorrelation at the first 5 lags, while EUR/PLN squared returns show a similar trend up to the 10th lag, and EUR/CZK squared returns are strongly partially correlated at the first four lags. High partial autocorrelation can also be detected for EUR/GBP squared residuals in the 1st, 3rd, 9th, and 16th lags, for EUR/RUB squared returns at the 1st, 2nd, 11th, 18th, and 21st lags. In terms of commodities, Brent squared residuals exhibit strong partial autocorrelation at the first five lags, while gas squared residuals are significantly partially autocorrelated at the first four lags.

Additionally, the residuals were used to perform the ARCH test to uncover underlying ARCH effects. Test results confirmed that ARCH-type modelling is feasible for all four exchange rate returns (EUR/HUF p-value = 2.2E-16, EUR/PLN p-value = 2.2E-16, EUR/CZK p-value = 2.2E-16, EUR/GBP p-value = 4.827E-16, EUR/RUB p-value = 2.2E-16, brent_returns p-value = 2.2E-16, gas_returns p-value = 2.2E-16). The Lagrange Multiplier test returned similar results (EUR/HUF p-value = 2.2E-16, EUR/PLN p-value = 2.2E-16, EUR/CZK p-value = 2.2E-16, EUR/GBP p-value = 2.2E-16, EUR/RUB p-value = 2.2E-16, brent_returns p-value = 2.2E-16, gas_returns p-value = 2.2E-16), providing further validation for the use of GARCH-models.

These results indicate that while there is slight autocorrelation in the return series for all seven variables, residuals behave mostly as white noise, indicating that using residuals in ARCH-type regressions is a plausible framework.

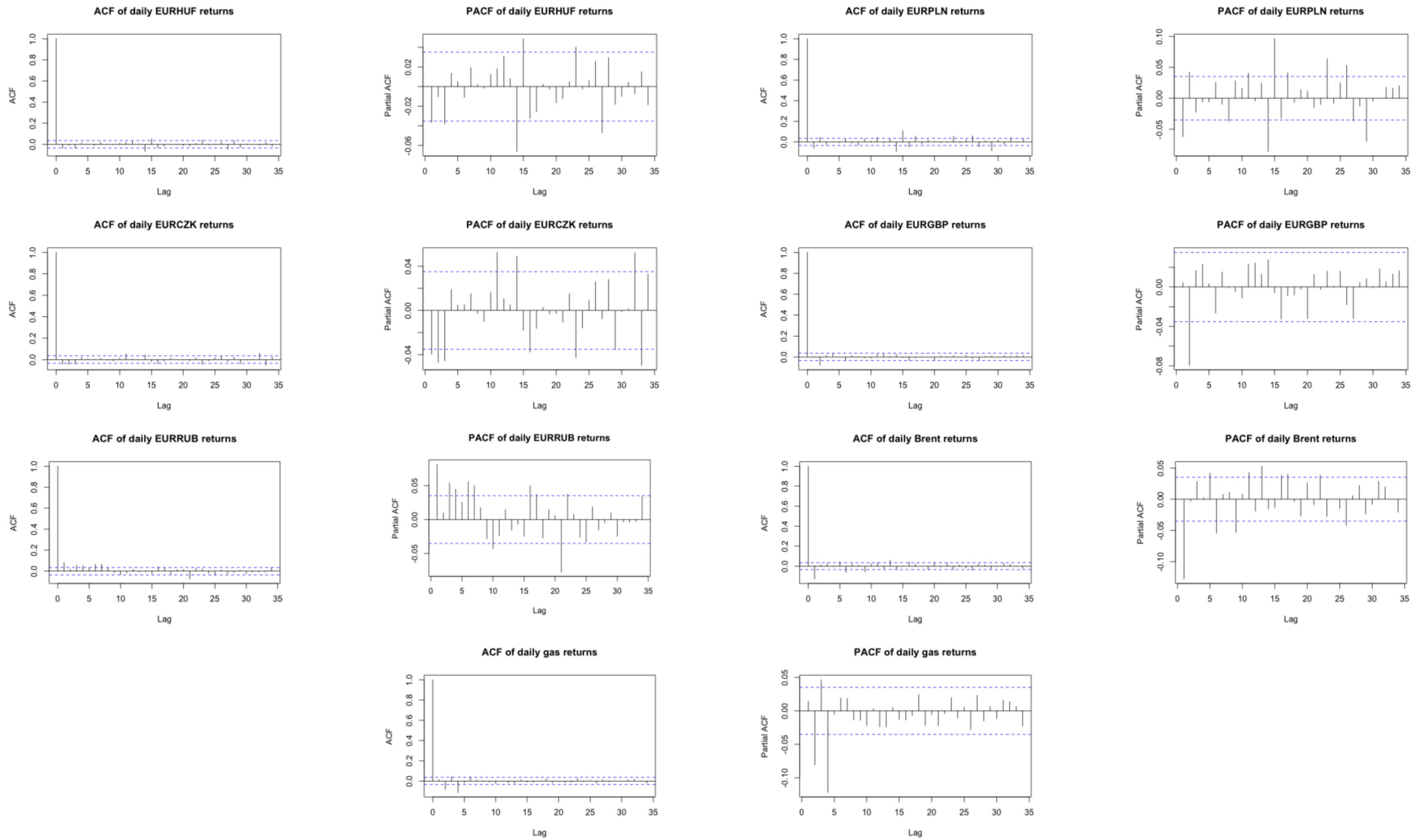


Figure 5: Autocorrelation and partial autocorrelation functions of daily returns.(source: own calculations)

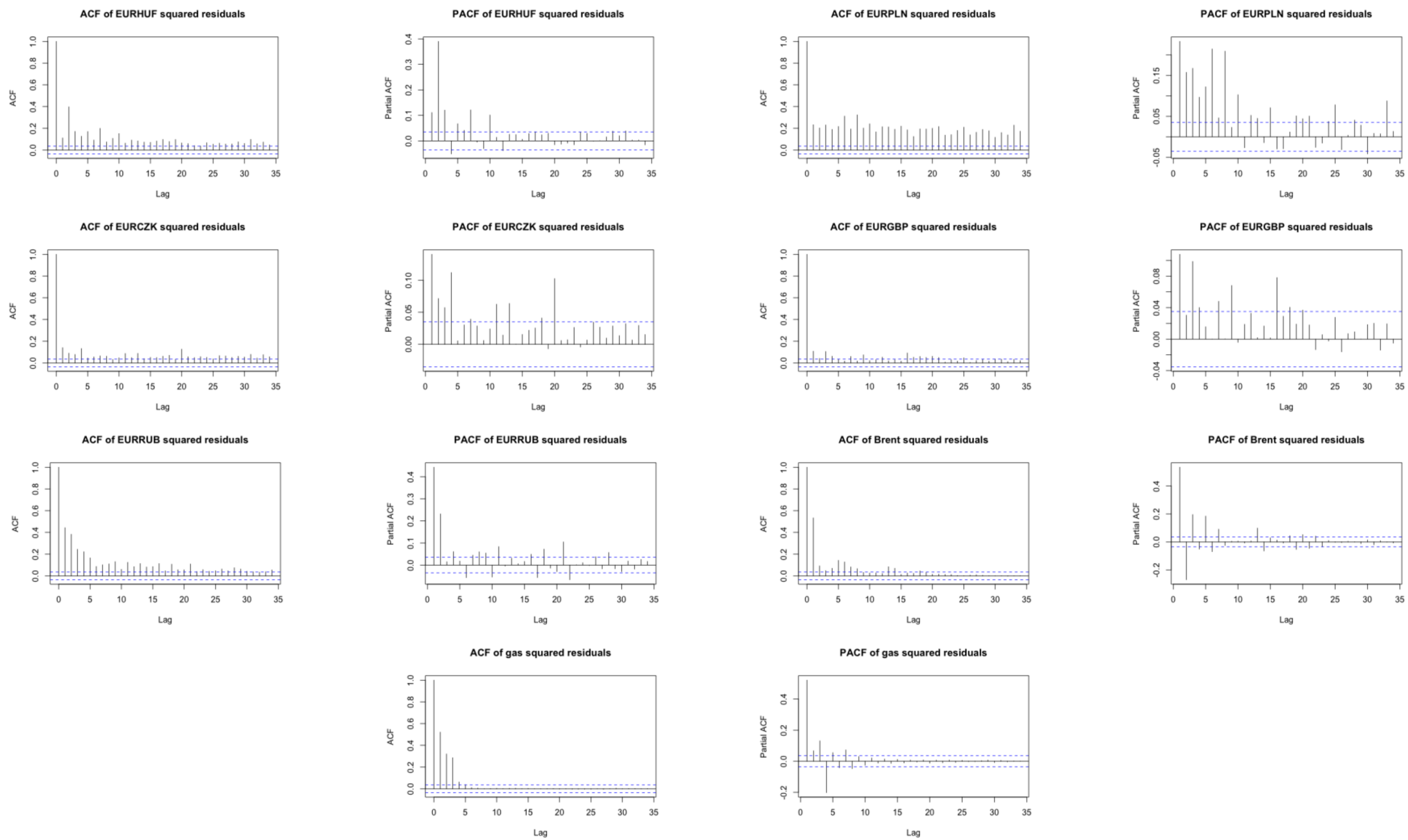


Figure 6: Autocorrelation and partial autocorrelation functions of ARMA(p,q) squared residuals. (source: own calculation)

4.2.Univariate GARCH(1,1) models

To analyse the individual volatility structure of each of the four exchange rates separately, three different versions of GARCH(1,1) models were developed on the ARMA(p,q) residual – obtained in Section 4.1.4. – to adapt to the nature of the data series from different perspectives. The 1-lag GARCH specification was chosen due to the dispersion in the ACF and PACF structures of the return series. Model versions were then compared to each other based on the traditional model performance indicators to detect the best fitting model for the currencies. The model outputs and their respective performance indicators are summarised in Figure 7.

4.2.1. SGARCH(1,1)

As a benchmark, a standard GARCH(1,1) model was developed for the four exchange rate returns, assuming normal distribution within the time series.

Model outputs confirmed the presence of volatility clustering and volatility persistence as both the ARCH term (α_1) and the GARCH term (β_1) values were statistically significant at a 5% significance level. Considering the stationarity criterion $\alpha_i + \beta_i$, all models can still be considered stationary, despite all parameters being very close to 1. This indicates that, while being stationary, volatility shocks within the series carry over for a long time, and the effect of shocks vanishes only slowly, providing further evidence for volatility clustering (SC_{EURHUF} = 0,9988, SC_{EURPLN} = 0,9981, SC_{EURCZK} = 0,9989, SC_{EURGBP} = 0,9946). Another interesting finding is that for EUR/HUF and EUR/PLN returns, the ARCH coefficients are relatively large compared to EUR/CZK and EUR/GBP returns, suggesting that in the case of the forint and the zloty, returns carried over from the previous day influence current volatility more substantially than in the case of the koruna and the pound. At the same time, this phenomenon is compensated by lower GARCH coefficients (i.e. a smaller magnitude of volatility carried over from the previous day), which in turn are higher for the latter two exchange rates.

To assess the performance of this model specification, weighted Ljung-Box tests were performed on the standardised residuals and the standardised squared residuals. The Pearson goodness-of-fit tests were also executed for the four models.

When inspecting the results of the Ljung-Box test, the model specification's ability to capture autocorrelation was shown as the null hypothesis could not be rejected for any of the lags.

In terms of the standardised squared residuals, the Ljung-Box test again uncovered some slight dispersion across the data series. While for EUR/HUF, EUR/PLN and EUR/GBP, the test did not indicate any ARCH and GARCH effects present in the squared residuals, the p-value for higher lags of EUR/CZK squared residuals caused the null hypothesis to be rejected, displaying statistically significant conditional heteroskedasticity that could not be captured within the standard GARCH(1,1) framework.

Finally, the Pearson goodness-of-fit test yielded universal results across the entire sample as the null hypothesis of normal distribution had to be rejected for all four exchange rate returns. This result is not unexpected considering the non-normal distribution and excess kurtosis of the return series.

4.2.2. GJR-GARCH(1,1)

To account for the asymmetry in the return series, a GJR-GARCH(1,1) model was also fit for the four exchange rate returns.

In terms of the ARCH and GARCH parameters, model outputs showed strong similarities with the SGARCH(1,1) specifications, and both values were statistically significant for each of the four models. Looking at the magnitude of the coefficients, the GJR-GARCH models yielded similar results to the standard framework: the forint's and the zloty's current volatilities seemed to be more exposed to the returns observed in the previous day than the koruna and the pound, and are compensated by a lower magnitude of volatility carried over from the previous day. Considering the asymmetry term γ_1, however, EUR/GBP returns behaved differently from the other three exchange rate returns as in this case, the coefficient turned out to be statistically insignificant. Another source of dispersion within the data could be detected when inspecting the sign of the γ terms. For the forint and the zloty, the coefficients were negative, indicating that positive shocks to the exchange rate return (i.e. depreciation of the CE currency) will impact future volatility more than appreciation would. In case of the koruna and the pound, however, γ was positive in sign, indicating an opposite effect compared to that of the other two exchange rates. Finally, the analysis of the persistence criterion $\alpha_1 + \frac{\gamma_1}{2} + \beta_1 \approx 1$ highlighted strong volatility persistence across all four exchange rates, indicating that shocks to the exchange rate return fade slowly from the volatility structure, thereby causing the development of volatility clusters (PC_{EURHUF} = 0.9985, PC_{EURPLN} = 0.9988, PC_{EURCZK} = 0.9988, PC_{EURGBP} = 0.9944).

Similarly to the standard model version, performance indicators were also assessed for all the GJR-GARCH models.

As for the weighted Ljung-Box test performed on the standardised residuals, results show some differences compared to the SGARCH models: since for EUR/HUF, EUR/CZK, and EUR/GBP, the null hypothesis could not be rejected due to the p-values lying above the 5% significance level, it could be concluded that no leftover autocorrelation was present in the error terms. In terms of EUR/PLN, the null hypothesis had to be rejected at the first lag by a slight margin, indicating the presence of minimal leftover autocorrelation that was left uncaptured by the current model selection.

The weighted Ljung-Box test on the standardised squared residuals for this model specification yielded dispersing results across the four exchange rate series. As the null hypothesis could not be rejected for EUR/HUF, EUR/PLN and EUR/GBP, it can be inferred that the GJR-GARCH model performs well in capturing the conditional heteroskedasticity within the model framework, leaving squared residuals as white noise processes. As for EUR/CZK, GJR-GARCH did not perform well as p-values indicated the presence of leftover autocorrelation in the squared residuals, causing the null hypothesis to be rejected.

Finally, similarly to the results obtained from the previous model setup, the Pearson goodness-of-fit test resulted in the rejection of the null hypothesis for all four models, once again indicating the non-normality of the samples.

4.2.3. EGARCH(1,1)

As a third model variation, an EGARCH(1,1) model was fit to all exchange rates to offer an alternative approach for capturing the non-normal nature of the data series.

Aligning with previous model outputs, ARCH and GARCH terms are statistically significant in all four models (except for the pound where the ARCH coefficient is insignificant), providing further evidence for volatility clustering and volatility persistence. When evaluating the coefficients, the patterns are again similar to previous model versions, with the forint's and the zloty's volatilities being more exposed to the after-effect of the previous day's return and being compensated by lower dependence to the volatilities carried over from the day before. Furthermore, it is also important to mention that in case of the koruna, the ARCH-coefficient is even negative, indicating that depreciation in the exchange rate on the previous day reduces volatility on the current day. A novelty compared to the other two model variations can be detected when inspecting the mean terms, μ and ω. While for the SGARCH and GJR-GARCH models, these parameters were statistically insignificant in all models, in the EGARCH models, mu was statistically significant for EUR/HUF, EUR/PLN, and EUR/CZK, while omega was significant in all cases. Moreover, significant and positive γ_1 values in all four models suggest that the volatility structures of the exchange rates are exposed to an asymmetric effect, and hence, the leverage effect is present.

Finally, to produce comparable results, model performance was assessed for this model specification as well. As for the weighted Ljung-Box test on standardised residuals, EUR/PLN turned out to be an outlier in terms of first-order lags, suggesting that this model version fails to properly account for all the autocorrelation within the sample. The weighted Ljung-Box test for the standardised squared residuals also highlighted some dispersion across the samples: test results did not produce enough evidence to reject the null hypothesis in all cases but for the higher-order lags for EUR/HUF and EUR/CZK, indicating that conditional heteroskedasticity is still present in the squared residuals.

The Pearson goodness-of-fit test also yielded results that are in alignment with previous model versions. Due to the low p-values, the null hypothesis had to be rejected for all four samples, indicating the non-normality of the data.

4.2.4. Evaluation of model performance

To select the best-fitting model for each exchange rate pair, the models were first compared based on the traditional minimising framework (i.e. by inspecting the AIC, BIC and HQC values across model specifications per exchange rate return), and then based on their forecasting performance indicators. The summary of forecasting metrics is displayed in Figure 7, while modelling and forecasting accuracy plots are visualised in Appendix 3.

When considering the minimising framework, EGARCH(1,1) outperformed all other model variations for all four variables, which could be expected due to the non-normality of the sample.

When inspecting the forecasting accuracy measures, there was a visible variance across the different exchange rates regarding the optimal model fit.

For EUR/HUF returns, the SGARCH and GJR-GARCH models performed equally well based on their RMSE, MSE, MAE, and MAPE values, even though MAPE turned out to be surprisingly high for all specifications. In the case of EUR/CZK and EUR/GBP returns, the SGARCH specification outperformed the alternative model versions in terms of RMSE, MSE, and MAE, while MAPE values were inconclusive in both cases. Finally, for EUR/PLN, EGARCH outperformed all other model specifications in terms of RMSE, MSE, and MAE values. Like in the case of EUR/CZK, MAPE again turned out to be inconclusive.

This result indicates that while EGARCH is the best model specification for describing the existing volatility structure of the forint’s exchange rate, it fails to outperform the other specifications when it comes to forecasting for most of the currencies.

EURHUF
SGARCH(1,1)

Optimal parameters

	Estimate	Std. Error	t-value	Pr(>|t|)
mu	0.000102	0.000072	1.40967	0.15864
omega	0	0.000001	0.48657	0.62656
alpha1	0.110531	0.021872	5.05353	0
beta1	0.888316	0.019118	46.46514	0

LogLikelihood	11045.71

Information criteria	
Akaike	-7.8533
Bayes	-7.8448
Shibata	-7.8533
Hannan-Quinn	-7.8502

Weighted Ljung-Box test on standardised residuals

	statistic	p-value
Lag[1]	1.209	0.2715
Lag[2*(p+q)+(p+q)-1][2]	1.576	0.3439
Lag[4*(p+q)+(p+q)-1][5]	4.321	0.2166
d.o.f	0	

Weighted Ljung-Box test on standardised squared residuals

	statistic	p-value
Lag[1]	1.329	0.2489
Lag[2*(p+q)+(p+q)-1][5]	5.554	0.1143
Lag[4*(p+q)+(p+q)-1][9]	8.232	0.116
d.o.f	2	

Adjusted Pearson goodness-of-fit test

group		statistic	p-value(g-1)
	20	100.6	4.19E-13
	30	109.4	2.91E-11
	40	130.6	8.17E-12
	50	141.3	6.94E-11

RMSE	7.8526E-05
MSE	6.1664E-09
MAE	3.7758E-05
MAPE	179.0135%

EURHUF
GJR-GARCH(1,1)

Optimal parameters

	Estimate	Std. Error	t-value	Pr(>|t|)
mu	0.000173	0.000073	2.36166	0.018193
omega	0	0	0.51625	0.605679
alpha1	0.132707	0.017007	7.80293	0
beta1	0.898958	0.015013	59.87976	0
gamma1	-0.066371	0.015586	-4.2584	0.000021

LogLikelihood	11053.52		
			0.9984795

Information criteria	
Akaike	-7.7571
Bayes	-7.848
Shibata	-7.8581
Hannan-Quinn	-7.8543

Weighted Ljung-Box test on standardised residuals

	statistic	p-value
Lag[1]	1.42	0.2334
Lag[2*(p+q)+(p+q)-1][2]	1.653	0.3275
Lag[4*(p+q)+(p+q)-1][5]	4.382	0.2102
d.o.f	0	

Weighted Ljung-Box test on standardised squared residuals

	statistic	p-value
Lag[1]	0.6217	0.4304
Lag[2*(p+q)+(p+q)-1][5]	3.6018	0.3081
Lag[4*(p+q)+(p+q)-1][9]	5.9748	0.3011
d.o.f	2	

Adjusted Pearson goodness-of-fit test

group		statistic	p-value(g-1)
	20	110	8.05E-15
	30	107.4	6.22E-11
	40	137.8	5.85E-13
	50	146.1	1.38E-11

RMSE	7.8526E-05
MSE	6.1664E-09
MAE	3.7758E-05
MAPE	179.0135%

EURHUF
EGARCH(1,1)

Optimal parameters

	Estimate	Std. Error	t-value	Pr(>|t|)
mu	0.000231	0.000065	3.5369	0.000405
omega	-0.177761	0.071581	-2.4833	0.013016
alpha1	0.056041	0.011013	5.0886	0
beta1	0.982372	0.00692	141.9639	0
gamma1	0.217245	0.036091	6.0194	0

LogLikelihood	11057.1

Information criteria	
Akaike	-7.8607
Bayes	-7.8501
Shibata	-7.8607
Hannan-Quinn	-7.8659

Weighted Ljung-Box test on standardised residuals

	statistic	p-value
Lag[1]	1.308	0.2528
Lag[2*(p+q)+(p+q)-1][2]	1.47	0.3681
Lag[4*(p+q)+(p+q)-1][5]	4.264	0.2229
d.o.f	0	

Weighted Ljung-Box test on standardised squared residuals

	statistic	p-value
Lag[1]	0.3953	0.52951
Lag[2*(p+q)+(p+q)-1][5]	8.0862	0.02805
Lag[4*(p+q)+(p+q)-1][9]	10.3722	0.04172
d.o.f	2	

Adjusted Pearson goodness-of-fit test

group		statistic	p-value(g-1)
	20	98.8	8.84E-13
	30	101.8	4.96E-10
	40	126.7	3.31E-11
	50	146.7	1.09E-11

RMSE	7.9289E-05
MSE	6.2868E-09
MAE	3.6387E-05
MAPE	207.6845%

EURPLN
SGARCH(1,1)

Optimal parameters	Estimate	Std. Error	t-value	Pr(>|t|)
mu	-0.000175	0.000062	-2.83436	0.004592
omega	0	0.000001	0.17266	0.862922
alpha1	0.101895	0.035686	2.85531	0.0043
beta1	0.896202	0.031676	28.29309	0
LogLikelihood	11369.46			
			0.998097	
Information criteria				
Akaike	-8.0835			
Bayes	-8.0751			
Shibata	-8.0835			
Hannan-Quinn	-8.0805			

Weighted Ljung-Box test on standardised residuals

	statistic	p-value
Lag[1]	3.84	0.05005
Lag[2*(p+q)+(p+q)-1][2]	3.908	0.07981
Lag[4*(p+q)+(p+q)-1][5]	6.132	0.08372
d.o.f	0	

Weighted Ljung-Box test on standardised squared residuals

	statistic	p-value
Lag[1]	0.4836	0.4868
Lag[2*(p+q)+(p+q)-1][5]	1.8568	0.6526
Lag[4*(p+q)+(p+q)-1][9]	3.0021	0.7586
d.o.f	2	

Adjusted Pearson goodness-of-fit test

group		statistic	p-value(g-1)
	20	46.11	4.79E-04
	30	60.72	5.02E-04
	40	85.13	2.79E-05
	50	101.23	1.69E-05

RMSE	3.0419E-05
MSE	9.2529E-10
MAE	1.8175E-05
MAPE	INF

EURPLN
GJR-GARCH(1,1)

Optimal parameters	Estimate	Std. Error	t-value	Pr(>|t|)
mu	-0.000112	0.000062	-1.80556	0.070988
omega	0	0	0.33163	0.740168
alpha1	0.12421	0.014616	8.49818	0
beta1	0.908288	0.013573	66.91641	0
gamma1	-0.067403	0.013837	-4.87123	0.000001
LogLikelihood	11380.84			
			0.9987965	
Information criteria				
Akaike	-8.0909			
Bayes	-8.0804			
Shibata	-8.0909			
Hannan-Quinn	-8.0871			

Weighted Ljung-Box test on standardised residuals

	statistic	p-value
Lag[1]	4.023	0.04489
Lag[2*(p+q)+(p+q)-1][2]	4.149	0.06877
Lag[4*(p+q)+(p+q)-1][5]	6.501	0.06842
d.o.f	0	

Weighted Ljung-Box test on standardised squared residuals

	statistic	p-value
Lag[1]	0.3412	0.5591
Lag[2*(p+q)+(p+q)-1][5]	1.6663	0.699
Lag[4*(p+q)+(p+q)-1][9]	2.8409	0.7849
d.o.f	2	

Adjusted Pearson goodness-of-fit test

group		statistic	p-value(g-1)
	20	47.59	2.94E-04
	30	59.72	6.69E-04
	40	69.88	1.73E-03
	50	99.13	3.00E-05

RMSE	3.0462E-05
MSE	9.2791E-10
MAE	1.8549E-05
MAPE	INF

EURPLN
EGARCH(1,1)

Optimal parameters	Estimate	Std. Error	t-value	Pr(>|t|)
mu	-0.000069	0.000034	-1.9991	0.045599
omega	-0.138261	0.017023	-8.1219	0
alpha1	0.060759	0.009925	6.1218	0
beta1	0.98667	0.001638	602.2469	0
gamma1	0.204809	0.011766	17.4064	0
LogLikelihood	11383.05			
Information criteria				
Akaike	-8.0925			
Bayes	-8.0819			
Shibata	-8.0925			
Hannan-Quinn	-8.0887			

Weighted Ljung-Box test on standardised residuals

	statistic	p-value
Lag[1]	3.988	0.04582
Lag[2*(p+q)+(p+q)-1][2]	4.029	0.07404
Lag[4*(p+q)+(p+q)-1][5]	6.481	0.06916
d.o.f	0	

Weighted Ljung-Box test on standardised squared residuals

	statistic	p-value
Lag[1]	0.4562	0.4994
Lag[2*(p+q)+(p+q)-1][5]	2.917	0.4224
Lag[4*(p+q)+(p+q)-1][9]	3.8743	0.6102
d.o.f	2	

Adjusted Pearson goodness-of-fit test

group		statistic	p-value(g-1)
	20	55.87	1.71E-05
	30	76.45	3.79E-06
	40	90.13	6.32E-06
	50	104.36	7.06E-06

RMSE	3.0206E-05
MSE	9.1240E-10
MAE	1.8064E-05
MAPE	INF

EURCZK
SGARCH(1,1)

Optimal parameters

	Estimate	Std. Error	t-value	Pr(>|t|)
mu	0.000021	0.000037	0.573757	0.56613
omega	0	0	0.088102	0.9298
alpha1	0.059039	0.00645	9.152926	0
beta1	0.939906	0.006013	156.306453	0

LogLikelihood	12504.63	
		0.998945
Information criteria	-8.8909	
Akaike	-8.8825	
Bayes	-8.8909	
Shibata	-8.8879	
Hannan-Quinn		

Weighted Ljung-Box test on standardised residuals

	statistic	p-value
Lag[1]	0.8275	0.363
Lag[2*(p+q)+(p+q)-1][2]	1.312	0.4072
Lag[4*(p+q)+(p+q)-1][5]	4.7396	0.1752
d.o.f	0	

Weighted Ljung-Box test on standardised squared residuals

	statistic	p-value
Lag[1]	3.3330	6.79E-02
Lag[2*(p+q)+(p+q)-1][5]	13.9580	8.44E-04
Lag[4*(p+q)+(p+q)-1][9]	21.9670	6.21E-05
d.o.f	2	

Adjusted Pearson goodness-of-fit test

group		statistic	p-value(g-1)
	20	323	3.82E-57
	30	390.7	5.78E-65
	40	423.8	3.98E-66
	50	458.9	5.91E-68

RMSE	2.1294E-05
MSE	4.5342E-10
MAE	8.4217E-06
MAPE	INF

EURCZK
GJR-GARCH(1,1)

Optimal parameters

	Estimate	Std. Error	t-value	Pr(>|t|)
mu	0.000032	0.000036	0.881407	0.378098
omega	0	0	0.067351	0.946302
alpha1	0.028702	0.00665	4.316112	0.000016
beta1	0.946045	0.006128	154.385099	0
gamma1	0.048146	0.007905	6.090931	0

LogLikelihood	2518.53	
		0.99882
Information criteria		
Akaike	-8.9001	
Bayes	-8.8895	
Shibata	-8.9001	
Hannan-Quinn	-8.8963	

Weighted Ljung-Box test on standardised residuals

	statistic	p-value
Lag[1]	0.441	0.5066
Lag[2*(p+q)+(p+q)-1][2]	0.9609	0.5111
Lag[4*(p+q)+(p+q)-1][5]	4.6146	0.1867
d.o.f	0	

Weighted Ljung-Box test on standardised squared residuals

	statistic	p-value
Lag[1]	6.755	0.0093467
Lag[2*(p+q)+(p+q)-1][5]	14.084	0.000782
Lag[4*(p+q)+(p+q)-1][9]	20.063	0.0001934
d.o.f	2	

Adjusted Pearson goodness-of-fit test

group		statistic	p-value(g-1)
	20	318.8	2.81E-56
	30	388.1	1.89E-64
	40	409.1	3.33E-63
	50	426.6	1.10E-61

RMSE	2.1719E-05
MSE	4.7170E-10
MAE	8.9747E-06
MAPE	INF

EURCZK
EGARCH(1,1)

Optimal parameters

	Estimate	Std. Error	t-value	Pr(>|t|)
mu	0.000083	0.000019	4.360000	1.30E-05
omega	-0.184316	0.003037	-60.683700	0.00E+00
alpha1	-0.043758	0.009319	-4.695600	3.00E-06
beta1	0.98242	0.000288	##########	0.00E+00
gamma1	0.191033	0.009788	19.517400	0.00E+00

LogLikelihood	12542.06
Information criteria	
Akaike	-8.9168
Bayes	-8.9063
Shibata	-8.9168
Hannan-Quinn	-8.913

Weighted Ljung-Box test on standardised residuals

	statistic	p-value
Lag[1]	0.6319	0.4267
Lag[2*(p+q)+(p+q)-1][2]	1.0825	0.4722
Lag[4*(p+q)+(p+q)-1][5]	4.2103	0.229
d.o.f	0	

Weighted Ljung-Box test on standardised squared residuals

	statistic	p-value
Lag[1]	5.148	0.023278
Lag[2*(p+q)+(p+q)-1][5]	9.886	0.009849
Lag[4*(p+q)+(p+q)-1][9]	14.226	0.005489
d.o.f	2	

Adjusted Pearson goodness-of-fit test

group		statistic	p-value(g-1)
	20	364.4	1.09E-65
	30	388	2.00E-64
	40	395.9	1.29E-60
	50	416	1.25E-59

RMSE	2.1358E-05
MSE	4.5614E-10
MAE	9.0167E-06
MAPE	INF

EURGBP
SGARCH(1,1)

Optimal parameters	Estimate	Std. Error	t-value	Pr(>|t|)
mu	0.000045	0.000084	0.53029	0.59591
omega	0	0	0.77836	0.43636
alpha1	0.057793	0.00779	7.4188	0
beta1	0.936861	0.00747	125.41947	0
LogLikelihood	10940.79			
Information criteria			0.994654	
Akaike	-7.7787			
Bayes	-7.7702			
Shibata	-7.7787			
Hannan-Quinn	-7.7756			

Weighted Ljung-Box test on standardised residuals

	statistic	p-value
Lag[1]	0.007001	0.9333
Lag[2*(p+q)+(p+q)-1][2]	0.151276	0.885
Lag[4*(p+q)+(p+q)-1][5]	0.824803	0.8979
d,o,f	0	

Weighted Ljung-Box test on standardised squared residuals

	statistic	p-value
Lag[1]	0.0380	0.8454
Lag[2*(p+q)+(p+q)-1][5]	3.16798	0.3772
Lag[4*(p+q)+(p+q)-1][9]	4.78553	0.4616
d,o,f	2	

Adjusted Pearson goodness-of-fit test

group		statistic	p-value(g-1)
	20	88.55	5.98E-11
	30	103.01	3.20E-10
	40	116.56	1.17E-09
	50	137.93	2.15E-10

RMSE	3.6660E-05
MSE	1.3440E-09
MAE	1.9194E-05
MAPE	INF

EURGBP
GJR-GARCH(1,1)

Optimal parameters	Estimate	Std. Error	t-value	Pr(>|t|)
mu	0.000039	0.000085	0.45597	0.64841
omega	0	0	0.8129	0.41627
alpha1	0.055759	0.00454	12.28178	0
beta1	0.93496	0.007853	119.06047	0
gamma1	0.007447	0.01129	0.65964	0.50948
LogLikelihood	10941.05			
			0.9944425	
Information criteria				
Akaike	-7.7781			
Bayes	-7.7676			
Shibata	-7.7781			
Hannan-Quinn	-7.7743			

Weighted Ljung-Box test on standardised residuals

	statistic	p-value
Lag[1]	0.00426	0.948
Lag[2*(p+q)+(p+q)-1][2]	0.1416	0.8914
Lag[4*(p+q)+(p+q)-1][5]	0.79861	0.9033
d.o.f	0	

Weighted Ljung-Box test on standardised squared residuals

	statistic	p-value
Lag[1]	0.0321	0.8578
Lag[2*(p+q)+(p+q)-1][5]	3.1976	0.3721
Lag[4*(p+q)+(p+q)-1][9]	4.8328	0.4544
d.o.f	2	

Adjusted Pearson goodness-of-fit test

group		statistic	p-value(g-1)
	20	90.69	2.50E-11
	30	105.89	1.09E-10
	40	122.74	1.36E-10
	50	139.42	1.31E-10

RMSE	3.6706E-05
MSE	1.3473E-09
MAE	1.9200E-05
MAPE	INF

EURGBP
EGARCH(1,1)

Optimal parameters	Estimate	Std. Error	t-value	Pr(>|t|)
mu	0.000051	0.000084	0.60659	0.54412
omega	-0.111009	0.003171	-35.00381	0
alpha1	0.008339	0.008932	0.93367	0.35047
beta1	0.988979	0.00026	3802.37677	0
gamma1	0.12315	0.006318	19.49231	0
LogLikelihood	10947.13			
Information criteria				
Akaike	-7.7825			
Bayes	-7.7719			
Shibata	-7.7825			
Hannan-Quinn	-7.7786			

Weighted Ljung-Box test on standardised residuals

	statistic	p-value
Lag[1]	0.002564	0.9596
Lag[2*(p+q)+(p+q)-1][2]	0.112514	0.911
Lag[4*(p+q)+(p+q)-1][5]	0.497054	0.9581
d.o.f	0	

Weighted Ljung-Box test on standardised squared residuals

	statistic	p-value
Lag[1]	0.1849	0.6672
Lag[2*(p+q)+(p+q)-1][5]	3.184	0.3745
Lag[4*(p+q)+(p+q)-1][9]	4.7727	0.4635
d.o.f	2	

Adjusted Pearson goodness-of-fit test

group		statistic	p-value(g-1)
	20	93.96	6.54E-12
	30	95.74	4.65E-09
	40	118.33	6.37E-10
	50	135.4	4.97E-10

RMSE	3.6958E-05
MSE	1.3659E-09
MAE	1.9586E-05
MAPE	INF

Figure 7: Summary of GARCH(1,1) model specifications. (source: own calculation)

4.3.DCC-GARCH(1,1) models

To evaluate of dynamic correlation patterns across the variables of interest, a DCC-GARCH(1,1) model was fit to each of the four variables of interest. To measure the cross-dependencies related to energy dependence and the effect of Russia in this relationship, EUR/RUB residuals, Brent residuals, and gas residuals were included in all four model specifications. The summary of the DCC-GARCH models is shown in Figure 8.

The obtained model outputs show substantial similarities across the four samples. Based on the model outputs, individual ARCH-terms (α_i) of the variables of interest were were statistically significant only for EUR/CZK and EUR/GBP. At the same time, the β_i coefficients of the target variables seemed to be statistically significant in all four models. This indicates that in the case of the forint and the zloty, the unique effect of the previous day's return is marginal, while volatility clustering is still present in terms of the univariate volatility dynamics. In terms of Brent returns, α_{brent} was not statistically significant in any of the models, while β_{brent} had a substantial effect on the conditional covariance matrix in all cases. When it comes to EURRUB, both the short-term effect and the volatility persistence effect are justified as ω_{EURRUB}, α_{EURRUB}, and β_{EURRUB} all were statistically significant in all model versions. A similar pattern could also be detected in terms of gas returns as all model parameters (μ_{gas}, ω_{gas}, α_{gas}, β_{gas}) are substantial in the four model versions.

To assess the behaviour of the joint conditional covariance matrix, α_{DCC} and β_{DCC} must be evaluated. As shown in model outputs, $\alpha_{DCC}$is statistically insignificant in all four models, implying that the weight of standardised residuals carried over from the previous period does not substantially influence the current state of the conditional covariance matrix. When considering β_{DCC}, the parameter is statistically significant in all four models, suggesting that the conditional correlations carried over from the day before will have a substantial effect on the conditional correlation matrix on the current day. This indicates long-term persistence in the correlation matrix. Finally, the plausibility of the DCC framework was evaluated by deriving the stationarity terms for all models, assuming stationarity when $\alpha_{DCC} + \beta_{DCC} < 1$. Stationarity could be shown in all four models ($s_{EURHUF} = 0.8666$, $s_{EURCZK} = 0.8666$, $s_{EURPLN} = 0.9432$, $s_{EURGBP} = 0.9084$).

EURHUF
DCC-GARCH(1,1)

Optimal parameters

	EURHUF	brent_returns	EURRUB	gas_returns
mu	0.00008	0.00001	-0.00007	-0.00113
omega	0	0	0.00001	0.00007
alpha1	0.11166	0.11393	0.11365	0.26139
beta1	0.88734	0.88507	0.86601	0.73761
Log-Lik	12171.6356	11154.82145	7752.42121	5786.12122

Model	DCC(1,1)
Estimation	2-step
Distribution	mvnorm
No. Observations	3112
Log-Likelihood	36896.87
Av.Log-Likelihood	11.86

Optimal parameters

	Estimate	Std. Error	t value	Pr(>|t|)
[EURHUF].mu	0.0001	0.0001	1.0578	0.2901
[EURHUF].omega	0.0000	0.0000	0.1045	0.9168
[EURHUF].alpha1	0.1117	0.0923	1.2100	0.2263
[EURHUF].beta1	0.8873	0.0826	10.7407	0.0000
[brent_returns].mu	0.0000	0.0001	0.0834	0.9335
[brent_returns].omega	0.0000	0.0000	0.1991	0.8422
[brent_returns].alpha1	0.1139	0.0608	1.8726	0.0611
[brent_returns].beta1	0.8851	0.0578	15.3237	0.0000
[EURRUB].mu	-0.0001	0.0003	-0.1948	0.8455
[EURRUB].omega	0.0000	0.0000	2.0464	0.0407
[EURRUB].alpha1	0.1136	0.0172	6.6106	0.0000
[EURRUB].beta1	0.8660	0.0144	60.3460	0.0000
[gas_returns].mu	-0.0011	0.0006	-2.0105	0.0444
[gas_returns].omega	0.0001	0.0000	3.5026	0.0005
[gas_returns].alpha1	0.2614	0.0431	6.0642	0.0000
[gas_returns].beta1	0.7376	0.0318	23.1636	0.0000
[Joint]dcca1	0.0039	0.0025	1.5637	0.1179
[Joint]dccb1	0.9479	0.0248	38.2215	0.0000

Information criteria	
Akaike	-23.697
Bayes	-23.651
Shibata	-23.697
Hannan-Quinn	-23.68

Pearson correlation coefficients

	EURHUF	brent_returns	EURRUB	gas_returns
EURHUF	1.0000	0.0088	-0.0556	-0.0187
brent_returns	0.0088	1.0000	0.0025	0.0202
EURRUB	-0.0556	0.0025	1.0000	0.0871
gas_returns	-0.0187	0.0202	0.0871	1.0000

EURCZK
DCC-GARCH(1,1)

Optimal parameters

	EURCZK	brent_returns	EURRUB	gas_returns
mu	0.00001	0.00001	-0.00007	-0.00113
omega	0	0	0.00001	0.00007
alpha1	0.05974	0.11393	0.11365	0.26139
beta1	0.93922	0.88507	0.86601	0.73761
Log-Lik	13875.9934	11154.82145	7752.42121	5786.12122

Model	DCC(1,1)
Estimation	2-step
Distribution	mvnorm
No. Observations	3112
Log-Likelihood	38601.17
Av.Log-Likelihood	12.4

Optimal parameters

	Estimate	Std. Error	t value	Pr(>|t|)
[EURCZK].mu	0.0000	0.0000	0.1291	0.8973
[EURCZK].omega	0.0000	0.0000	0.0277	0.9779
[EURCZK].alpha1	0.0597	0.0291	2.0539	0.0400
[EURCZK].beta1	0.9392	0.0267	35.1620	0.0000
[brent_returns].mu	0.0000	0.0001	0.0834	0.9335
[brent_returns].omega	0.0000	0.0000	0.1991	0.8422
[brent_returns].alpha1	0.1139	0.0608	1.8725	0.0611
[brent_returns].beta1	0.8851	0.0578	15.3256	0.0000
[EURRUB].mu	-0.0001	0.0003	-0.1948	0.8455
[EURRUB].omega	0.0000	0.0000	2.0476	0.0406
[EURRUB].alpha1	0.1136	0.0172	6.6136	0.0000
[EURRUB].beta1	0.8660	0.0144	60.3432	0.0000
[gas_returns].mu	-0.0011	0.0006	-2.0106	0.0444
[gas_returns].omega	0.0001	0.0000	3.5015	0.0005
[gas_returns].alpha1	0.2614	0.0431	6.0661	0.0000
[gas_returns].beta1	0.7376	0.0319	23.1534	0.0000
[Joint]dcca1	0.0032	0.0041	0.7799	0.4355
[Joint]dccb1	0.8633	0.0466	18.5091	0.0000

Information criteria	
Akaike	-24.793
Bayes	-24.746
Shibata	-24.793
Hannan-Quinn	-24.776

Pearson correlation coefficients

	EURCZK	brent_returns	EURRUB	gas_returns
EURCZK	1.0000	-0.0276	-0.0454	0.0043
brent_returns	-0.0276	1.0000	0.0025	0.0202
EURRUB	-0.0454	0.0025	1.0000	0.0871
gas_returns	0.0043	0.0202	0.0871	1.0000

EURPLN
DCC-GARCH(1,1)

Optimal parameters

	EURPLN	brent_returns	EURRUB	gas_returns
mu	-0.0001	0.00001	-0.00007	-0.00113
omega	0	0	0.00001	0.00007
alpha1	0.09715	0.11393	0.11365	0.26139
beta1	0.90177	0.88507	0.86601	0.73761
Log-Lik	12596.4813	11154.82145	7752.42121	5786.12122

Model	
Estimation	2-step
Distribution	mvnorm
No. Observations	3112
Log-Likelihood	37321.87
Av.Log-Likelihood	11.99

Optimal parameters

	Estimate	Std. Error	t value	Pr(>|t|)
[EURPLN].mu	-0.0001	0.0001	-1.4655	0.1428
[EURPLN].omega	0.0000	0.0000	0.0645	0.9486
[EURPLN].alpha1	0.0972	0.0834	1.1645	0.2442
[EURPLN].beta1	0.9018	0.0740	12.1874	0.0000
[brent_returns].mu	0.0000	0.0001	0.0834	0.9335
[brent_returns].omega	0.0000	0.0000	0.1990	0.8423
[brent_returns].alpha1	0.1139	0.0609	1.8709	0.0614
[brent_returns].beta1	0.8851	0.0578	15.3096	0.0000
[EURRUB].mu	-0.0001	0.0003	-0.1948	0.8455
[EURRUB].omega	0.0000	0.0000	2.0466	0.0407
[EURRUB].alpha1	0.1136	0.0172	6.6094	0.0000
[EURRUB].beta1	0.8660	0.0143	60.3544	0.0000
[gas_returns].mu	-0.0011	0.0006	-2.0110	0.0443
[gas_returns].omega	0.0001	0.0000	3.5022	0.0005
[gas_returns].alpha1	0.2614	0.0431	6.0663	0.0000
[gas_returns].beta1	0.7376	0.0318	23.1676	0.0000
[Joint]dcca1	0.0028	0.0027	1.0350	0.3007
[Joint]dccb1	0.9405	0.0393	23.9482	0.0000

Information criteria	
Akaike	-23.97
Bayes	-23.924
Shibata	-23.97
Hannan-Quinn	-23.9954

Pearson correlation coefficients

	EURPLN	brent_returns	EURRUB	gas_returns
EURPLN	1.0000	0.0036	-0.0559	-0.0063
brent_returns	0.0036	1.0000	0.0025	0.0202
EURRUB	-0.0559	0.0025	1.0000	0.0871
gas_returns	-0.0063	0.0202	0.0871	1.0000

EURGBP
DCC-GARCH(1,1)

Optimal parameters

	EURGBP	brent_returns	EURRUB	gas_returns
mu	0.00007	0.00001	-0.00007	-0.00113
omega	0	0	0.00001	0.00007
alpha1	0.05373	0.11393	0.11365	0.26139
beta1	0.94092	0.88507	0.86601	0.73761
Log-Lik	12158.95727	11154.8215	7752.42121	5786.12122

Model	DCC(1,1)
Estimation	2-step
Distribution	mvnorm
No. Observations	3112
Log-Likelihood	36884.55
Av.Log-Likelihood	11.85

Optimal parameters

	Estimate	Std. Error	t value	Pr(>|t|)
[EURGBP].mu	0.0001	0.0001	0.8832	0.3771
[EURGBP].omega	0.0000	0.0000	0.2423	0.8086
[EURGBP].alpha1	0.0537	0.0159	3.3769	0.0007
[EURGBP].beta1	0.9409	0.0164	57.3030	0.0000
[brent_returns].mu	0.0000	0.0001	0.0834	0.9335
[brent_returns].omega	0.0000	0.0000	0.1993	0.8420
[brent_returns].alpha1	0.1139	0.0608	1.8742	0.0609
[brent_returns].beta1	0.8851	0.0577	15.3348	0.0000
[EURRUB].mu	-0.0001	0.0003	-0.1949	0.8455
[EURRUB].omega	0.0000	0.0000	2.0470	0.0407
[EURRUB].alpha1	0.1136	0.0172	6.6117	0.0000
[EURRUB].beta1	0.8660	0.0143	60.3525	0.0000
[gas_returns].mu	-0.0011	0.0006	-2.0111	0.0443
[gas_returns].omega	0.0001	0.0000	3.5029	0.0005
[gas_returns].alpha1	0.2614	0.0431	6.0679	0.0000
[gas_returns].beta1	0.7376	0.0318	23.1688	0.0000
[Joint]dcca1	0.0010	0.0031	0.3210	0.7482
[Joint]dccb1	0.9074	0.1355	6.6981	0.0000

Information criteria	
Akaike	-23.689
Bayes	-23.643
Shibata	-23.689
Hannan-Quinn	-23.673

Pearson correlation coefficients

	brent_returns	EURRUB	gas_returns	EURGBP
brent_returns	1.0000	-0.0266	-0.0173	-0.0348
EURRUB	-0.0266	1.0000	0.0025	0.0202
gas_returns	-0.0173	0.0025	1.0000	0.0871
EURGBP	-0.0348	0.0202	0.0871	1.0000

Figure 8: Summary of DCC-GARCH(1,1) model specifications. (source: own calculation)

4.3.1. Dynamic conditional correlations

The main advantage of DCC-GARCH models lies in the possibility of the analysis of the time-varying dynamic correlations. Hence, conditional correlation matrices were derived for the model specifications and were then plotted pairwise to obtain a visual representation of the dynamics across different variables, which can be seen in Figure 9.

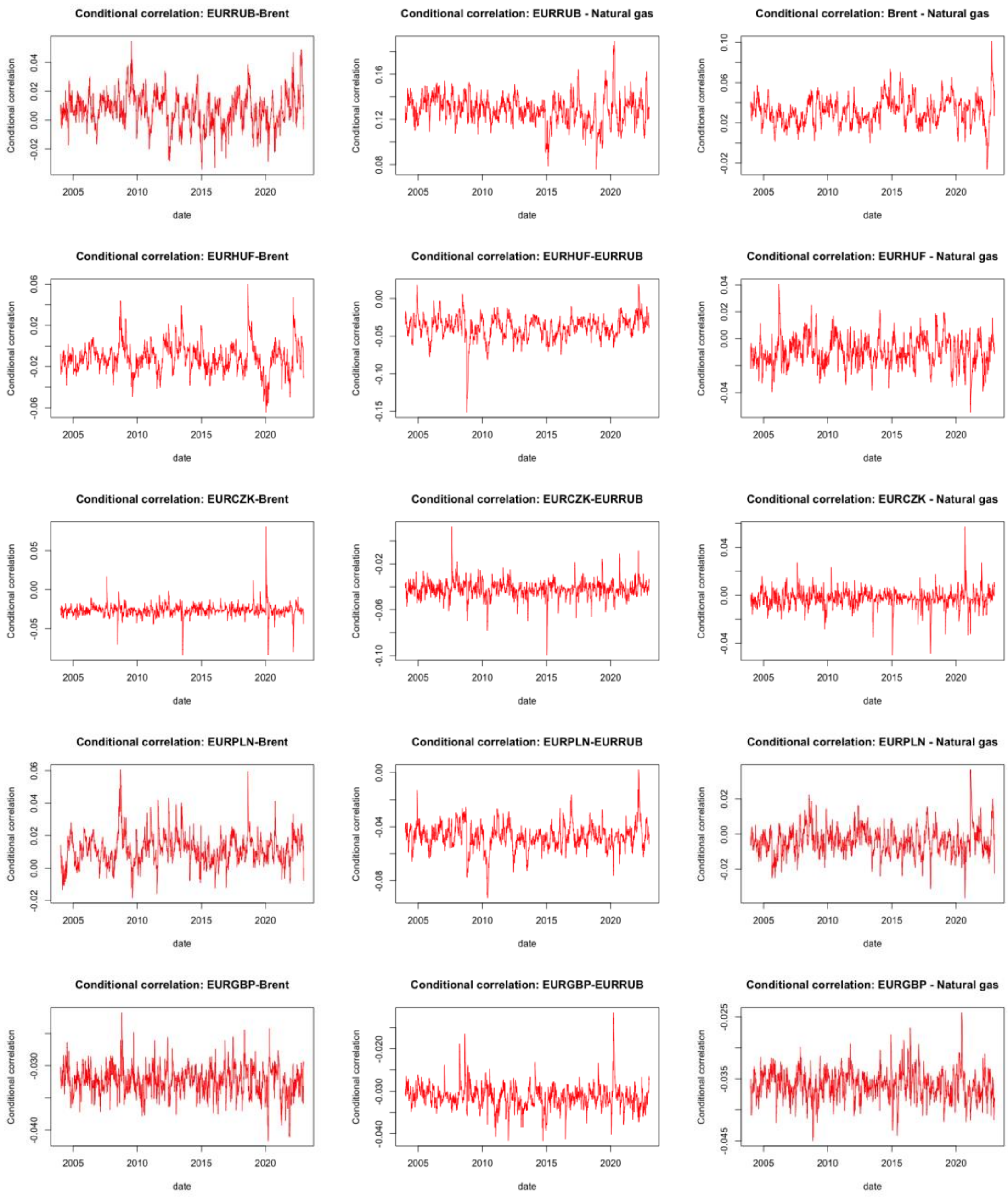


Figure 9: Conditional correlations based on DCC-GARCH(1,1) outputs. (source: own calculations)

4.3.1.1. Dynamic correlations between the regressors

For the assessment of the effect of Russian energy dependence, it is pivotal to understand the underlying correlation between the regressors themselves, i.e., the conditional correlations between EUR/RUB and Brent, EUR/RUB and gas, and Brent and gas returns. These relationships are universal across the four models, making their effects universally comparable for all four exchange rates of interest.

As depicted by Figure 9, the correlation between EUR/RUB and Brent is on average slightly positive but exhibiting large fluctuations over time both in a positive, and in a negative direction (ranging between -0.04 and 0.06). This result could be expected since Russia originates a large share of its revenues from the export of primary energy sources worldwide (OECD, 2020b). The exchange rate is hence not only positively correlated with global oil prices but is also very sensitive to changes in the market. In a similar manner, being one of the largest oil exporters in the world, the exposure of global oil price to the changes in the rouble's exchange rate seems also plausible. The conditional correlation is particularly high in the positive domain in times of turbulences in the market (in 2009, during the Global Financial Crisis and from 2020 onwards, covering the COVID-19 crisis and the Ukrainian military conflict). The increasing positive correlation since the start of the Ukrainian conflict – indicating higher oil prices along a depreciation in the rouble's exchange rate – can be traced back to (1) increased military expenses on the Russian side which cause the devaluation of the rouble, (2) the embargo on Russian primary energy imports imposed by the EU and G7 countries which resulted in a drop in Russian exports, causing increasing demand on global energy markets that drove up prices (S&P Global, 2023). The largest negative correlations can be observed around 2015 and 2016, signalling both the downgrade in Russia's government bond rating by Moody's (AFP, 2015) and the consecutive currency crisis, as well as the effect of Russian intervention in the Syrian civil war (Osborn – Stewart, 2015). First, the devaluation of Russian government bonds from Baa2 to Ba1 (thereby indicating speculative status) caused increased daily volatility – and consequently, strong depreciation – in the exchange rate of the rouble. This caused the global market to be flooded with rouble which in turn pushed down oil prices.

While the relationship between global oil prices and the rouble is not substantial overall, in terms of the evaluation of conditional correlations between EUR/RUB and natural gas, the interdependence is clearly visible. Conditional correlations over the observed time periods are strongly positive, ranging between 0.08 and 0.2. As Russia relies more heavily on its natural gas exports in its trade balance than on its oil exports, the more pronounced positive relationship with the global natural gas market could be expected. The strong positive relationship signals that depreciations in the rouble's exchange rate are accompanied by a rise in global gas prices. The result is not unexpected as Russia-related news create uncertainty and high demand on global gas markets, thereby driving up prices. At the same time, uncertainty on the market causes a loss of trust in the Russian economy, thereby causing devaluation in the rouble's exchange rate. This effect is the most visible from 2020 onwards, where the uncertainty around gas supplies was first caused by the COVID crisis and later by the export sanctions imposed on Russia which resulted in a global energy crisis.

Finally, the conditional correlations between the two commodities were also assessed. As expected, global gas prices and global oil prices are on average positively correlated, with only slight fluctuations over time. An interesting finding is that in 2022, there is an observable change in the dynamics between the two variables: gas and oil became negatively correlated for the first time in the observation period at the beginning of the Russian-Ukrainian conflict, signalling that markets could consider these two assets as hedges against each other. This unexpected negative correlation swiftly turned into a large positive spike by the end of 2022, signalling cautious market expectations amid the military conflict and tight commodity supplies (Kearney, 2022).

4.3.1.2.Dynamic conditional correlations in the EUR/HUF model

The conditional correlations derived from the EUR/HUF DCC-GARCH model are summarised in the second row of Figure 9.

EUR/HUF exhibits overall negative conditional correlations with Brent prices, while there is a visible oscillation throughout the sample period, taking on values within the [-0.06; 0.06] range. The overall negative correlation is in line with the findings of Kočenda and Moravcová (Kočenda – Moravcová, 2019), claiming that curing the period 2004-2018, the correlation between EUR/HUF and EUR/USD was for the most time negative. This suggests that as global oil prices increase, markets are flooded with U.S. dollars, causing a depreciation in the dollar's exchange rate, and therefore, an appreciation in importing countries' exchange rates. Positive spikes can be identified during the Global Financial Crisis, around 2014 (during the time of the Russian energy dispute (BBC, 2014)), around 2018, and at the beginning of 2022. This is in line with previous expectations that crisis periods create uncertain market environment, making investors run for safer assets, such as commodities and safe-haven currencies, thereby causing a depreciation in more volatile currencies. Moreover, increases in crude oil prices cause a significant rise in demand for the dollar, thereby causing a depreciation in the currencies of importing countries. Additionally, there is a strong spike in the negative domain at the very beginning of 2020, showing market reaction to the COVID pandemic. This was caused by the sudden decrease in global demand for primary energy products in reaction to the pandemic, causing a large drop in crude oil prices (KSH, 2024a) that was not accompanied by a similar-degree change in the forint's exchange rate.

In terms of EUR/RUB, there is a considerable negative correlation that remains so for almost the entire sample period. It is important to mention that unexpectedly, there is no large oscillation in the conditional correlation patterns against the rouble. The only considerable negative spike can be dated around the Global Financial Crisis, caused by the sudden devaluation of the rouble in reaction to the fall in global commodity prices (The New York Times, 2008). At the beginning of 2022, around the time of the Ukrainian crisis, the correlation increased marginally into the positive domain, but the effect was short-lived as correlation measures normalised within the consecutive days.

Finally, the Hungarian forint shows very slight negative conditional correlation with natural gas prices. While oscillations within the [-0.05; 0.04] range are frequent, the identification of extremities would be difficult. This might be explained by the fact that global gas prices create a risk for the Hungarian state when negotiating long-term contracts (LTCs) with their supplying partners, which can potentially lead to an impact on the forint's exchange rate by influencing market beliefs. The only significant positive spike can be dated to 2006 when the correlation increased into the positive domain, caused by the fallout in the Russia-Ukraine gas dispute, leading to a significant rise in gas prices, thereby directly affecting the dependent forint (Parfitt, 2006). Another, this time negative spike can be dated to the time of the COVID crisis, when a large negative spike occurred, in a similar way as in the case of crude oil prices.

4.3.1.3.Dynamic conditional correlations in the EUR/CZK model

The third row in Figure 9 displays dynamic conditional correlations derived from the EUR/CZK DCC-GARCH model.

When it comes to the evolution of conditional correlations against Brent prices, EUR/CZK proved to be the most resilient. While the correlation is slightly negative – aligning with findings concerning the forint and the pound – the koruna shows marginal co-movement patterns with global oil prices, usually taking on values within the [-0.10; 0.10] range. This allows for any extremities that occurred during the observation period to be isolated. The most prominent negative spikes occurred in 2008, during the Global Financial Crisis, in 2014 (marking a sudden drop in crude oil prices (World Bank, 2018)), in 2020, at the beginning of the COVID pandemic, and at the beginning of the Ukrainian conflict in 2022. Negative spikes are in contrast with other CE countries as during these periods, both the forint and the zloty showed an increase in conditional correlations against oil prices, in both cases reaching well into the positive domain. This suggests that the Czech Republic can effectively rely on its own crude oil reserves in Southern Moravia, thereby hedging itself against increased market risk in turbulent times, thereby causing an appreciation in the exchange rate. Positive spikes can be detected in 2007, marking the sudden disruption of incoming flows on the Druzhba pipeline following the Russia-Belarus energy dispute (Parfitt, 2007), and at the beginning of the COVID crisis in 2020, just before the large negative spike in correlation. This sudden shift, as well as the quick normalisation of conditional correlations indicates that Czech policymakers reacted effectively to the COVID-shock, thereby mitigating exchange rate risk.

In terms of correlations with EUR/RUB, the koruna shows similar pattern to the case of oil prices. While the correlation is negative – aligning with findings for the forint and the zloty – movements again are not of large magnitude, allowing for the appropriate detection of single shocks. Such shocks happened in 2008, at the beginning of the Global Financial Crisis, when as a unique occurrence, correlation between the koruna and the rouble turned into the positive domain, and at the beginning of 2015, when due to the Russian currency crisis, the correlation reached an all-time low point, hitting a correlation coefficient of -0.10. The fact that the Ukrainian conflict did not have significant effects in the conditional correlation patterns is a good representation of the Czech Republic's ambiguity and trading diversification against Russia (Binhack - Tichý, 2012).

Finally, the correlation with natural gas is again similar to the correlation patterns observed for the koruna. In the case of natural gas, correlation is practically zero, implying no correlation between global gas price movements and movements in the EUR/CZK exchange rate. This finding is interesting considering that the Czech Republic imports almost its entire annual gas supply from Russia. Hence, much like the case of

Hungary, low correlation is potentially caused by the fact that the Czech Republic has long-term gas contracts with its suppliers (Binhack - Tichý, 2012, Misik, 2016), making the economy not particularly exposed to market shifts. Spikes again can be easily identified within the sample: the largest negative spikes occurred in 2014-2015 (suggesting the Czech Republic's ability utilise its natural gas storages even in times when the Russian energy disputes in 2014 (BBC, 2014)), and in 2018, as a reaction to a sudden surge in global prices (S&P Global, 2019). The only positive correlation shock can be dated to 2021, marking a sudden increase in global natural gas prices (EIA, 2022) (which is shown in Appendix 1), even though this spike was not significant either. These findings show that while the koruna is somewhat sensitive to gas price shifts in times of uncertainty, the co-movement is not Russia-specific.

4.3.1.4.Dynamic conditional correlations in the EUR/PLN model

Conditional correlation measures related to the Polish zloty are depicted in the fourth row in Figure 9.

In terms of correlations with Brent prices, EUR/PLN shows similar patterns to those of EUR/HUF, but interestingly, in this case, the correlation tends to be overall positive in the observation period. This implies that – unlike the other three exchange rates – increases in global oil prices tend to be associated with depreciation in the zloty's exchange rate. This might be explained by the fact that crude oil is not as pivotal in the Polish energy mix as in other countries, as discussed in Section 2. Furthermore, Poland's own crude oil resources and diversification alternatives might also serve as further explanation for this reverse phenomenon. Seasonality within the oscillations, as well as the co-movements highlight the similarities across Hungary and Poland when it comes to their respective primary energy exposures. EUR/PLN exhibited a significant correlation spike with Brent prices in 2008, at the beginning of the Global Financial Crisis, which swiftly turned into a negative correlation in the upcoming period. This signalled the quick adjustment of the zloty to falling global demand. Similarly to the forint, the zloty also exhibited another strong positive spike in 2018, however, unlike the forint, the zloty did not exhibit strong co-movements with Brent prices at the beginning of 2022. This suggests that Poland can effectively rely on its strategic oil reserves stored on the Baltic coastline (Sharples, 2012) and Western crude oil trade in times of turbulence, thereby keeping the zloty's correlation with global crude oil prices under control.

Another similarity between EUR/PLN and EUR/HUF can be detected when evaluating the conditional correlations against EUR/RUB. In the case of the zloty, the correlation with the rouble is again overall significantly negative, mostly to the same magnitude as for the forint. The main difference between the two CE currencies is that the zloty seems to exhibit lower levels of oscillation than the forint: the typical correlation ranges between -0.10 and 0.00 during the observation period, with the largest negative spike occurring in 2010, and the largest positive spike occurring at the beginning of 2022.

Considering correlation against natural gas prices, there is yet another similarity between the two CE currencies. Just like in the case of the forint, the correlation with gas prices is in general slightly negative in the case of the zloty as well. It is important to note, however, that correlation remains insignificant throughout the sample period. This provides further support to the hypothesis that CE countries can mitigate their exposure to the global gas market by signing long-term contracts with their suppliers, thereby also ensuring their energy security, as discussed in Section 2. Oscillations again are very frequent, indicating the close interdependence between EUR/PLN and global gas prices. Like for the forint, in the case of the zloty, there is a strong negative spike in 2021 that can be attributed to the sudden jump in gas prices (depicted in Appendix 1). Yet, unlike in the case of the forint, the correlation turned into a strong positive correlation within a short time, indicating Poland's exposure to global gas markets due to its role as one of the largest European gas redistribution hubs.

4.3.1.5.Dynamic conditional correlations in the EUR/GBP model

Finally, as a benchmark, correlations were also evaluated for the EUR/GBP model, which are presented in the last row of Figure 9. Results confirm the assumption that the British pound exhibits different correlation patterns both with commodity prices and with the Russian rouble due to its different market position and trading relationship with Russia than those of the CE region.

Much like the rest of the analysed exchange rates, the pound also exhibits on average negative conditional correlations with Brent prices. It is important, however, that while a significant correlation is present, the magnitude of oscillation is marginal in comparison with EUR/HUF and EUR/PLN. This is also supported by the fact that

EUR/GBP exhibits the smallest oscillation range in terms of correlation with Brent prices out of the four exchange rates: values range between -0.045 and -0.025 throughout the entire sample period. The only three noticeable extremities occurred in 2008 (in a positive direction, during the Global Financial Crisis), in 2020 in a negative direction due to the COVID crisis, and in early 2022, again in a negative direction, at the beginning of the Ukrainian conflict. This finding aligns with previous findings.

Considering correlations with EUR/RUB, as expected, EUR/GBP also exhibits on average negative values. While fluctuations within this range were common, the extent of co-movements did not significantly change during the sample period. The only noteworthy spike in the correlation dynamics occurred at the beginning of 2020 during the pandemic crisis, in a positive direction, but overall, correlation still remained negative. Much like in the case of EUR/CZK, the British pound did not exhibit significant co-movements with the rouble around the time of the Ukrainian conflict, indicating its relative independence from Russia-related events.

At last, correlations with natural gas prices showed some dispersion from the other three variables of interest as conditional correlations of the pound stayed within the negative domain throughout the entire observation period. While small fluctuations seem to be constant, the magnitude of these is visibly marginal: the largest spikes occurred during the Global Financial Crisis in 2008 in a negative direction, while the largest positive shocks happened in early 2020, during the COVID crisis. Again, the pound showed no co-movement changes with natural gas prices around the time of the energy crisis caused by the sanctions imposed on Russia in 2022, representing the benefits of the diversification of primary energy trading partners by the United Kingdom, as well as the fact that for the UK, Russia is by far not the largest crude oil and natural gas supplier. This diversification allowed the United Kingdom to stay safe in terms of energy supplies and therefore, indifferent to natural gas price changes even in times when markets were turbulent.

4.4.Measuring spillover effects

As the last step of the analysis, the Diebold-Yilmaz volatility spillover index was calculated for each model version to assess directional causalities among the variables. The current analysis was performed following the methodology of Kočenda - Moravcová

(Kočenda – Moravcová, 2019), using 200-day rolling windows. Figure 10 illustrates the summary statistics of the Diebold-Yilmaz indices for the four model versions.

	EURHUF	brent_returns	EURRUB	gas_returns	FROM
EURHUF	96.18	1.41	1.55	0.87	3.82
brent_returns	1.52	95.24	1.37	1.87	4.76
EURRUB	2.76	2.52	93.8	0.92	6.2
gas_returns	0.74	1.93	1.41	95.92	4.08
TO	5.01	5.85	4.33	3.66	18.85
Inc.Own	101.19	101.09	98.13	99.58	**Index**
NET	1.19	1.09	-1.87	-0.42	**6.28/4.71**
NPT	2	2	1	1	

	EURCZK	brent_retur	EURRUB	gas_returns	FROM
EURCZK	96.86	1.3	1.06	0.78	3.14
brent_returns	1.24	95.47	1.34	1.95	4.53
EURRUB	1.41	2.67	94.98	0.94	5.02
gas_returns	1.22	2	1.65	95.14	4.86
TO	3.87	5.97	4.05	3.66	17.55
Inc.Own	100.73	101.44	99.03	98.8	**Index**
NET	0.73	1.44	-0.97	-1.2	**5.85/4.39**
NPT	2	3	1	0	

	EURPLN	brent_returns	EURRUB	gas_returns	FROM
EURPLN	95.31	1.67	2.38	0.64	4.69
brent_returns	1.43	95.15	1.55	1.87	4.85
EURRUB	3.93	2.72	92.34	1.01	7.66
gas_returns	0.75	2	1.83	95.41	4.59
TO	6.11	6.39	5.76	3.51	21.78
Inc.Own	101.43	101.54	98.1	98.93	**Index**
NET	1.43	1.54	-1.9	-1.07	**7.26/5.45**
NPT	2	3	1	0	

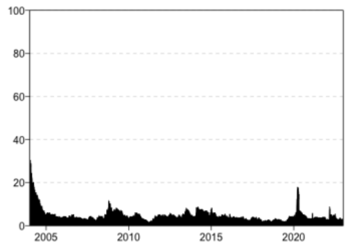
	brent_returns	EURRUB	gas_returns	EURGBP	FROM
brent_returns	95.05	1.28	1.87	1.79	4.95
EURRUB	2.54	95.16	0.97	1.33	4.84
gas_returns	1.93	1.56	95.71	0.8	4.29
EURGBP	1.11	1.27	0.92	96.7	3.3
TO	5.58	4.11	3.76	3.92	17.37
Inc.Own	100.63	99.27	99.47	100.62	**Index**
NET	0.63	-0.73	-0.53	0.62	**5.79/4.34**
NPT	2	1	1	2	

Figure 10: Summary of volatility spillovers. (source: own calculations)

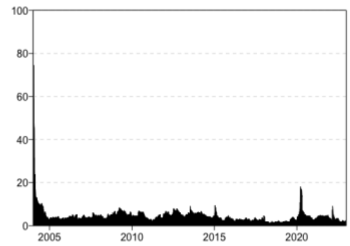
Considering the TCI/ Index values at the lower right corner of each table, each model performs quite homogenously: across all models, the share of the forecast error variance in one index attributable to innovations in all the other indices in the model are within the 4-6 percent band, with EUR/PLN exhibiting the strongest total connectedness.

When comparing diagonal values to off-diagonal values, it is clearly visible that the own volatility of each currency is the main determinant in explaining volatility spillovers, providing further support to previous literature (Bubák et al, 2011, Kočenda – Moravcová, 2019) This effect is equally strong for all four currencies, ranging between 95.31 and 96.86, also implying that the other considered variables do not have significant spillover effect. At the same time, off-diagonal values are not substantial in comparison: here, the largest bidirectional relationship can be detected between EUR/HUF and EUR/RUB in terms of the EUR/HUF model, EUR/PLN and EUR/RUB for the EUR/PLN model, while for the EUR/CZK and EUR/GBP models, the strongest bidirectional spillover can be seen for Brent and gas.

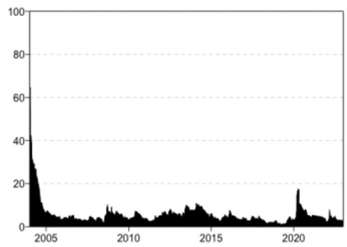
Examining the individual effect of each variable on the system of the respective model variables (row 5 in each table) also uncovered interesting findings. In the forint model, Brent exhibited the largest individual effect on other model variables, closely followed – surprisingly – by the forint, while the effect of gas and the rouble are not as substantial. In the zloty model, the effects of the zloty, the rouble and Brent were similarly strong, and on average, they were more substantial than the individual effects measured in the forint model. Finally, the koruna and pound models performed quite differently than the aforementioned two specifications as in these cases, Brent had the only substantial individual effect on the entire system. Based on these findings, it can be concluded that out of the four exchange rates of interest, the zloty and the forint have the most substantial individual effects in terms of volatility transmission, while this effect is the weakest for the koruna. This effect – albeit tested on different variables – is aligned with the findings of Kočenda and Moravcová (Kočenda – Moravcová, 2019).



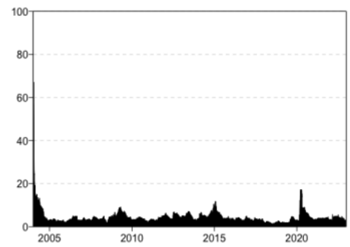
Total connectedness for EUR/HUF



Total connectedness for EUR/CZK



Total connectedness for EUR/PLN

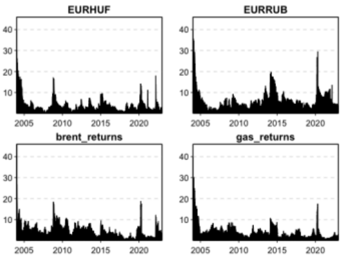


Total connectedness for EUR/GBP

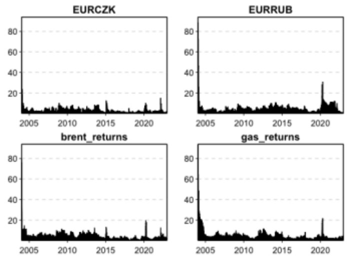
Figure 11: Diebold-Yilmaz total connectedness measures for the variables of interest. (source: own calculations)

When considering the evolution of total connectedness measures over the sample period, the four currencies show similar patterns, as shown in Figure 11. Total spillover in each case is the highest at the beginning of the sample period (in 2004), especially so for the CE currencies. Following their entry into the European Union, spillovers decrease in all four systems. Furthermore, all four series react similarly to large-scale uncertainties on the global market which are marked by jumps in total spillover measures. Such spikes can be universally observed around the time of the Global Financial Crisis, at the time of the Russian currency crisis in early 2015 and at the beginning of the COVID-19 pandemic in early 2020. Interestingly, the Ukrainian conflict does not result in significant jumps in total spillovers. In general, total connectedness remains overall relatively low throughout the sample period, even during times of crisis.

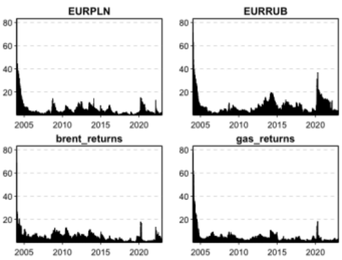
Figure 12 summarises the evolution of the directional spillover effects from the individual variables on the system, while Figure 13 illustrates the directional volatility spillovers from the system to the individual variables.



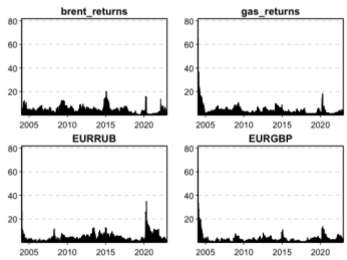
Directional volatility spillovers FROM the EUR/HUF model variables



Directional volatility spillovers FROM the EUR/CZK model variables

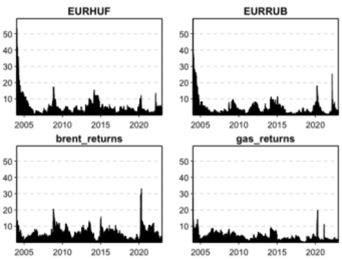


Directional volatility spillovers FROM the EUR/PLN model variables

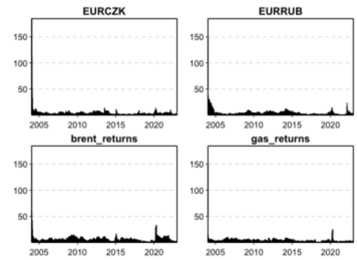


Directional volatility spillovers FROM the EUR/GBP model variables

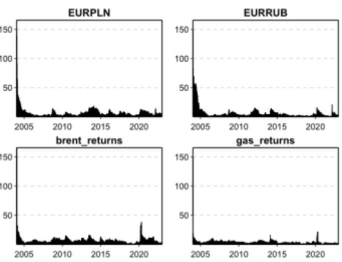
Figure 12: Directional volatility spillovers from model variables. (source: own calculations)



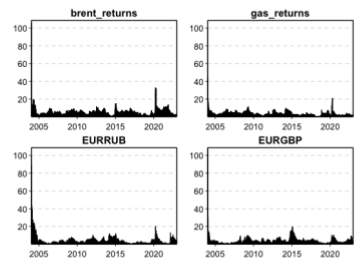
Directional volatility spillovers TO the EUR/HUF model variables



Directional volatility spillovers TO the EUR/CZK model variables



Directional volatility spillovers TO the EUR/PLN model variables

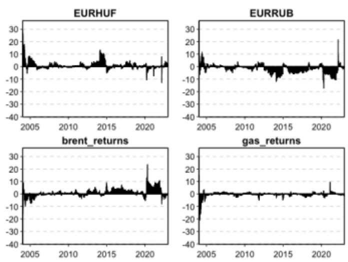


Directional volatility spillovers TO the EUR/GBP model variables

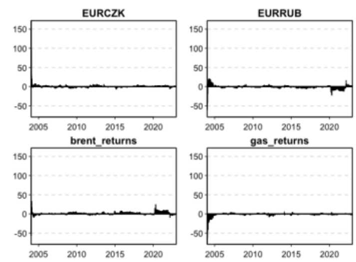
Figure 13: Directional volatility spillovers to model variables. (source: own calculations)

In terms of individual effects, previous findings of the forint's and the zloty's exposure are again supported. In terms of these models, the individual effects of the currencies of interest are significantly stronger than in the case of the koruna and the pound, specifically around periods of market uncertainties. It can be seen that during the GFC, both the forint and the zloty reach the highest directional spillover values on their respective systems out of the four currencies as this effect is practically marginal for the koruna, and very light for the pound. This phenomenon can be explained by the depreciation patterns both in the forint's and the zloty's exchange rates over the sample periods, as depicted in Figure 1, and also deducted by Kočenda and Moravcová (Kočenda – Moravcová, 2019). Similarly, the rouble exhibits the largest individual effect in the forint and zloty models, highlighting that the rouble has a significant role in volatility transmission. This can be traced back to the close economic ties of Hungary and Poland with Russia, especially in terms of primary energy: as the rouble is susceptible for changes on the commodities market, and the forint and the zloty are susceptible to the supplies of Russian primary energy sources, this any shock to the rouble can easily carry on to currencies which are closely related to it.

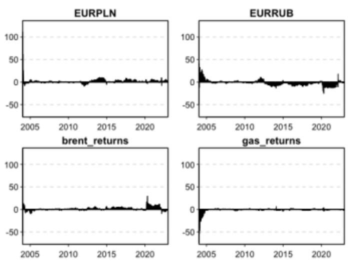
While the spillover effects of the system on the individual variables is marginal in all other cases, it reaches substantially higher levels in the forint model and shows high fluctuations around crisis periods. This indicates that the Russia-related commodity price movements on the market expose the forint's exchange rate to high levels of volatility, significantly impacting the currency's purchasing power on global markets.



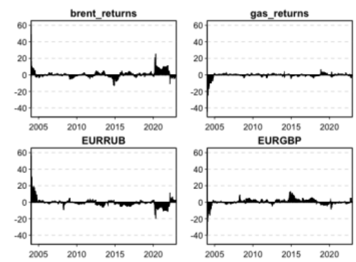
Net volatility spillovers in the EUR/HUF model



Net volatility spillovers in the EUR/CZK model



Net volatility spillovers in the EUR/PLN model



Net volatility spillovers in the EUR/GBP model

Figure 14: Net volatility spillovers. (source: own calculations)

Finally, net spillover trends were considered, and are visualised on Figure 14. Overall, all four systems seem to be relatively unaffected by system-wide spillovers as patterns never reach significantly high values throughout the sample period. Out of the four currencies of interest, the forint again seems to be the most exposed currency to changes in within its own domain. Both in the early stages of Hungary's EU membership, as well as during the period of 2014-2015 (indicating the time of general uncertainty around Russia's energy supplies towards Western Europe, as discussed above), the forint acts as a volatility transmitter in its own system, while the period from 2020 onwards is quite ambiguous, signalling the Hungarian economy's increased exposure to commodity market-related news, especially in relation to Russia. Pairwise, in this system, the rouble acts as a net volatility receiver, especially at the beginning of the sample period, and from 2013 onwards. This might be explained by the strengthening economic relationships between the two countries, thereby influencing market beliefs. The rouble's volatility-receiving patterns are also detectable within the frameworks of the koruna, the zloty, and the pound models, but in these cases, this effect seems to be less pronounced than in the case of the forint. Furthermore, the forint model also shows substantially larger spillovers from Brent to the system, implying the potential of global oil prices to heavily impact the forint-centred system, especially around periods when global primary energy supplies are scarce. Interestingly, this effect again is not as pronounced in any of the other models. Finally, gas prices act as net volatility receivers at the early stages of the observation period, but then smooth out and remain unaffected by any of the systems for the rest of the observation period.

4.5.Evaluation of research results

Results obtained from the analysis indicate that while there is indeed correlation between commodity prices and CE exchange rates, as well as between the EUR/RUB exchange rate and CE exchange rates, their magnitude is not particularly large.

In terms of correlation with the Russian rouble, all four exchange rates exhibit slightly negative time-varying conditional correlations, with the Hungarian forint displaying the widest fluctuation band of all four exchange rates of interest. In terms of the other three currencies, oscillations are restricted to a narrower range, while in case of the Czech koruna and the British pound, large changes in correlation are barely visible. These findings support the assumption that countries that have strong economic ties to Russia – in this case, Hungary and Poland – are exposed to larger co-movements with the Russian exchange rate than the currencies of countries who approach Russia cautiously. It is also important to note, however, that negative correlation would indicate that the forint and the zloty can potentially be considered to some extent as hedges against the rouble, a finding worthy of further research.

Regarding correlation with Brent prices, the forint, the koruna, and the pound all exhibit overall negatively correlation, while correlation is very slightly in the positive domain for the zloty. In terms of fluctuations, the forint and the zloty again are the most volatile in terms of reacting to market movements. In the case of the koruna, spikes observed in the sample period are large, but they vanish within a short period of time, signalling the koruna's resilience against market movements. Finally, the pound does not show any significant movements over time, and conditional correlations remain largely insignificant throughout the observation period. Negative correlation with most exchange rates is a plausible conclusion since all countries are net importers of crude oil and are hence heavily exposed to the global market. Nevertheless, negative correlation indicates that this relationship is more complex, and the effect of the co-movements with the U.S. dollar cannot be omitted. The analysis of such a complex relationship might serve as a good basis for future research.

At last, correlation with natural gas prices was found to be overall very insignificant for all three CE currencies. This is a plausible finding considering that all CE countries import their gas supplies by signing long-term contracts with their supplying partners, thereby mitigating market risk.

Considering the directional effects within the system, the effect of Russia-related news on the commodity markets also has some effects on Central European national currencies, which could be detected using the Diebold-Yilmaz spillover index. Out of the four systems, the forint displayed the largest exposure to movements in gas prices, crude oil prices, and shifts in the rouble's exchange rate against the euro. While volatility spillovers in case of the zloty, the koruna and the pound followed similar trajectories, in those cases, the magnitude of the spillover from the system to the individual variable was not significant. Results signal that Russian energy dependence plays a significant role in determining the off-diagonal volatility structure of the forint, thereby signalling the Hungarian currency's increased exposure to Russian-related news in terms of commodities. Still, in terms of total connectedness, the forint, the zloty, and the koruna perform similarly over the observation period. Overall, results show that the presence of Russian energy influence can be detected in the exchange rate volatility structure of Central European countries, especially for the forint and for the zloty. However, this effect is not particularly strong, and the majority of the volatility continues to be explained by each currency's own diagonal volatility structure.

5. Concluding remarks

The aim of the current thesis was to provide a detailed inspection of the effect of Russian energy dependence on the exchange rate volatility dynamics of three Central European national currencies, the Hungarian forint, the Polish zloty, and the Czech koruna. While several studies have been conducted in the topics of Russia's energy monopoly in Central Europe, exchange rate volatility and volatility spillovers in the V4 region, and the relationship between oil price and exchange rate volatility, the effect of Russian energy dependence has not yet been examined due to the complexity of the analysis. Hence, the current thesis aims to provide some new insight into this niche in academic research by focusing on two research questions. First, the thesis aims to understand the how the dependence on Russian primary energy imports impacts the Hungarian forint's exchange rate volatility. Second, the thesis aims to extend the analysis of this impact to two the two other Central European national currencies, the zloty, and the koruna.

For the analysis, univariate and multivariate GARCH modelling was used on time series data, covering the period between 2004 (marking the entrance of Central European countries to the European Union) and 2022, to allow for the effects of the Ukrainian war to become visible. To provide a benchmark for measuring the effect of Russian dependence, the British pound was chosen as a comparable currency, as Russia is a non-pivotal supplier in the British primary energy mix. In terms of variable selection, modelling used daily EUR/HUF, EUR/PLN, EUR/CZK, EUR/GBP, and EUR/RUB exchange rate returns, daily Henry Hub gas price returns, and daily Brent crude oil price returns.

Following the analysis of descriptive statistics and the necessary ARMA(p,q) transformations, residuals were used to develop three univariate GARCH(1,1) model specifications for each of the four exchange rates of interest. Model specifications in each case signalled the presence of volatility clusters and volatility persistence over time. Furthermore, GJR-GARCH and EGARCH models highlighted the significance of asymmetric shocks to all the variables. After comparing specifications, EGARCH(1,1) was found to be the best-performing model version for explaining the individual volatility structure of daily exchange rates.

To analyse the relationship between commodity prices, rouble exchange rates, and the variables of interest, DCC-GARCH(1,1) models by Engle (Engle, 2002) were applied to the four exchange rates. The analysis of joint model parameters highlighted long-term persistence in the correlation matrix. The analysis of dynamic correlation indicated that the forint exhibits the strongest (albeit still relatively weak) time-varying co-movement with EUR/RUB and Brent returns, while natural gas prices are not significantly correlated with any of the currencies. While conditional correlation patterns for the zloty, the koruna, and the pound show similar patterns over the observation period, their co-movements are not as pronounced, highlighting the Hungarian economy's increased exposure to Russia-related news on the commodities market. Finally, the findings of the DCC-GARCH models were further supported by the implications derived from the analysis of the Diebold-Yilmaz spillover index.

It is important to highlight that this analysis has several limitations. First, the current thesis uncovers interdependencies and spillover effects by considering the relational effects of variables to each other within a DCC-GARCH model. While this framework provides a flexible solution to capture time-varying joint relationships without the overcomplication of the estimation process, it fails to account for any causal relationships that would highlight the direct effect of the joint effect of variables on the variable of interest. Future research might get a better picture of the evolution of joint effects within these systems by applying more complex variable structures that allow for the investigation of causality. Second, the current thesis does not involve the U.S. dollar as a control variable, and only uses euro-based exchange rates and commodity prices. As commodities tend to be traded in dollars, changes in the EUR/USD exchange rates are also potentially influencing the equation systems, thereby creating a risk in modelling, the effects of which might be accounted for in future research. Third, in terms of variable selection, due to the hard availability of Russian commodity price data, global commodity prices were applied as proxies. As commodities might be priced differently by different suppliers, future research might attempt to obtain data for Russia-based gas and crude oil prices. Finally, further analyses might obtain more accurate results by also experimenting with a wider range of error distributions and/ or different multivariate GARCH model selections. Finally, to avoid overcomplication in modelling, the current analysis does not apply structural breaks to the time series, thereby considering the entire observation period as one time frame. The application of structural breaks, or alternatively, the separation of the observation period into sub-samples might potentially provide possibilities for a more in-depth analysis of the relationship between variables in crisis and in boom periods.

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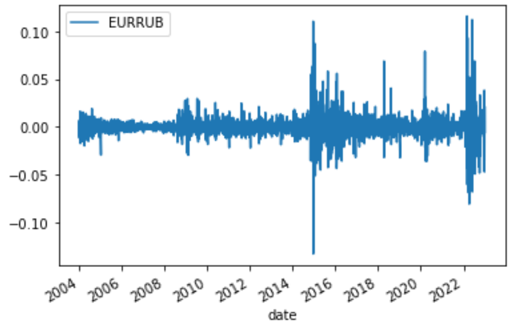
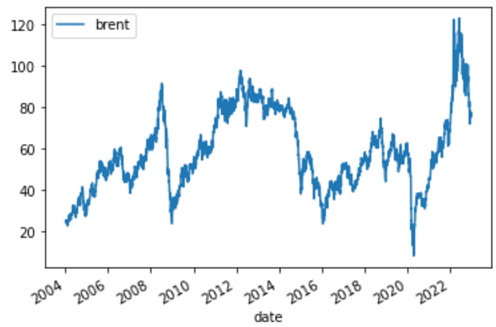
7. Appendices

7.1.Appendix 1: Daily prices and exchange rates for EUR/RUB exchange rates, natural gas, and Brent crude oil

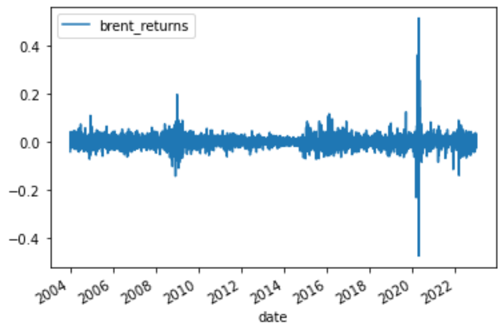
Daily closing exchange rates - EUR/RUB



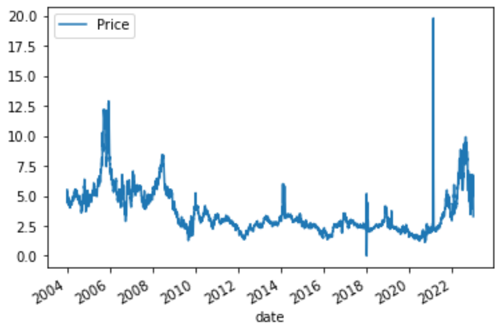
Daily exchange rate returns – EUR/RUB



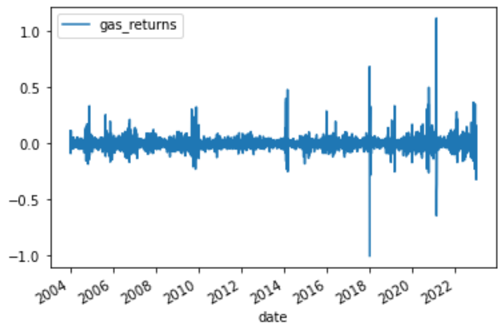
Daily closing price – Brent crude oil



Daily price returns – Brent crude oil



Daily closing price – Natural gas



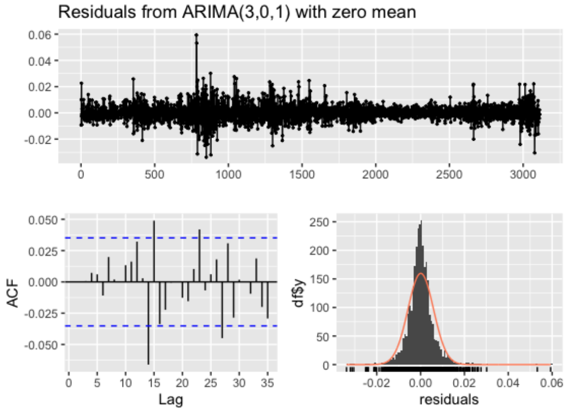
Daily price returns – Natural gas

Appendix 1: Daily prices and exchange rates for EUR/RUB, natural gas, and Brent crude oil. (source: own construction)

7.2.Appendix 2: Individual ARMA(p,q) model outputs of modelling variables

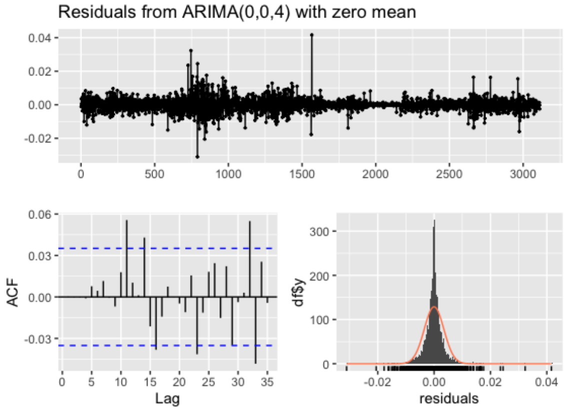
EURHUF
ARIMA(3,0,1) with zero mean

Coefficients				
	ar1	**ar2**	**ar3**	**ma1**
	-0.2235	-0.0184	-0.0408	0.1867
s.e.	0.3263	0.0219	0.018	0.3262
sigma^2	3.41E-05			
log likelihood	11590.57			
AIC	-23171.14			
AICc	-23171.12			
BIC	-23140.93			
	ar1	**ar2**	**ar3**	**ma1**
p-value	0.49338825	0.40105243	0.02356701	0.56713711
Ljung-Box test on residuals				
Q*	2.44			
degrees of freedom	6			
p-value	0.8751			



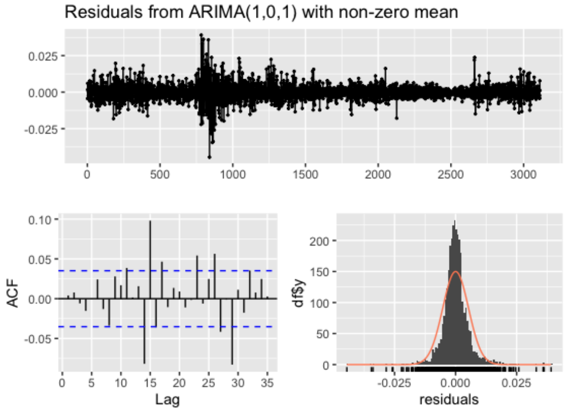
EURCZK
ARIMA(0,0,4) with zero mean

Coefficients				
	ma1	**ma2**	**ma3**	**ma4**
	-0.0429	-0.046	-0.0402	0.0268
s.e.	0.0179	0.0179	0.0179	0.0179
sigma^2	1.22E-05			
log likelihood	13195.16			
AIC	-26380.32			
AICc	-26380.3			
BIC	-26350.11			
	ma1	**ma2**	**ma3**	**ma4**
p-value	0.0167022	0.011	0.02446353	0.13348974
Ljung-Box test on residuals				
Q*	1.8199			
degrees of freedom	6			
p-value	0.9355			



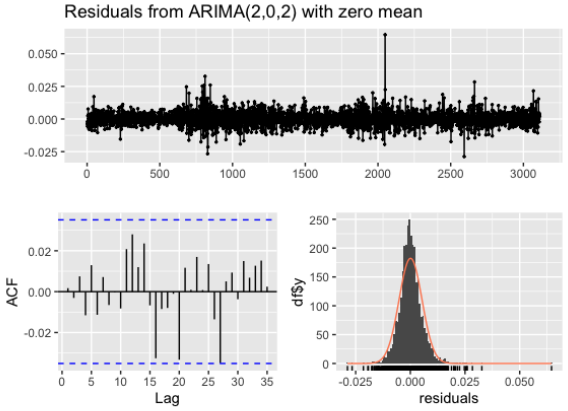
EURPLN
ARIMA(1,0,1) with non-zero mean

Coefficients			
	ar1	**ma**	**mean**
	-0.583	0.5206	2.00E-04
s.e.	0.1331	0.1393	1.00E-04
sigma^2	2.79E-05		
log likelihood	11901.15		
AIC	-23794.3		
AICc	-23794.28		
BIC	-23770.12		
	ar1	**ar2**	**intercept**
p-value	1.19E-05	1.86E-04	5.18E-02
Ljung-Box test on residuals			
Q*	10.328		
degrees of freedom	8		
p-value	0.2428		



EURGBP
ARIMA(2,0,2) with zero mean

Coefficients				
	ar1	**ar2**	**ma1**	**ma2**
	-0.1412	-0.5324	0.1451	0.4595
s.e.	0.1488	0.189	0.1558	0.1985
sigma^2	2.76E-05			
log likelihood	11919.2			
AIC	-23828.39			
AICc	-23828.37			
BIC	-23798.18			
	ar1	**ar2**	**ma1**	**ma2**
p-value	0.3427	0.0049	0.3519	0.0206
Ljung-Box test on residuals				
Q*	2.0549			
degrees of freedom	6			
p-value	0.9146			



EURRUB
ARIMA(3,0,1) with zero mean

Coefficients

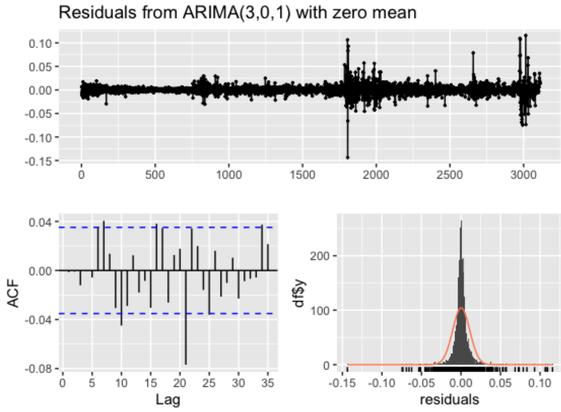
	ar1	ar2	ar3	ma1
	0.7873	-0.052	0.0571	-0.7119
s.e.	0.074	0.0234	0.0193	0.0724

sigma^2	1.17E-04
log likelihood	9674.9
AIC	-19339.79
AICc	-19339.78
BIC	-19309.58

	ar1	ar2	ar3	ma1
p-value	0	0.0259	0.00313678	0

Ljung-Box test on residuals

Q*	19.418
degrees of freedom	6
p-value	0.003513



Brent
ARIMA(1,0,0) with non-zero mean

Coefficients

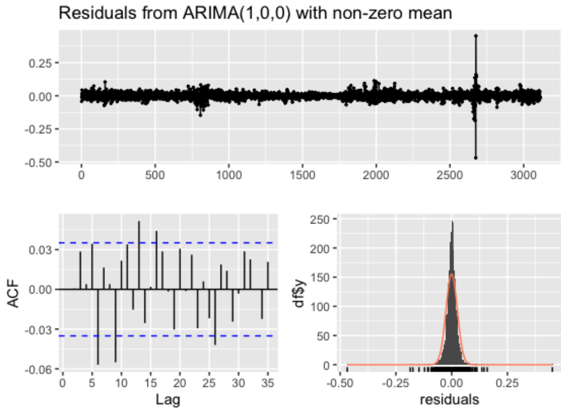
	ar1	mean
	-0,1279	0,0011
s.e.	0,0178	0,0004

sigma^2	6.44E-04
log likelihood	7017.39
AIC	-14028.78
AICc	-14028.78
BIC	-14010.65

	ar1	intercept
p-value	6.36E-13	9.11E-03

Ljung-Box test on residuals

Q*	28.186
degrees of freedom	9
p-value	0.000888



Henry Hub natural gas
ARIMA(4,0,0) with zero mean

Coefficients

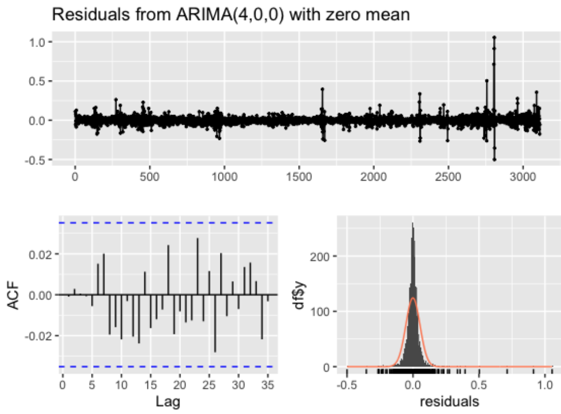
	ma1	ma2	ma3	ma4
	0.0251	-0.0917	0.0491	-0.1227
s.e.	0.0178	0.0178	0.0178	0.0179

sigma^2	2.89E-03
log likelihood	4685.15
AIC	-9360.3
AICc	-9360.28
BIC	-9330.09

	ma1	ma2	ma3	ma4
p-value	1.59E-01	2.68E-07	5.82E-03	6.27E-12

Ljung-Box test on residuals

Q*	5.5561
degrees of freedom	6
p-value	0.4747

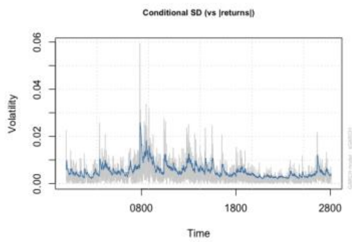


Appendix 2: Individual ARMA(p,q) model outputs of modelling variables. (source: own calculations)

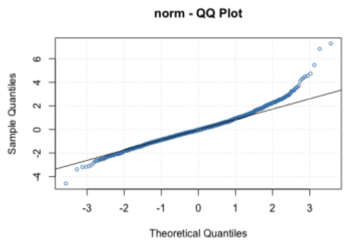
7.3.Appendix 3: Modelling and forecasting accuracy plots

SGARCH(1,1) models

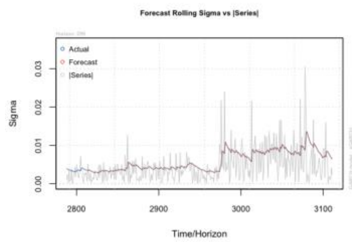
EUR/HUF



Conditional standard deviation

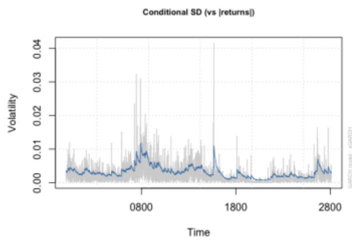


QQ plot

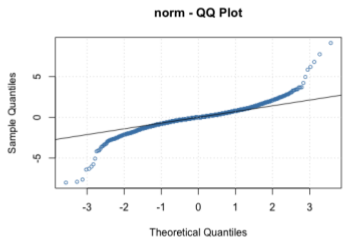


Forecasted against actual volatility

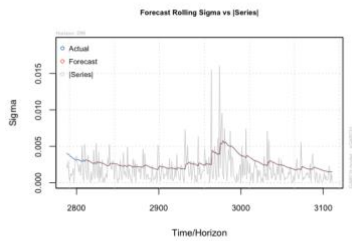
EUR/CZK



Conditional standard deviation

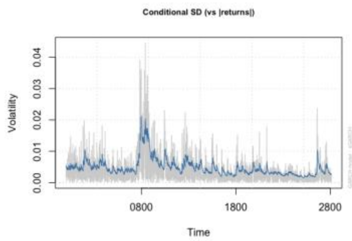


QQ plot

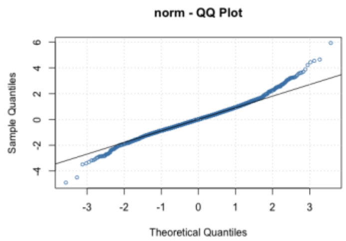


Forecasted against actual volatility

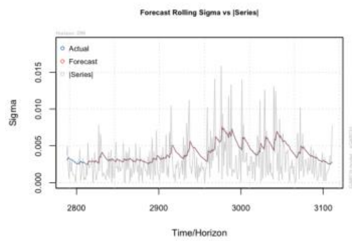
EUR/PLN



Conditional standard deviation

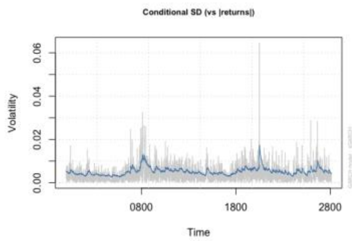


QQ plot

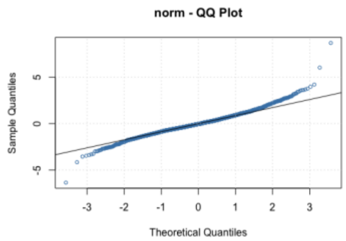


Forecasted against actual volatility

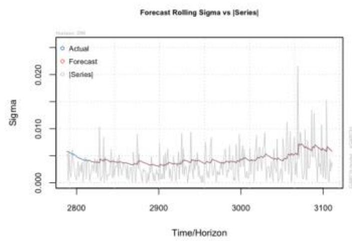
EUR/GBP



Conditional standard deviation



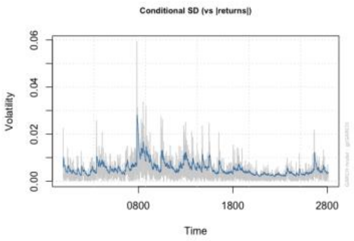
QQ plot



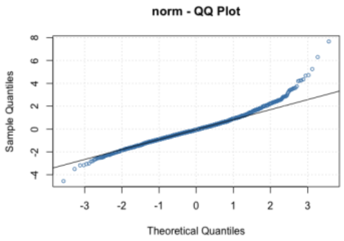
Forecasted against actual volatility

GJR-GARCH(1,1) models

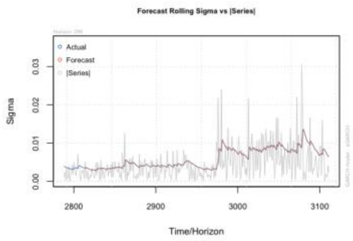
EUR/HUF



Conditional standard deviation

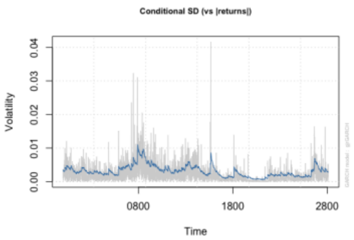


QQ plot

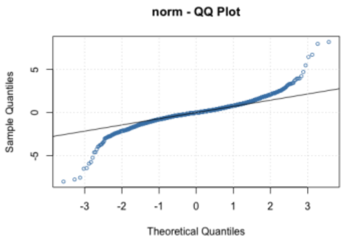


Forecasted against actual volatility

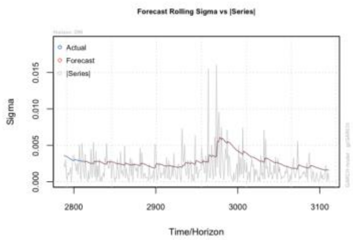
EUR/CZK



Conditional standard deviation

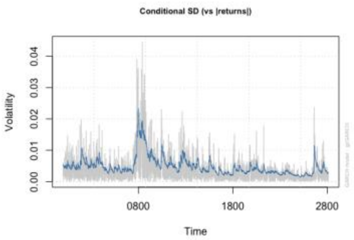


QQ plot

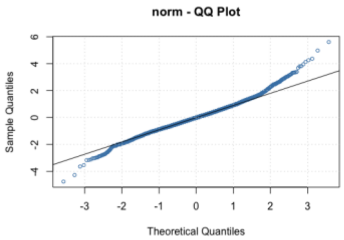


Forecasted against actual volatility

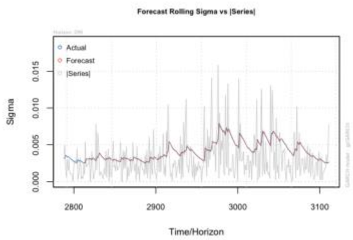
EUR/PLN



Conditional standard deviation

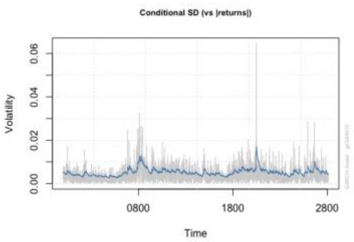


QQ plot

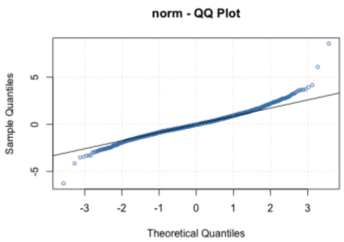


Forecasted against actual volatility

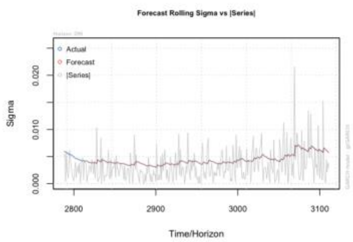
EUR/GBP



Conditional standard deviation



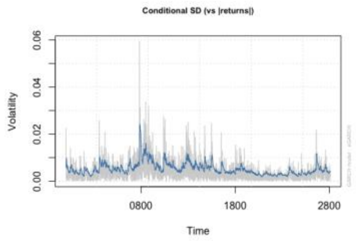
QQ plot



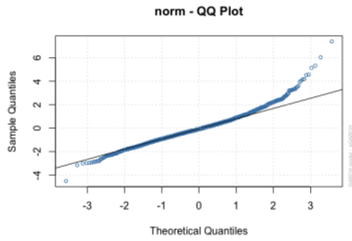
Forecasted against actual volatility

EGARCH(1,1) models

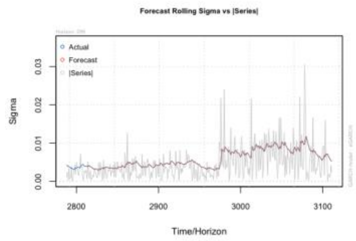
EUR/HUF



Conditional standard deviation

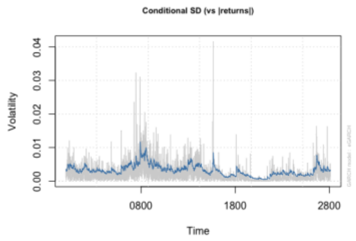


QQ plot

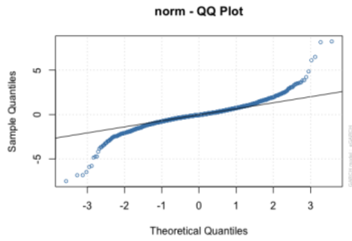


Forecasted against actual volatility

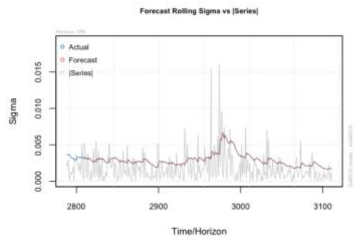
EUR/CZK



Conditional standard deviation

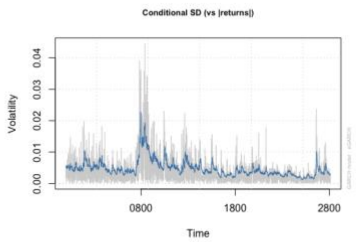


QQ plot

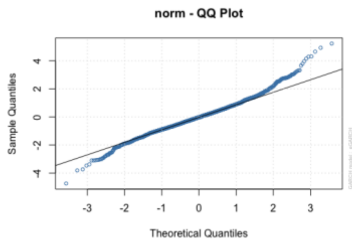


Forecasted against actual volatility

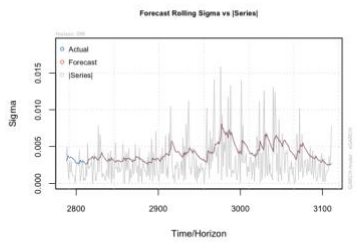
EUR/PLN



Conditional standard deviation

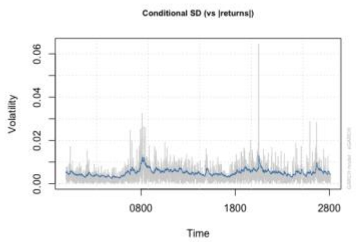


QQ plot

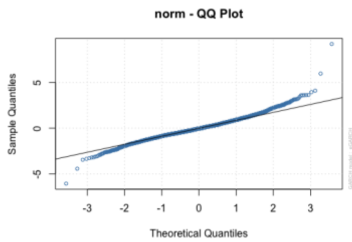


Forecasted against actual volatility

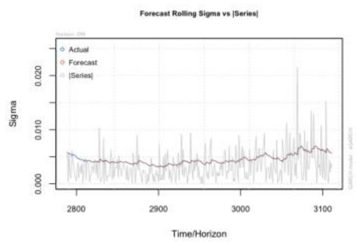
EUR/GBP



Conditional standard deviation



QQ plot



Forecasted against actual volatility

Appendix 3: Modelling and forecasting accuracy plots. (source: own calculations)