# EVOLUTION OF EFFICIENCY IN ELECTRICITY MARKETS

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# EVOLUTION OF EFFICIENCY IN ELECTRICITY MARKETS

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# DECLARATION OF ORIGINALITY

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# ABSTRACT

## Evolution of Efficiency in Electricity Markets

This study aimed to analyse the change in efficiency in spot and future electricity markets in selected European countries through the measured period considering the market couplings. We have analysed ten different countries' spot and futures markets using five efficiency measures. We have used entropy measure to understand the randomness in the markets. Our tests to calculate the Hurst measure has aimed to capture the long-term memory in the price series. We used fractal dimension to measure the roughness and irregularity of price series. Ex-post risk premiums are calculated to understand the spot and future market relations. Expected spread analysis has provided insight regarding the liquidity in the markets. Based on quantitative analysis, we can conclude that these markets carry some common characteristics. We can also point out that there is progress towards less inefficiency in the markets, especially after introducing structural and regulatory changes. Application of moment statistics and regularity statistics on such a data set helps make broader deductions. Finally, our results provide insight into the expected structures of other markets if they follow similar developments.

# ÖZET

## Elektrik Piyasalarında Verimlilik Gelişimi

Bu çalışma, seçilmiş Avrupa ülkelerindeki spot ve vadeli elektrik piyasalarındaki verimlilik değişimini, piyasa birleşmelerini dikkate alınarak ölçülen süre boyunca analiz etmeyi amaçlamıştır. Beş verimlilik ölçütü kullanarak on farklı ülkenin spot ve vadeli işlem piyasaları incelenmiştir. Piyasalardaki rastgeleliği anlamak için entropi ölçütü kullanılmıştır. Hurst ölçütünü hesaplamaya yönelik testlerle, fiyat serilerindeki uzun süreli hafıza davranışının yakalanması amaçlamıştır. Fiyat serilerinin pürüzlülüğünü ve düzensizliğini ölçmek için fraktal boyutları hesaplanmıştır. Ardıl risk primleri, spot ve vadeli piyasa ilişkilerini anlamak için hesaplanmaktadır. Tahmini alım satım marjı analizi ise, piyasalardaki likidite hakkında fikir vermektedir. Nicel analize dayanarak, bu pazarların bazı ortak özellikler taşıdığı sonucuna varabiliriz. Özellikle yapısal ve düzenleyici değişiklikler sonrasında piyasalarda daha az verimsizliğe doğru ilerleme kaydedildiğini de belirtmek mümkündür. Moment istatistiklerinin ve düzenlilik istatistiklerinin böyle bir veri seti üzerinde uygulanması, daha geniş çıkarımlar yapılmasına yardımcı olmaktadır. Son olarak, sonuçlarımız, benzer gelişmeleri takip etmeleri halinde diğer pazarların sahip olabilecekleri yapı karakterleri hakkında da fikir vermektedir.

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As Mustafa Kemal Atatürk said, "The truest guide in life is science." I am very happy to be able to contribute even a drop to this ocean of science.

This dissertation is dedicated to my father.

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# ABBREVIATIONS

| | |
|---|---|
| ADF | Augmented Dickey-Fuller |
| ApEn | Approximate entropy |
| BE | Belgium |
| CALPX | California Power Exchange |
| CH | Switzerland |
| CWE | Central West Europe |
| CZ | Czechia |
| DE | Germany |
| DFA | Detrended fluctuation analysis |
| EEX | European Energy Exchange |
| EMH | Efficient Market Theory |
| ES | Spain |
| FR | France |
| GARCH | Generalized Auto Regressive Conditional Heteroskedasticity |
| GB | United Kingdom |
| GPH | Geweke & Porter-Hudak |
| HHI | Herfindahl-Hirschman Index |
| HU | Hungary |
| IT | Italy |
| M+1 | Month ahead |
| NL | Netherlands |
| OLS | Ordinary least squares |
| OTC | Over the Counter |
| PJM | Pennsylvania, New Jersey, and Maryland System Operator |
| R | R programming tool |
| TSO | Transmission system operator |
| WLS | Weighted least squares |

# CHAPTER 1

# INTRODUCTION

Energy markets have been in the scope of economic debates as they directly and indirectly affect the rest of the economy as the primary cost source. Electricity markets are unique components of energy markets. While most countries are controlled by governments and closed to competition, they have been part of liberalization among the European countries in the last 30 years. Within the course of this process, mostly vertically integrated monopolistic structures have begun to deconstruct.

Today still, there are dominant power producers in many European countries, which is not a preferred situation for competitive markets. However, there have been regulatory changes to promote competition with the entrance of new investments and alleviated cross border trades. The backbone of the electricity markets is the day ahead (spot) markets, and market couplings are the cornerstones of the integration of European electricity markets. Following several EU directives and agreements, a single European target model is being implemented ongoing. Even though there are agreements on the target model framework, there are significant differences among the countries regarding the electricity markets. It is also believed that long-term trading can develop purely with commercial activities if the abovementioned spot markets function efficiently. However, there is no agreement among the stakeholders to which extent these markets are efficient.

This study aims to understand the evolution of efficiencies in the European electricity markets in line with the changes and the developments throughout the analyzed period. A proper understanding of the efficiency of the electricity markets is vital as they also impact long term investments and hedging decisions of companies and financial institutions.

The Efficient Market Theory (EMH) of Fama (1970) has always been the primary framework for efficiency analysis in finance theory. We focus on the weak and sem-strong form of the theory that all information is reflected in the prices.

The scope of our study will be to revisit the existing literature on the efficiency subject and apply five different measures to catch the moment and regularity statistics of the price series. We focus on ten European markets for the periods 2008 to 2021. This period includes intensive changes in the markets and different global events such as the Fukushima nuclear disaster, Covid-10 lockdowns, and Brexit.

Our study aims to fill the gap in the research on the efficiency and the electricity markets by providing insights by measuring the implications of structural changes in financial terms. We will approach the target markets by evaluating subsamples selected according to the structural breaks, namely the market couplings. Moreover, we will not only focus on the spot markets, but we will also show the futures markets' results while evaluating the spot-futures price relations. Our analysis will be cross country, cross-product and across different periods. It can provide insight into the expected structures of the electricity markets after intended policy changes.

The dissertation is organized as follows. Chapter 2 provides general information on electricity markets and the background of policy developments. Chapter 3 includes the literature review on the Efficient Market Hypothesis and empirical studies on efficiency tests of electricity and other commodity markets. Chapter 4 explains the methodology used in the analysis throughout the study. Theoretical backgrounds of the test are provided meticulously. The data set is described in chapter 5. Chapter 6 hosts the detailed results for each test measure, followed by a discussion part where the outcomes of the results are discussed in detail. Chapter 7 concludes the study. Detailed results of the tests in Chapter 6 are presented in Appendixes A to F.

# CHAPTER 2

# ELECTRICITY MARKETS OVERVIEW AND BACKGROUND

In order to understand the mechanism of electricity markets, it is essential to understand the characteristics of the underlying product: electrical energy (electricity). This is because some basic properties of electricity play a vital role in designing markets worldwide.

## 2.1 Characteristics of electricity as commodity

Firstly, electricity is considered an almost non-storable commodity in its form. This fact leads to the point that demand and supply in the system should continuously match. Otherwise, system crashes or severe electricity cuts can occur. It requires active management of the system in real-time or finding solutions to missing or excess demands or supplies in the system. It is known that battery technology has been developing rapidly in recent years; however, the installed power level and output performance are far from keeping the macro grids online. Therefore, their effects can be negligible or not commercial. However, the developments in the near future carry the vast potential to reshape the electricity markets.

Other properties of electricity require unique approaches too. Since electrons always flow towards the least resistance, it is impossible to change flow direction via interventions from outside. System operators must respect the transmission lines' capacity and decrease the supply if the capacities are reached. Otherwise, the whole system can face outages.

During its journey to the least resistant area, the electricity's speed equals the light speed. This phenomenon makes any momentary touches on the system impossible. In other words, system operators have to manage the perfect match of demand and supply and flow of the electricity before the delivery term. (The delivery term is the moment when the electricity is produced and consumed in real-time.) In most modern markets, the decisions and planning are handled one day before, in day ahead markets. Day ahead markets are the main markets where the prices occur. (The prices used in this study refer to day ahead prices.) The market participants schedule their programs accordingly once the demand and supply are matched for the following day.

Due to the complex nature of the electricity systems, a possible variation due to physical constraints from the day ahead schedule might cause severe issues in other parts of the grid. Therefore, system operators must be sure to allocate some of the production units for emergency cases to manage the system's frequency, voltage, and stability. In addition, the system operator controls another market called the "balancing market" in most markets, where the last resort power supply is managed. While the participation of the demand side of the market into the balancing mechanism is possible in certain countries, the balancing is handled by decreasing and increasing the production in the majority of the markets.

In modern electricity markets, with the great support of technological progress such as real-time data collection, it is possible to make trades with other market participants even after the scheduling deadline. This specific market is called the intraday market. It allows market participants to match each other's positions before the delivery term so that the system operator does not need to run the balancing mechanism. In some markets, intraday trading is possible until 15 minutes before the real-time delivery.

## 2.2 Components of electricity markets

Physical electricity markets consist of generation, consumption, transmission and distribution systems. Each of these systems plays a vital role in balancing supply and demand.

Production is the activity of converting different energy sources into electrical energy in power plants. The unit electricity production cost of each power plant differs. These differences may be due to the cost of resources used or initial capital investments such as renewable energy, where marginal cost is almost negligible. In profit-driven liberal markets, all power plants aim to work for a profit. However, depending on their costs and profit targets, each requires a different price level that would make them operational. For example, renewable energy plants prefer to work at every price level because they do not have marginal costs. In contrast, natural gas conversion plants operate at prices above their fuel costs.

Power plants, which can prepare a generation plan based on intervals ranging from 15 minutes to one hour, are grouped by the system operator according to their costs and flexibility. Baseload generating plants, such as nuclear power plants, usually operate continuously because their marginal costs are low, but they cannot react flexibly. Power plants with more flexible working opportunities meet a significant part of daily production because they can be quickly activated. In addition, there are power plants that can operate more flexibly but consume more expensive fuel. They are mostly used in emergency cases. The expected demand is the basis for the activation of all these different sources. The price formation that will be discussed in the following sections actually depends on the commissioning of these power plants.

The demand side of the markets is consumption. The necessity of equal supply and demand due to the nature of electricity reveals that consumption plays a vital role at least as much as production. It includes the daily consumption of millions of people and industries, large buildings and facilities. Of course, in many markets, small consumers deal with regulated tariffs, not directly at market prices. However, the demands of consumers are also effective in the price formation in the markets. This shows that any factor that may affect electricity consumption may affect prices. In addition, unlike many commodities and products, the price elasticity of the end-users is deficient. Considering the abovementioned characteristics and the negligible demand elasticity, spot prices are very sensitive to short term uncertainties. (Bunn and Chen, 2013)

Another essential element of the electricity market is the transmission system. It connects the production and consumption systems through high voltage lines. Due to their high investment costs and their existence in public spaces, these systems are monopolistic and state-owned in many countries. Transmission system operator (TSO) institutions manage these transmission systems. Some countries may have more than one TSO, but only one operates in a specific area. Independent system operators operate on the basis of regions in almost all of the European markets, which are the subject of this study. There are similar market designs in all of them.

TSOs are also natural players in the energy flow between countries. Because, depending on the properties of electricity mentioned above, they must act in harmony. They operate the lines between countries and ensure that electrical energy flows from excess supply to excess demand with hourly or even 15-minute planning. They must also control frequencies, interruptions, and fluctuations in their territory and cross-border transactions. Since these capacities also indicate the amount of energy that can enter or exit the market, they play an essential role in forming prices according to the size of the market. As examined in this study, as the harmony between the markets increases, the efficiency in capacity utilisation between countries increases and the losses decrease.

Distribution services play a crucial role in electricity markets as well. That is because distribution systems cover energy transport in high voltage systems at low voltage to reach the end-user using the electrical infrastructure distribution systems that one encounters daily.

In a market where different actors play a role, pricing is needed, which would guide the investments as an indicator. This paved the way for energy exchanges. With the price formation, productivity differences between regions and countries and new investments emerged. The European market, which is the subject of the study, has been liberalised with almost similar methods.

### 2.3 Pricing mechanisms

For the competitive pricing principle to work, the connection of the producers to the transmission system should be ensured so that they can submit their offers. Auctions are opened for each hour of the delivery day, mostly one day in advance. This period has been reduced to 15 minutes in some countries. Prices in this auction are called day ahead prices and are considered market prices. Although the algorithms of the models differ between markets, the "merit order" system is widely used. This is the price ordered by the producer at the point where the demand is met. The purchase price is determined that way for all manufacturers. It is believed that this situation causes severe price fluctuations but increases productivity in the long run.

Figure 1 exhibits an example of merit order pricing. Consumption demand can be met only if natural gas power plants start operation.

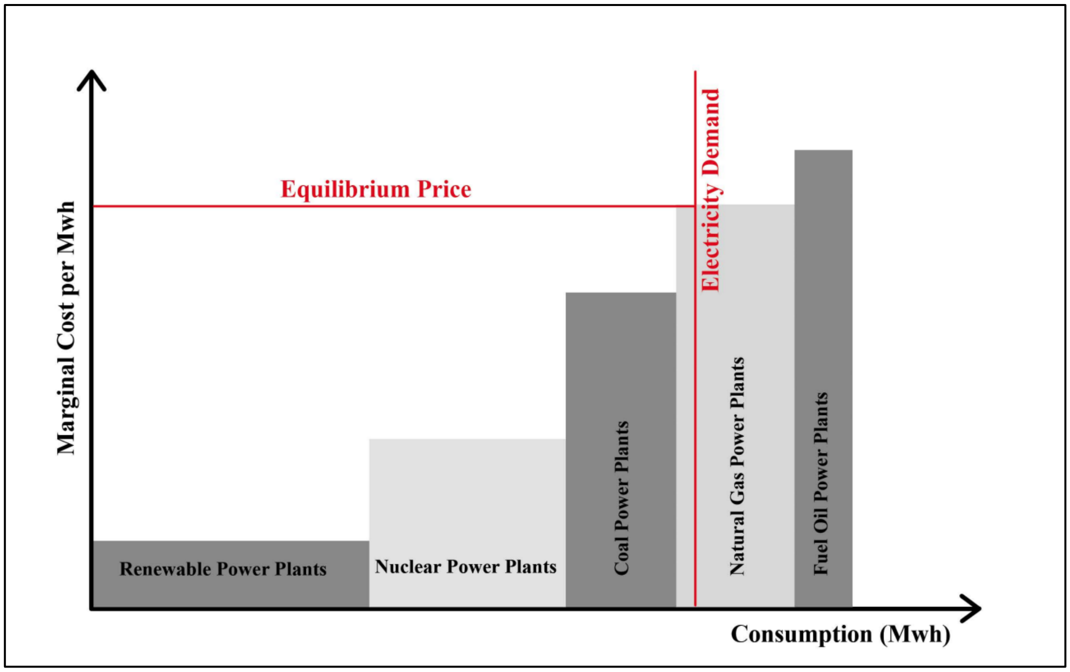

Figure 1.  Merit order price formation

Accordingly, the price for that hour would be determined on the marginal cost level. The difference between the equilibrium price and marginal cost for other power plants is marginal profits. Since there are different types of offers according to the characteristics of the markets, prices are calculated by optimising via complex computer calculations. Although there may be other approaches according to the needs of each market, there are similar models that try to solve the same problem. As (Acemoglu, Kakhbod, and Ozdaglar 2017) state, pooling markets are where suppliers and consumers put their offers to a centrally operated pool and then an equilibrium price is calculated. In OTC markets, these two parties agree separately and inform the system operator about the transaction.

Although the balance was achieved in the day ahead markets, both intra-day and balancing markets were formed because real-time production and consumption forecasts would not be exactly as planned. Intraday markets work with the logic of stock exchanges by matching open buy and sell offers. These markets are based on the principle that a participant with energy surplus delivers energy to another one in shortage. However, the balance may be a problem in real-time even after these transactions. At this stage, the system operator ensures the balance in the system by using the producers and consumers who can step in or out quickly. In many countries, having to buy or sell in the balancing market involves paying a penalty. Therefore, each participant tries to make the best forecast the day before.

In addition to trading in the day ahead and intraday markets, there is also "forward trading", defined as the delivery of electrical energy over extended periods. Electricity forward contracts represent the obligation to buy or sell a fixed amount of electricity at a pre-specified contract price, known as the forward price, at a specific delivery time. Electricity forwards can be tailored according to the needs of the counterparties. "Baseload" forward contracts, which involve delivering equal power over 24 hours, provide energy delivery on a day, weekend, week, month, quarter, or year. Special contracts, such as "peak" contracts, provide continuous delivery during the day only (e.g., 7 am to 9 pm). There may be blocks of other timeframes as well.

Since final consumers can consume at their connection capacity as they wish, producers face real-time volume uncertainty due to the problems of power plants or random generation regimes of renewable sources such as wind or solar. Therefore, the risk of reaching the desired volume can be managed by using different contracts as the delivery time approaches. For example, the trading company can purchase baseload energy according to its average demand with a forward contract of one or two years. It can then profile its need with quarterly, monthly, and weekly contracts. Payment is made according to the difference arising from the finalised price in a predetermined term. This practice increases the liquidity in the market as it eliminates the collateral requirement in long-term transactions. (Kristiansen, 2007)

Electricity futures have the same payoff structure as electricity forwards. However, like other financial futures, electricity futures are well regulated for contractual terms, transaction requirements, and trading venues. Another noteworthy difference between electricity futures and forwards is the quantity of power delivered. The delivery quantity specified in electricity futures contracts is often significantly smaller than that in forward contracts traded over the counter in bilateral transactions. Since electricity futures are exclusively traded in organised platforms by numerous market participants, their prices reflect a broader consensus of the market compared to forward contracts designed according to the needs of the counterparties involved. (Deng and Oren, 2006)

## 2.4 Cross-border trade

International trade in electricity is minuscule by the standard of overall trade in goods and services. However, between 2010 and 2019, an average of 80 countries reported activity of electricity export. (Source: Comtrade UN data) Taking island states and non-existing interconnection lines in a lot of countries into consideration, it is relevant to claim that electricity is commercialised internationally. Unlike the other commodities, electricity can be traded physically only via unique cable connections between countries called interconnectors. An electricity interconnector is a cable connecting two different markets or pricing areas. (In some countries, there is more than one pricing zone. i.e.. Italy)

As stated by Antweiler (2016) cross-border power trade has unique characteristics that differentiate it from conventional trade. There are physical constraints due to the capacity of the transmission lines on the tradeable amount. Moreover, the trade can be in two ways simultaneously, unlike the conventional international trade. Therefore, it is not very common to position a market as all-time exporter or importer of electricity.

## 2.5 Market integration and couplings

In order to develop the integration and competition in the energy sector in which national markets can develop in coordination with each other, alignment in strategic policies should have been a priority.(Karan and Kazdağli, 2011) European Union has issued directives to open the markets (e.g. Directive 2003/54/ EC), reduction of obstacles to cross-border trades (Regulation 1228/2003) and guarantee of access to the networks for the third parties (e.g. Directive 2003/54/EC).(Zachmann, 2008) As stated by Karan and Kazdağli (2011), European Commission has taken steps to encourage each member to progress towards a more integrated market. Furthermore, European Commission issued additional directives to challenge the divergences across the countries (Directive 25009/75/EC, 2009) with a clear target of an integrated single European market (Morales and Hanly, 2018).

Integrated markets can be considered "super-grid"s where cross border flows are an integral part of the electricity market. "Market coupling" is another definition for transforming cross border bilateral trades into transactions occurring under super-grids where exchanges operate in a harmonised way.

According to Antweiler (2016) these mechanisms provide several environmental and economic benefits. The ability to deliver the power to more distant markets is an incentive for increasing the generation capacity. As renewable energy sources complement conventional production methods, greater integration can improve system reliability, leading to environmental production. Abrell and Rausch (2016) states that thanks to the renewable energy penetration, European level enhanced cross-border power trade has the potential to create 1.6-2.6 billion USD per year, according to 2011 figures.

Nevertheless, the growing share of renewable energy requires increased transmission capacities and integrations (Antweiler, 2016). Poplavskaya et al. (2020) also states that the efficiency of congestion management should be increased to add more renewable resources to the European system. Moreover, balancing annual demand variations could have been more difficult without integration. (Bahar and Sauvage, 2013)

# CHAPTER 3

# LITERATURE REVIEW

In the following section, studies that draw the framework of efficiency theory in financial markets are summarized and followed by empirical studies specifically on energy related commodity markets.

## 3.1 Efficient Market Theory

Initial milestones for efficient markets can be traced down to Robert Brown, who has examined the behaviour of flower pollen grains in water (Brown, 1828). He noticed that the movement of grains is random as a result of sensitive compounds with water molecules. Later on, those movements which to be named Brownian motion are applied to capital markets by French mathematician Louis Bachelier. In his study (Bachelier, 1900), he defended that government bond prices reflected expectations about buyers and sellers' past, today, and future. Thus, there would not be any expectation of price rise or fall in a balanced market. Since then, there have been numerous studies to discover the structure behind the movements of the market prices. Milestones in financial research have been published where the random walk of the prices has been discussed dominantly. (Sewell, 2011)

The term “efficient” was first used in Fama’s (1965) article. He defined an efficient market as

*“a market where, given the available information, actual prices at every point in time represent very good estimates of intrinsic values.”*

The same year (Samuelson, 1965) published “Proof that properly anticipated prices fluctuate randomly”, in which he provided the first formal economic argument for “efficient markets” without using the term “efficient”(Delcey 2019). He focused on the concept of a martingale.

In his famous article Fama, (1970), explained three levels of market efficiency. According to Fama, if there is no change in an efficient market where all the information is reflected in the prices, there is only one reason for this: unexpected new information does not reach the market. The security price will move up or down in the face of such information. However, the increase or decrease will be balanced by a large number of unimportant events in favour of the price coming to the market and the small number of significant adverse events. This situation in securities prices is due to the martingale feature of the prices. The Martingale feature means that the gambler’s situation in the next round will not differ from his current situation in a fair game. Fama stated that EMH is closely connected to the random walk theory for this reason.

Fama stated that there could be three different activity levels in the securities market. If current and past prices do not provide a meaningful prediction of future price changes, the market is weak-form efficient. Therefore, using past prices, technical analysis methods that predict future market changes will not work.

If the current price of stocks reflects all publicly disclosed information, then the market is semi-strong form efficient. The semi-strong form also includes the weak form efficiency. As a result, fundamental analysis methods for estimating returns using firm-sector-economic variables will not work in these markets.

A market is strong-form efficient if prices reflect all available information, public or confidential. Prices also reflect “insider information”.

According to the review of Sewell (2011), only less than half of the literature related to EMH supports the efficiency of the markets. The majority of the oppositions were during the 1980s and 1990s, mainly to the ability of prices to “fully” reflect the information set. As it is widely accepted, it is not possible to measure a strong form of efficiency except for some models that can “estimate”. Nevertheless, in his 1991 article Fama states that short horizon returns (daily, weekly) can be predicted, which would be against the strong form of EMH (Fama, 1991). Accordingly, the vast majority of the literature for efficiency testing focuses on weak and semi-strong forms of EMH.

Later on, behavioural finance studies increased the contradictions to the theory as inefficiencies are not only results of irrational behaviours or irrational decisions are not only taken by the amateurs. (Degutis and Novickytė, 2014)

According to Danthine (1977) tests of market efficiency are simultaneous tests of the efficient utilisation of information and the possibility of expressing market equilibrium in terms of expected returns. Cochrane states that efficiency is ideal in perfect competition and supply and demand equilibrium of real-world markets in a recent article(Cochrane, 2014). Accordingly, empirical works would find how far a market is from that ideal point.

Finally, in a recent interview(Chicago Booth Review, 2016), Fama states that EMH is not always true, but it is a model to build strategies on. He says we know that markets are not efficient, but the question is how inefficient they are.

## 3.2 Empirical studies

Higgs & Worthington (2003) tested the informational efficiency of the Australian spot electricity markets. Since there was no well-functioning electricity market, they utilised prices in regional electricity spot markets from 1999 to 2001. To test the existence of random walks in the prices they used multiple variance test statistics with both homoscedastic and heteroskedastic variances. They used Chow and Denning's well-respected methodology described in the 1993 article, extending Lo & MacKinlay's (1988) procedure. These are the methods used in this study for testing multiple variance ratios. As expected, their results showed that Australian spot electricity prices do not follow a random walk, so they are not informationally efficient. Those prices, especially in South Australia and Queensland, were forecastable using autoregressive modelling techniques.

In another publication from 2003, Shawky et al. analysed the statistical properties of wholesale electricity spot and futures prices in the New York Mercantile Exchange for the physical delivery at the California- Oregon border. The authors believe that the characteristics of the electricity market are consistent with the efficient markets. They estimated minimum variance hedge ratios between spot and futures markets for daily and monthly products for the years 1998 and 1999 by using GARCH specification. They concluded that even though the calculated hedge ratio of 1.629 was higher than the expected value for other commodities, it was acceptable due to high volatility in electricity spot prices. Furthermore, they proved the dynamic relation between spot and futures return by using a vector autoregression which showed that positive shocks to spot prices have more impact on electricity prices than future prices.

Arciniegas et al. (2003) had one of the pioneering studies comparing efficiency degrees of different electricity markets. Their study aimed to answer if the inefficiency of the electricity market had a significant role behind California's energy crisis in 2000. They performed three tests to measure the efficiencies of California, New York and PJM (Pennsylvania region) electricity markets from 1998 to 2001. Firstly, they evaluated the predictability of the prices by testing their stationarity using the Augmented Dickey-Fuller (ADF) unit root test. It was counted as efficient if both the day ahead and real-time prices were stationary for a specific hour. As the number of such hours increased, efficiency increased accordingly. Secondly, they looked for the arbitrage opportunities by comparing the expected returns in the day ahead and real-time prices using the cointegration analysis. In the efficient conditions, these two markets are expected to be cointegrated. Thirdly, they analysed if persistent price differences existed between the day ahead and real-time markets. In an efficient market where the day ahead price incorporates all available information for all market participants, real-time prices should converge to the day ahead prices. Finally, using an OLS estimator, the authors measured the hours in which the day ahead prices were unbiased predictors of the real-time prices.

As a result of the above tests, the authors pointed out that California and PJM markets' efficiency improved over time while the markets matured. Furthermore, the crisis in California was not related to a lack of efficiency. On the other hand, in another study, the California electricity market was far from being sufficiently competitive (Borenstein & Holland, 2005). Even though the authors do not approach the subject within the frame of the EMH, they show evidence that the structural characteristics of the market can affect its efficiency. They prove that any interventions to favour a segment of the market participants, such as flat-rate pricing for consumers or capacity subsidies, distort the market and weaken the efficiency.

Another methodology suggested for evaluating the efficiency of the electricity markets was measuring the correlation with the fuel prices (Lu, Dong, and Sanderson 2005). The authors used the Australian National Electricity Market data to analyse if the electricity market can accurately do price signaling. The correlation of daily prices proved that electricity and gas prices are positively related, but it failed to illustrate how quickly the market reacts to fundamental changes.

An approach similar to our methodology was in the study of Uritskaya and Serletis (2008). They measure efficiency as the deviation from the efficient market condition. They use the detrended fluctuation analysis (DFA) algorithm to identify scale-dependent fractal exponents to detect price correlations in different time scales. Their approach let them identify intrinsic autocorrelations stemming from memory effects. Accordingly, they can gather quantitative information on the distribution of price correlations for different time scales. The authors applied their methodology to two electricity markets, Alberta and Mid-Columbia (Mid-C), and the AECO Alberta natural gas market for 2001 to 2006. Their results showed that price fluctuations are significantly different from a Brownian walk for both electricity markets, while the AECO Alberta Gas market was more consistent with the efficient market hypothesis.

In the study, which used the data from the term just before the analysed period in our analysis, Growitsch and Nepal (2009) tested the efficiency of the German wholesale electricity market using the data from European Energy Exchange (EEX) future markets and OTC prices between 2005 to 2008. They analysed the efficiency and liquidity of the market by using cointegration analysis and error-correction modelling. Their finding suggests that EEX cannot provide efficient price reference to the power market as it lacks liquidity. On the other hand, wholesale electricity prices are integrated with EEX prices, which help stabilise the market's volatility. However, their econometric results had shown that the market still lacks efficiency.

Yang et al. (2009) analyse the efficiency of one of the oldest electricity markets, the Nordic electricity futures market, between 1996 and 2003. The authors evaluate the efficiency of the market from three aspects, namely the market validity, the price discovery function and the hedge function. A validity test is performed by using a variance ratio test considering the heteroscedastic and non-stationary nature of the prices. The results support that the prices have a random walk process; in other words, the market satisfies the weak-form efficiency.

Additionally, the Z score improved significantly after Denmark and Finland joined the second stage (2000-2003). The price discovery function is tested by cointegration theory. They proved that futures and spot prices are cointegrated. Finally, the hedging performance of the market is evaluated based on the generalised autoregressive conditional heteroskedasticity (GARCH) model. According to the results, it is possible to reduce the market risk to a certain level. It is possible to conclude that the Nordic electricity market has moved towards efficiency as trading mechanisms and liquidity improved through the years.

Capitán Herráiz and Rodríguez Monroy (2008) used monthly and quarterly futures contracts between august 2006 and September 2008 to analyse the efficiency of Spanish, German and Nordic power markets and the brent oil, natural gas and coal markets by evaluating ex-post risk premiums. They point out that average risk premia have been positive in power and gas markets while negative in coal and brent oil markets. Their finding supports that even though forward risk premiums diminish as the delivery term approaches for each futures contract, they still carry a considerable amount of risk premium, showing the inefficiency of the markets.

Haugom and Ullrich (2012) used real-time and day ahead prices in the PJM electricity market for the period 2000 to 2010 for analysing the time-varying relationship between them. Their results show that the market is matured, and there is no consistent evidence that market participants can gain economic profit using recent data. Moreover, the day ahead prices have converged to be unbiased predictors of the real-time prices. Asan and Tasaltin (2017) applied similar tests to the Turkish electricity market by using the hourly day ahead (spot) and real-time prices between 2009 and 2016. The authors tested if there existed arbitrage opportunities between the two markets. The study supports a positive ex-post risk premium in the day ahead prices, especially during high demand hours. On the other hand, risk premium converges to zero over time when rolling estimations are used, which is a sign of evolution towards efficiency in the market.

Kristoufek and Lunackova (2013) analysed the long-term properties of the hourly day ahead spot electricity prices in the Czech Republic between 2009 and 2012. Authors apply detrended fluctuation analysis, which is also controlled by another long-term memory test GPH estimator. Their approach allowed them to separate seasonal effects from long term memory. Their result for the Hurst exponent is approximately 1.1, which is under the Hurst score of 1.5, meaning that the analysed electricity prices are non-stationary but strongly mean-reverting. This property distinguishes electricity prices from other financial assets, compliant with the unique property of non-storability.

Kristoufek and Vosvrda (2013)'s work in which the authors analysed the efficiency of 25 different commodities has considerably influenced our study. The authors utilised the Efficiency Index(EI) proposed in Kristoufek and Vosvrda (2013b) to evaluate efficiency scores of the analysed commodities by measuring the distance from the most efficient point in each measure's specific scale. This composite index consists of three measures, namely Approximate entropy, Hurst exponent, and fractal dimension, which are discussed in detail in the following section. They used logarithms and returns of the month ahead futures prices between 2000 and 2013. According to the analysis results, energy commodities are the most efficient while agricultural commodities are the least efficient ones.

David et al. (2020) used a similar approach to measure the efficiency degree of ethanol and gasoline prices before and after the institutional politics in the fuel sector in

Brazil. They applied the EI of Kristoufek and Vosvrda (2013) into two periods, 2011-2015 and 2016-2018. Their results supported that lower EI values in the second term indicate a path towards a more efficient market status after new energy policies were implemented.

Lin, Ting-Hsin Hsu, and Huang (2014) had a different approach to test the efficient market theory in energy indices. Using the data between 1982 and 2009, they have proved that even though some strategies are better than others, technical analysis strategies cannot be used to create substantial economic profit in energy markets when transaction costs are taken into account. Their finding supports the efficient market theory.

Ballester, Climent, and Furió (2016) analysed the Spanish electricity market using three components: spot prices, futures prices and over the counter (OTC) forward prices. They used the prices of the contracts with one month, one quarter and one year ahead delivery terms and the spot prices between 2007 and 2014. In order to test the weak form efficiency hypothesis, they applied variance ratio tests. Their results imply that markets with three different delivery terms support the efficiency theory. The Spanish futures market does not contradict the semi-strong form of the EMH. In other words, the futures price is an unbiased estimator of the conditional expectation of the future spot price. They have also found price discovery relationships between future prices and OTC forward prices.

Morales and Hanly (2018) had a similar approach to our study, and they intended to analyse the efficiency before and after a structural change. In their study, they used the prices between 2004 and 2014 from three well developed electricity markets: Scandinavia (NordPool), the UK (APX/ICE) and Germany (EEX/Phelix). Furthermore, they divided the sample between two periods before and after the introduction of the 2009/72/EC Directive (13th July 2009). Authors tested the efficiency of the markets by measuring their stationarity, cointegration and volatility properties to understand if the markets have random walk behaviour. They utilised a selection of econometric tests, like the Variance Ratio test, cointegration techniques and the GARCH model. Their results show that these markets are inefficient as they do not follow a random walk. However, the authors point out that there is progress towards the desired efficiency after the introduction of the EC directive.

Instead of applying a pre-chosen structural break date, Lee and Lee (2009) employed a panel data stationarity test that considers multiple structural breaks at different unknown dates for each tested time series. They examined the EMH for total energy prices in OECD countries over the period 1978 to 2006. Their finding suggests that energy crises significantly impacted energy prices, leading to structural breaks. However, on the other hand, they also suggest that shocks to energy prices are temporary.

Another similar method to our study was of Papaioannou et al., (2019), which had different test components to measure the efficiency of several electricity markets. Authors developed an efficiency index inspired by the EI (Kristoufek and Vosvrda, 2013) by using Hurst exponent for long term memory, fractal dimension and entropy measures. In addition, they have included variance-ratio and Herfindahl-Hirschman Index (HHI) for measuring the competition in the analysed countries. The index quantifies the level of efficiency by measuring the deviation from the desired result for the random walk of the market. They have applied their tests on the daily prices of Italia, Spain, Greece and

NordPool electricity markets between 2005 and 2013. None of these markets has had results enough to be considered efficient in the weak form of the EMH. However, the index approach allowed to compare the markets with each other. The ranking of the four markets starting from the less inefficient is Nordpool, Spain, Italy, and Greece.

Similarly, Camelia, Cristina, and Amelia (2017) developed another index to measure the efficiency in capital markets. Even though the target markets are different their approach to build the index carries similarities with our study. They developed an index using five estimates for informational entropy, run test, Hurst exponent, long-term correlation coefficient and fractal dimension. The authors applied the index to nine emerging capital markets and three developed markets using the daily data between 2000–2016. Their results support that developed capital markets are the most efficient, followed by advanced emerging markets, while Greece and Romania have the least efficient markets.

Even though it is not directly testing EMH, Botterud, Kristiansen, and Ilic (2010)'s study is also worth quoting as they consider electricity a storable commodity, unlike the vast majority of the literature. They point out that even though they are not storing the electricity itself, hydro reservoir systems can play a role as storage to apply convenience yield and storage cost theories to electricity commodity. The authors used the weekly spot and future prices between 1996 and 2006 in Nordpool. Their results show that hydro reservoir levels and convenience yields have an inverse relationship and the risk premium in futures contracts is persistently negative over the analysed period. In response, Weron and Zator (2014) studied a more extended and more recent period (1998 – 2010) of the same data from NordPool. They considered Garch residuals in their regression models to avoid possible bias in the linear model of Botterud et al. (2010) that can be coming from the simultaneity problem, the effect of correlated measurement errors and the impact of seasonality on the regression results. Contradictorily, the results showed positively related water reservoir levels and risk premiums.

The study of Kellard et al. (1999) has been interesting for researchers since it was one of the earliest studies to propose comparing the degree of inefficiencies of analysed market prices. They used monthly to quarterly data of Brent Crude oil, gas oil, soybeans, live hogs, live cattle and Deutsch mark between 1976 and 1996. Their analysis showed that futures and spot prices are cointegrated so that the long-run equilibrium holds. However, on the other hand, there are inefficiencies in the short run in most of the markets covered, and the degree of the inefficiency may be measured by the forecasting performance of the futures prices compared to the best fitting quasi-error correction model. Even though the results for 28 days suggest more inefficiencies, when the horizon is extended to 56 days, the gas oil, soybean and the DM/$ market were then found to be efficient.

Peroni and McNown (1998)'s earlier study on the efficiency of crude oil, heating oil and gasoline futures traded at Nymex had similar results supporting the market efficiency. The authors used the observations between 1979 and 1996 to apply two informative tests and found evidence that spot and futures prices in these three markets are cointegrated with an intercept of zero and a slope equal to unity.

In another empirical analysis on the efficiency of commodities markets, Westerlund and Narayan (2013) used the daily price data of crude oil, gold, silver and platinum between 2005 and 2011. The authors introduced the weighted least squares (WLS) method to test the slope of the cointegration of spot and futures prices instead of the widely used OLS method. Their results support that EMH accurately describes the gold, silver, and platinum markets while not working for the oil.

# CHAPTER 4

# METHODOLOGY

In this chapter detailed description of applied methodology is provided. Starting with theoretical explanation technical details are presented for each measure. Approximate entropy, Hurst exponent, fractal dimension, ex-post risk premium and spread analysis are explained, respectively.

## 4.1 Approximate entropy

Entropy is used for detecting dependencies and deterministic chaotic patterns in financial time series. This method, which was previously used in the field of health sciences, has been widely used to measure the non-linear dependence in financial series. Entropy statistically refers to the disorder in a time series and the unpredictability of the fluctuations in the series. It indicates that there is no information in the system with high entropy, and therefore, the system moves randomly.

Low entropy means that the system is determined deterministically. For example, suppose there are N corresponding numbers of observations with n variables. Each variable can be represented as a vector in an N-dimensional space. It is clear that the positions of the vectors in this space will not be absolute but determined by probability. Two extreme cases can be considered for shaping vectors (i.e. variables) in space. Firstly, it is a state of complete disorder and randomness in which all vectors are dispersed in this space in such a way as to express no relationship, that is, maximum entropy, and secondly, it is a state of complete determination, where all vectors are concentrated at a few points, that is, low-entropy. In the first case, one can say that the irregularity related to the variables is the highest, and in the second case, the irregularity is minimized. The actual situations are between these two extremes.

Pincus (1991) defined Approximate Entropy (ApEn) as follows.

Consider a times series with equally spaced observations:

$$u(1), \dots \dots, u(N)$$

An integer $m$ (the length of data runs) and $r$ (the upper threshold for a distance defined below) is fixed.

By making $X(i) = [u(i), \dots, u(i+m-1)]$ a sequence as below is built:

$$x(1), \dots, x(N-m+1)$$

Then ApEn is defined as:

$$\text{ApEn} = \Phi^{\,m}(r) - \Phi^{\,m+1}(r)$$

where

$$\Phi^{\,m}(r) = \frac{\sum_{i=1}^{N-m+1} ln\, C_i^m(r)}{N-m+1}$$

is:

$$C_i^m(r) = \frac{number\{x(j) : d[x(i), x(j)] \leq r, 1 \leq i, j \leq N+m+1, j \neq i\}}{N-m+1}$$

$d$ is a distance between $x$ and $x^*$ which is provided by:

$$d[x(i), x(j)] = max_{k=1,2,\ldots,n}(|u(i+k-1) - u(j+k-1)|)$$

Pincus, Gladstone, and Ehrenkranz (1991) defines heuristically that ApEn measures how logarithmically likely that runs of close patterns during $m$ observations remain close on following incremental comparisons. ApEn can also be defined as:

$$\frac{\sum_{i=1}^{N-m} \ln\left(\frac{C_{N-m+1}^{m}(r)}{C_{i}^{m}(r)}\right)}{(N-m+1)(N-m)} \qquad (1)$$

The purpose of ApEn is to estimate how random a data series is without having any prior knowledge about the background of the data. This property makes it applicable to limitless research areas (Delgado-Bonal and Marshak, 2019). That property is crucial for applying to electricity markets. Each country has a different market structure, but price data are in the same form, compliant with the ApEn algorithm’s need that requires equally spaced measurements over time. If repetitive patterns of fluctuation in a time series are more than another, this phenomenon leads to more predictability. ApEn shows how often similar patterns of observations will ve followed by similar observations. More complex processes have higher ApEn. (Moody, 2015)

Like Shannon entropy, approximate entropy can bring unbiased results in large and infrequent outliers in the data. These outliers usually do not have a binding effect in the data structure but are quantified as mean or variance in moment statistics.(Delgado-Bonal and Marshak, 2019) This is handy for electricity data as we can observe rare spikes in the prices. ApEn cannot have negative results due to its foundations in information theory, and it can be applied without cleaning the dataset from trends. It must be noted that the data series should be measured with equal spaces.

According to Pincus and Kalman (2004) for practical and broad usability, tools to measure irregularities in the data should be able to provide robust qualitative results across different models and applications. Even though it is used for confirming theories, ApEn satisfies this mandate with its applicability to data from complicated models. This property is vital for significant data analysis.

Pincus and Huang (1992) state that the applications of ApEn to medical data worked well to distinguish normal from abnormal data while moment statistics were not able to produce robust results. ApEn has this capability through several properties. Firstly, it is almost not affected by the noise below the filter level. It is also robust to outlier data points. It is capable of providing meaningful information with 1000 points. ApEn is bounded for stochastic and deterministic processes. Kristoufek and Vosvrda (2013) state that a bounded entropy measure is needed for Efficiency Index. It is also proven that increasing ApEn indicates the increasing process complexity of these processes. SampEn is another similar approach that was developed later on; however, its advantages are primarily for shorter time series (Yentes et al., 2013). Each dataset has at least 1000 observations that ApEn can be used in our study.

Pincus and Goldberger (1994) recommend that for appropriate interpretation of the measure, the systems with too large noise (if signal/noise is consistently less than 3) the validity of ApEn with a lot of other calculations would be questionable. Also, even though it brings a new dimension to data analysis, it is not a magnitude statistic that cannot replace statistics such as mean or standard deviation. A better approach would be using them together.

## 4.2 Hurst exponent

Long term memory phenomenon in univariate series was proposed by Mandelbrot (1972) primarily for use in hydrodynamics. Being named after Harold Edwin Hurst related to his studies in the Nile River, Hurst exponent is the standard description tool for long term memory behaviour in data. It finds whether the time series is persistent, whether it contains a trend, in other words, whether high increases follow high increases. Alternatively, mean-reverting can be a time series, meaning low returns follow high wins. It is easy to deduce this from the test results. Mostly, a relatively long time series is needed for the Hurst time series. (The data set that is the subject of our study is suitable for this purpose.) The purpose of needing a long data set is to compare the data set by dividing it into many subsamples.

It has been used a lot in applied finance because it is easy to implement and insightful. While other efficiency tests are very dependent on the period selections, the Hurst exponent detects whether the dependencies are in the long term.

Since this measure can quantify the persistence degree in similar price change patterns, it has been related to the weak form EMH. If the subsequent data has long memory dependence in the returns, the random walk hypothesis and efficiency hypothesis are voided accordingly(Eom et al., 2008). Moreover, long term dependence may potentially lead to the prediction of future returns by using the information contained in existing data, which would contradict the weak-form EMH(Cajueiro and Tabak, 2004).

Studies have used the Hurst exponent as an efficiency measure in financial markets. The relationship between long-term memory, predictability and potential efficiency has been discussed in numerous studies and in many cases, signs of long-term memory characterized the less developed markets. So that,  López-García et al. (2019) proposed an extension of the Fama-French model with long term memory component using Hurst exponent. And in another empirical study, (Horta, Lagoa, and Martins (2014) showed that there was a significant increase in correlation between the local Hurst exponents during the 2008 crisis.

H is widely used as the sign of the Hurst exponent, and if the data are following the random walk, H=0.5. In other words, the range of cumulative deviations should increase in direct proportion to the root of time. If the H value is different from 0.5, the observations are no longer independent and carry the memory of all previous events. This memory is called long-term memory. Theoretically, it lasts forever and is different from short-term memory. Therefore, the available data reflect all the events that occurred in the past. The current time series is considered a non-permanent series. They are primarily averaging systems. If the system has risen in the previous period, the downward trend is strong in the next period.

Conversely, if it fell in the previous period, it is more likely to rise in the next period. The non-permanence is due to the Hurst exponent being far from 0.5. Since such series have continuous returns, they are more variable than random series. The examined time series is accepted as a random series; in other words, the present moment does not affect future events. They are independent and unrelated.

$0.5 < H < 1$ indicates that the deviations of the process are persistent, that is, there is a dependency, long memory structure. This type of series is the series that is permanent or that strengthens the trend. If the series has risen in the previous period, it is more likely to continue its rise in the following period. Thus, the trend keeping behaviour is visible. The strength of the disposition reinforcement behaviour or persistence increases as the Hurst exponent approaches 1. Reversely, a Hurst value under 0.5 indicates an anti-persistent process implying that a positive movement is expected to be followed by a negative movement. While the persistent process is trending, the anti-persistent process fluctuates more frequently than the random process. (Krištoufek, 2010)

The long-term memory process is expressed in time and frequency domains for the formal mathematical definition. When data series have autocorrelation, a value in the time series is correlated with its another value in the series, which is specific times increment before or after the value. In the time domain, in a long memory process, this autocorrelation decays over time based on a power-law applied on below autocorrelation function( $\theta(l)$) with time lag $l$ (Papaioannou et al., 2019) :

$$\theta(l) = Cl^{-\delta}$$

where $C$ is a constant and Hurst exponent is related to $\delta$ by:

$$H = 1 - \frac{\delta}{2}$$

In the frequency domain, the spectrum $f(\lambda)$ with frequency $\lambda$ of the long-range dependent process diverges at the origin so that $f(\lambda) \propto \lambda^{1-2H}$ (Pilgrim and Taylor, 2018)

There have been several estimation techniques developed both in time and frequency domains. Boutahar and Khalfaoui (2011) groups the methodologies into three categories: Heuristic, semiparametric and parametric methods. While the earlier methods were heuristics, the second category includes frequency domain estimation and wavelet methods. The maximum likelihood function is used as a parametric method. According to Couillard, even if data sets are created using Brownian motion, finite sets will result in a Hurst exponent larger than 0.5 that more sophisticated tests would be needed to evaluate the significance of long-term dependences. On the other hand, some estimators are affected by short term bias. Accordingly, we choose the consistent and asymptotically normal Local Whittle and GPH estimators similar to Kristoufek and Vosvrda (2013) ‘s study.

### 4.2.1 Local Whittle estimator

Numerous researchers have preferred the Local Whittle estimator due to its implementation simplicity and preferable asymptotic properties. (Arteche and Orbe, 2017)

Being firstly introduced by Künsch (1987), it was developed by Robinson (1995). It is used to estimate the Hurst exponent based on the periodogram. Firstly, the shape of the spectral density of the series satisfying the below equation should be specified Shang (2020):

$$f(\lambda) \sim G\lambda^{1-2H} = G\lambda^{-2d} \; as \; \lambda \to 0+$$

where $0 < G < \infty, 0 < H < 1$ and $-\frac{1}{2} < d < \frac{1}{2}$

$Q(G, d)$ is defined as the objective function:

$$Q(G,d) = \frac{1}{m_\diamond}\sum_{j=1}^{m_\diamond}\left\{ln\left(G\lambda_j{}^{-2d}\right) + \frac{I\left(\lambda_j\right)}{G\lambda_j{}^{-2d}}\right\}$$

$m_\diamond$ in $\lambda_j = \frac{(2\pi j)}{n}, j = 1, \dots, m_\diamond$ is a positive integer which satisfies $m_\diamond < \frac{n}{2}, m_\diamond \to \infty$ and $m_\diamond \equiv o\ (n)$ ((Robinson, 1995)

The estimates are :

$$\left(\hat{G}, \hat{d}\right) = \underset{0<G<\infty, d\in\Theta}{argmin}\ Q(G,d), \tag{2}$$

Self-similarity measure $d_0, \Theta = [\nabla_1, \nabla_2]$ is closed interval of acceptable estimates of true value where $\nabla_1\, and\, \nabla_2$ are numbers picked such that $-\frac{1}{2} < \nabla_1 < \nabla_2 < \frac{1}{2}$ (Robinson, 1995)

Shang (2020) alternatively obtains:

$$\hat{d} = \underset{d\in\Theta}{\operatorname{argmin}}\, R(d)$$

where

$$R(d) = \ln\hat{G}\ (d) - \frac{2d}{m_\diamond}\sum_{j=1}^{m_\diamond} ln\,\lambda_j,$$

$$\hat{G}(d) = \frac{1}{m_\diamond}\sum_{j=1}^{m_\diamond}\lambda_j{}^{2d}\, I(\lambda_j),$$

Robinson (1995) showed that $\hat{d}$ is consistent estimator of $d_0$ and as $n \to \infty$ , $\sqrt{m_\diamond}\left(\hat{d} - d_0\right) \to N\left(0, \frac{1}{4}\right)$

### 4.2.2 GPH Estimator

This method, named after Geweke & Porter-Hudak (1983), is based on a regression equation derived from the logarithm of the spectral density function of a model. Boutahar and Khalfaoui (2011) formally describes that the model includes two steps, initial is to estimate $d$. This method evaluates d without explicitly specifying the short memory (ARMA) parameters in the time series. (Baum, 2013)

The spectral density function which will provide the sample from its pole is illustrated as Boutahar and Khalfaoui (2011):

$$f\chi(\lambda) = \left[4\sin^2\left(\frac{\lambda}{2}\right)\right]^{-d} f\varepsilon(\lambda)$$

$f\varepsilon(\lambda)$ is the finite and continuous function between $[-\pi, \pi]$ which provides the spectral density of $\varepsilon_t$. Log-spectral density is expressed accordingly:

$$\log\{f\chi(\lambda)\} = \log\{f\varepsilon(0)\} - d \log\left\{4\sin^2\left(\frac{\lambda}{2}\right)\right\} + \log\left\{\frac{f\varepsilon(\lambda)}{f\varepsilon(0)}\right\}$$

With $T$ number of observations and $m$ number of Fourier frequencies $\lambda_j = 2\pi j / T$ where $j = 1,2, \ldots, m$, $I\chi(\lambda_j)$is the periodogram to be evaluated. It is important to note that the choice of $m$ carries a crucial role as it has a considerable effect on the estimation results. We applied $m = T^{0,6}$ as suggested by Phillips and Shimotsu (2004).

Let $\log\{f\varepsilon(0)\}$ to be the constant,

$\log\left\{4\sin^2\left(\frac{\lambda_j}{2}\right)\right\}$ to be the exogenous variable, and

$\log\left\{\frac{I\chi(\lambda_j)}{f\chi(\lambda_j)}\right\}$ to be the disturbance error. The regression is:

$$\log\{I\chi(\lambda_j)\} = \log\{f\varepsilon(0)\} - d\ \log\left\{4\sin^2\left(\frac{\lambda_j}{2}\right)\right\} + \log\left\{\frac{f\varepsilon(\lambda_j)}{f\varepsilon(0)}\right\}$$

$$+\log\left\{\frac{I\chi(\lambda_j)}{f\chi(\lambda_j)}\right\}$$

There are two assumptions of the GPH estimation. $\log\left\{\frac{f\varepsilon(\lambda_j)}{f\varepsilon(0)}\right\}$ is negligible in low frequencies, and $\log\left\{\frac{I\chi(\lambda_j)}{f\chi(\lambda_j)}\right\}$, $j = 1,2,\ldots,m$ are asymptotically i.i.d.

Then the regression is:

$$\log\{I\chi(\lambda_j)\} = \alpha - d\log\left\{4\sin^2\left(\frac{\lambda_j}{2}\right)\right\} + e_j$$

Where $e_j \sim i.i.d(-c, \pi^2/6)$ Let $Y_j = -\log\{4\sin^2(\lambda_j/2)\}$, the estimator is an OLS estimate of the regression of $\log\{I\chi(\lambda_j)\}$ where $\alpha$ and $Y_j$ are constant. The estimate of $d$:

$$\hat{d}_{GPH} = \frac{\sum_{j=1}^{m}(Y_j - \bar{Y})\log\{I\chi(\lambda_j)\}}{\sum_{j=1}^{m}(Y_j - \bar{Y})^2} \qquad (3)$$

Where $\bar{Y} = m^{-1}\sum_{j=i}^{m} Y_j$ and $m = g(T)$ with $\lim_{T\to\infty} g(T) = \infty\ and\ \lim_{T\to\infty} g(T)/T = 0$

If $T \to \infty$ and $|d| < 1\ /\ 2$ the formulation is:

$$\sqrt{m}(\hat{d}_{GPH} - d) \sim N\left[0, \frac{\pi^2}{6}\left\{\sum_{j=1}^{m}(Y_j - \bar{Y})^2\right\}^{-1}\right]$$

### 4.3 Fractal dimension

It came to the fore when Mandelbrot (1983) wanted to measure the length of the coast of England in real terms. As the scale gets larger, more precise measurements will be made, and more lengths will be calculated. Measuring all shores with a ruler will mean that the length goes to infinity. Fractal geometry deals with roughness and irregularity. An object is self-similar if it combines smaller copies of itself. While not all fractals are self-similar, or at least not entirely self-similar, many do. In an object similar to itself, the parts or components that make up the object are similar to the object's whole. Irregular details or patterns are repeated on ever-smaller scales and can last forever in purely abstract objects; so that when each part of each part is enlarged, it still resembles the whole of the object. This fractal phenomenon can be easily observed in snowflakes and tree bark. All natural fractals of this type, and some mathematically self-similar, are stochastic (probabilistic), i.e. random; therefore, they only scale statistically.

Each small part is a small copy of the whole. Self-similarity is directly related to fractals, and the fractal size of the object indicates the degree of self-similarity. Self-similarity is an iterative process, and the structure repeats itself at every scale. Fractals are self-similar because they scale the same in all directions.

According to Theiler (1990) fractal objects are similar to Russian dolls, which are nested within one another. Its dimensions are rational numbers. When considering a ball of yarn, its size varies depending on where it is examined. If viewed from space, it can be thought of as a point and said to be '0' dimensional, and if viewed very closely, it can be seen as a spherical and '3' dimensional. The sizes of fractals also vary depending on how much space they bend and break. If it covers a fractal plane, its size is between 1-2; if it is in a curved shape, it is between 2-3. Like other time-series data, electricity prices are expected to have a fractal dimension between 1-2.

According to Mandelbrot's definition, fractal dimension:

$$D = \lim_{a \to 0} \frac{\log N}{\log(\frac{1}{a})}$$

In some cases, the fraction value will be the same at each step, and the fraction will approach the D limit, which is a fixed value.

$$D = {\log N}\Big/{\log(\frac{1}{a})}$$

The series does not have to be rough or smooth similarly in all specific parts while the degree of roughness can also vary with time. (Kristoufek and Vosvrda, 2013)

The smoothness of an isotropic surface can be characterized by its fractal dimension. A very smooth surface with an endlessly shifting tangent plane would have a fractal dimension $D_3$ = 2. However, if the surface is very rough or irregular, in the limit irregularity increases as the fractal dimension approaches $D_3$ = 3. (Constantine and Hall, 1994)

Different software can use different methods in fractal dimension calculation. However, the basic logic of all the methods used is that the size of fractals will not change even if they are handled at different scales, as explained above.

Generally, fractal analysis methods treat time-series structures as one of these two approaches: as a geometric figure without a specifically defined aspect ratio or an arranged record of a process that exhibits a measurable degree of randomness. (Pilgrim and Taylor, 2018)

One way to measure the fractal dimension of a curve is the box-counting method. First, the curve is covered with small squares, then the squares through which the curve passes are counted.

This method is repeated with the squares getting smaller and smaller.

If p and q are the numbers of consecutive squares used to cover the curve, the fractal dimension of the curve is:

$$\frac{\log(\frac{p}{q})}{\log 2}$$

For a random series, $D$ = 1.5. In real markets, short-term characteristics cannot be captured with long term evaluation tests because these short-term behaviours can quickly disappear. However, these short-term trends cause roughening of the series, deviating $D$ from 1.5 (Kristoufek and Vosvrda, 2013)

If a market is characterized by short-term trends (local persistence), then $D < 1.5$ since the surface of the time series becomes smoother. On the other hand, if the market is dominated by short-term bursts of volatility (volatility clusters), then the market is mean-reverting or local anti-persistence with $D > 1.5$ since the time series is more coarsened.

Kristoufek and Vosvrda (2013) and Kristoufek (2012) characterize $D$ as follows:

- 1< $D$ ≤2 for univariate series.
- $D$ = 1.5, for a random walk (Bm) such that the TS has no long memory process and no local anti-correlations,
- $D$ <1.5, corresponds to short-term trends (local persistence) as the times series becomes smoother,
- $D$ >1.5, corresponds to volatility clusters, mean-reverting or local anti-persistence in the market.

However, estimating fractal dimension for univariate times series requires an alternative sophisticated estimator. The researchers develop several different estimators. Gneiting, Ševčíková, and Percival (2012) define that all methods follow a typical pattern, which is:

- A function of scale ε is developed by computing a numerical property (Q) of the time series
- An asymptotic power-law $Q\varepsilon \propto \varepsilon^{b}$ as the scale $\varepsilon \rightarrow 0$ turns into immeasurably small is obtained
- the scaling exponent, $b$ , is a linear function of the fractal dimension, $D$;
- using linear regression of $log\ Q(\varepsilon)$ on $log\ \varepsilon$ , $D$ is estimated with the possible smallest measurable value of the scale $\varepsilon$

In other words, essentially all methods for estimating fractal dimension seek linear relationships between the logarithm of a particular function and logarithm of its argument based on scaling laws. (Chan, Hall, and Poskitt, 1995)

Like Kristoufek and Vosvrda (2013) we calculated fractal dimensions using more advanced methods, Genton and Hallwood estimators.

### 4.3.1 Hallwood estimator

The Hallwoord estimator proposed by Hall and Wood (1993) is a box-counting method (see (Klinkenberg, 1994) for detailed specification of Box Counting method) which can operate in the smallest observable scale. Instead of the sum, the curve is covered by the area of the boxes.

Taking $\in_I = I/n$ as with the conditions $I = 1,2,3,\ldots n$ as a scale, the area is calculated as:

$$\hat{A}(l/n) = \frac{l}{n}\sum_{i=1}^{[n/l]} |X_{il/n} - X_{\underline{(i-1)l}\atop n}|$$

$[n/l]$ represents the integer part of $n/l$ . The estimator is represented formally as:

$$\widehat{D}_{HW} = 2 - \left\{\sum_{i=1}^{L}(S_l - \bar{S})\log\hat{A}(l/n)\right\}\left\{\sum_{i=1}^{L}(S_l - \bar{S})^2\right\}^{-1}$$

Where $L \geq 2$ , $S_l = \log\,(\,l/n)$ and $\bar{S} = \frac{1}{L}\sum_{l=1}^{L} S_l$

When $L = 2$ is used as suggested by Hall and Wood (1993) , the standard estimator is implemented as :

$$\widehat{D}_{HW} = 2 - \frac{\log\hat{A}(2/n\,) - \log\hat{A}(1/n\,)}{\log 2} \qquad (4)$$

### 4.3.2. Genton Estimator

This estimator initially proposed by Genton (1998) on the method of moments estimator of scale is developed later by Gneiting et al. (2012) and Gneiting and Schlather (2001). It suggests a robust variogram:

$$V_2\widehat{(l/n)} = \frac{1}{2(l-n)}\sum_{i=l}^{n}\left(X_{i/n} - X_{(i-l)/n}\right)^{-1}$$

While the Genton estimator is formally described as

$$\widehat{D_{RG}} = 2 - \frac{1}{2}\left(\sum_{i=1}^{L}(S_i - \bar{S})\log\left(V_2\widehat{(l/n)}\right)\right)\left(\sum_{i=1}^{L}(S_i - \bar{S})^2\right)^{-1}$$

Where, $L \geq 2, S_l = \log(l/n)\ and\ \bar{s} = (1/L)\sum_{i=1}^{L} S_i$

Similar to the Hallwood estimator, using $L = 2$ is suggested to mitigate the bias. Accordingly, the estimator is:

$$\widehat{D_{RG}} = 2 - \frac{\log\left(V_2\widehat{(2/n)}\right) - \log\left(V_2\widehat{(l/n)}\right)}{2\log(2)} \qquad (5)$$

### 4.4 Ex-post risk premium

One way to measure pricing accuracy is to understand whether there is a systematic difference between the risk premium occurring in future contracts, the futures contract's trade price, and the average price realised in the relevant period. Are these differences due to mispricing due to market inefficiency, or do they reflect the amounts paid by market actors to avoid risk?

According to Branger, Reichmann, and Wobben (2009), the factors that affect the risk premium is the risk preferences and hedging needs of market participants. While producers are willing to be protected against low or even negative prices, consumers aim to protect against unforeseeable price increases. The risk premium can be both positive and negative, and their characteristics differ from market to market (Weron and Zator, 2014).

According to Haugom and Ullrich (2012), the risk premium is expected to decrease (or converge to zero with better wording) as the markets mature. An ex-post risk premium that is not zero and supported by a perfect forecast can be considered the indication of market inefficiency. Domanski and Heath (2007) state that in efficient commodity markets, long-run future prices are expected to benchmark the expected marginal cost of production of the underlying commodity. Accordingly, Casula and Masala (2020) highlighted that risk premium varies seasonally after examining its dynamic evolution.

There have been numerous studies using this approach to evaluate the efficiency of different markets. In their seminal study, Bessembinder and Lemmon (2002) studied PJM and CALPX electricity markets for the periods between 1997 to 2000. They propose an equilibrium model for forward prices, assuming that both demand and supply sides are risk-averse. Using the non-storability property of electricity, their equilibrium model argues that forward premium is a function of the variance and the skewness of the spot price. According to their focus on risk-averse behaviour of the agents, the premium should correspond to the net hedging cost.

In another widely quoted study, Longstaff and Wang (2004) analyse the PJM market's forward premium between 2000-2002 and find a significant premium in the data. They related the premium to the unexpected changes in consumption, spot prices and the system's total revenues. They supported Besseminder and Lemmon. In 2012 Haugom and Ullrich (2012) extended their study up with 2000 to 2010 data, which supported a significant forward premium. On the other hand, the premium decreased more recently, indicating a move towards efficiency in the market. They explain that additional public information can play more minor role in forecasting prices; markets get more efficient while the agents gain experience.

Botterud et al. (2010)'s study criticised the model of Bessembinder and Lemmon (2002) and defended that it cannot be applied to hydro dominated markets where storability is possible in different forms. The study argues that high reservoir levels are associated with higher risk premiums in the electricity market. However, Weron and Zator (2014) provided evidence of reservoir levels' opposite effect on the risk premium. Nevertheless, forecast models for markets with imperfect indirect storability, such as hydro reservoirs, are expected to depend intensely on price expectations, and models should include time-varying risk premiums. (Huisman and Kilic, 2012) . In another study held by Jaeck and Lautier (2016), empirical results show that storability is not a prerequisite for a Samuelson effect to appear.

In a more general approach, Weron and Zator (2014) states that the expected variance of the spot price affects the risk premium is positive while expected skewness has the opposite effect. The possibility of price spikes has boosting effect on future prices.

Even though there are different approaches, some are due to inconsistent definitions of the risk and forward premiums.

In order to avoid misunderstanding, Botterud et al. (2010) and Weron and Zator (2014) use the opposite terminology then some of the other studies. For their study, if the futures price tends to be higher than the realised spot price, it is accepted as a negative risk premium. Since we apply the same methodology for calculating ex-post risk premium, we use the same terminology with the authors. When the sellers are more risk-averse than the buyers, they tend to accept lower future prices to secure their portfolio income, leading to a positive risk premium. On the contrary, the risk premium becomes negative when the buyers are risk-averse and aim to hedge their future spending as soon as possible. In formal explanation:

$$RP_{t,T} = ln(s_{t+T}) - ln\left(F_{t,T}\right) = ln\left\{\frac{s_{t+T}}{F_{t,T}}\right\} \qquad (6)$$

$s_{t+T}$ is the realized spot price value at time $t + T$ , and $F_{t,T}$ is the price of a futures contract quoted today with delivery period starting at this future date.

### 4.5 Spread analysis

While the spread between buy and sell offers in a market is widely accepted as an indicator of liquidity, studying long term dynamics via bid-ask spread for long periods requires extensive datasets. Moreover, the computational burden is unavoidable when vast data is used. In order to make the analysis of bid-ask spreads in the markets, the academia develops some proxies. (Guloglu and Ekinci, 2016)

In 1999, using foreign exchange (FX) market data, Ding (1999) proved that high amounts of transactions have a negative relation with bid-ask spreads while high volatility has a positive impact. Aitken et al. (2004) also showed that a high number of transactions thanks to electronic trading leads to significantly lower bid–ask spreads.

The seminal paper Roll (1984) provides a simple market microstructure without knowing the underlying bid-ask quotes and trade flow (i.e. whether a trade originates from a buyer or seller) by simply estimating the buy-sell margin from observed closing prices. This approach is beneficial for long historical datasets, which often have boundaries.

Roll (1984)'s study relies on four assumptions regarding the underlying market. Firstly, he assumes that the market is informationally efficient. Second, the price changes in the datasets carry stationary probability distribution. Thirdly, a constant spread, which is maintained by a market-maker, is enjoyed by all market participants. Moreover, sales and purchase transactions are the same with the probability of successively occurring. (Bryant and Haigh, 2001) If there is no new information in such a market, the price changes would be between the bid and ask prices, and two successive transactions of buy or sell would be the reason for price movement. So, calculating covariance of successive price movements and variances of price movements led Roll to prove that unconditional covariance of successive price changes is equal to calculated covariance conditional on no new information flow to the market.

Harris (1990) developed Roll's model and expressed $s$, the effective bid-ask spread using the daily closing prices, , $P_t$, as following:

$$-\frac{s^2}{4} = cov(\Delta p_t, \Delta p_{t+1})$$

$$s^2 = -4\, cov(\Delta p_t, \Delta p_{t+1})$$

$$\sqrt{s^2} = \sqrt{-4\, cov(\Delta p_t, \Delta p_{t+1})}$$

$$s = 2\sqrt{-\, cov(\Delta p_t, \Delta p_{t+1})} \tag{7}$$

In another study, Thompson and Waller (1987) used end-of-day prices similar to Roll but estimated the bid-ask spread from the absolute value of 5-day moving averages of the daily closing price. Chen et al. (2016). suggested another model similar to Roll's, but they use empirical characteristic functions instead of the sample autocovariance function. In addition, their closed-form expression for the spread is based on a limited amount of the model implied identification restrictions.

Holden and Holden (2009) also developed another spread proxy that uses three properties of daily price data: price clustering, serial price covariance use for midpoint prices on no-trade days, and the quoted spread available on no-trade days. Later, Corwin and Schultz (2011) generated a new spread proxy using daily high and daily low prices.

# CHAPTER 5

# DATA DESCRIPTION

The data consists of electricity price data from ten European electricity markets, namely Belgium, Switzerland, Czechia, Germany, Spain, France, United Kingdom, Hungary, Italy and Netherlands. Price series are used for each market starting from 1-1-2008 to the end of 2021 when available. This period includes the extensive liberalisation and market change era in specially developed countries In Europe. As discussed in the market structure chapter, independent electricity exchanges and transmission operators around Europe have implemented numerous measures and policy changes to optimise resources efficiency and market integrations. Furthermore, in parallel with global economic trends and socio-economic targets such as a low carbon economy, we have witnessed intensive renewable energy investments during this period.

The sample countries, Belgium, Switzerland, Germany, France, United Kingdom and Netherlands are from Central West Europe (CWE), which already have a high track record of regional cooperation and relatively high physical interconnection capacities. Moreover, we have used the data from Czechia, Spain, Italy, and Hungary, each of which carries unique properties. They have more recently joined the price coupling mechanism compared to CWE countries.

Our data sources for day ahead prices are market operator websites and the primary data source Entso-E (European Association for The Cooperation Of Transmission System

Operators (TSOs) for Electricity) Transparency Platform. Moreover, we extracted the monthly baseload futures prices for each market using Reuters data stream.

For ten countries, the price series are created as follows: For "real" prices series, 24-hour average of the hourly day ahead prices[1] are calculated as the daily spot price. The series provides a non-stop daily price for the periods examined.

For the "futures" series, each daily futures price on day T of Month M corresponding to the average monthly price for baseload delivery at M+1 is considered as a daily price. Since the futures markets are open only on business days, prices occur only on those days. However, prices are used in continuous form. Moreover, to prevent bias in return calculation, the first values of each monthly contract are removed to create a consistent, continuous return series.

In compliance with the target of the study, price series are divided into separate samples based on the hypothetical structural break dates. For each market, the date for joining a market coupling mechanism or expansion of the existing market coupling mechanism with other countries are considered as break dates. Specifically, price data are sampled as stated in the Table 1. Future prices are also sampled in the same method however due to the fact that observations are less than day ahead prices, there are less data points. Table 2 and Table 3 show the descriptive statistics for given periods for each market. For ease of comparison between countries, as some energy exchanges do not allow negative prices, negative prices are converted to positive values by adding constant values.  Figures A1 to A20 (Appendix A) are the country specific day ahead and futures

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[1] Referring to spot price in European literature while corresponds to forward price in the US.

prices. Figures B1 to B18 (Appendix B) are country-specific graphics showing the distribution of day ahead prices and M+1 future prices based on the subsets prepared according to Table 1.

Table 1. Structural Break Dates for Day ahead Markets

| Country | Sample | Start Date | End Date | Event |
|---|---|---|---|---|
| BE | BE1 | 01/01/2008 | 01/04/2011 | coupling of GB and CWE markets |
| | BE2 | 01/04/2011 | 01/01/2021 | Brexit (decoupling of GB) |
| | BE3 | 01/01/2021 | 31/12/2021 | end of sample |
| CH | CH0 | 01/01/2008 | 31/12/2021 | end of sample |
| CZ | CZ1 | 01/01/2008 | 11/09/2012 | Coupling of CZ, HU and SK |
| | CZ2 | 11/09/2012 | 18/11/2014 | Romania joins (4MC) |
| | CZ3 | 18/11/2014 | 17/06/2021 | 4MC and CWE are coupled (SDAC) |
| | CZ4 | 17/06/2021 | 31/12/2021 | end of sample |
| DE | DE1 | 01/01/2008 | 09/11/2010 | CWE and Nordic markets coupling |
| | DE2 | 09/11/2010 | 03/02/2014 | launch of the NWE Price Coupling |
| | DE3 | 03/02/2014 | 17/06/2021 | 4MC and CWE are coupled (SDAC) |
| | DE4 | 17/06/2021 | 31/12/2021 | end of sample |
| ES | ES1 | 01/01/2008 | 13/05/2014 | SWE joins NWE |
| | ES2 | 13/05/2014 | 01/01/2021 | Brexit (decoupling of GB) |
| | ES3 | 01/01/2021 | 31/12/2021 | end of sample |
| FR | FR1 | 01/01/2008 | 09/11/2010 | CWE and Nordic markets coupling |
| | FR2 | 09/11/2010 | 03/02/2014 | launch of the NWE Price Coupling |
| | FR3 | 03/02/2014 | 01/01/2021 | Brexit (decoupling of GB) |
| | FR4 | 01/01/2021 | 31/12/2021 | end of sample |
| GB | GB1 | 23/03/2010 | 01/04/2011 | coupling of GB and CWE markets |
| | GB2 | 01/04/2011 | 30/09/2018 | IRE-GB coupling |
| | GB3 | 30/09/2018 | 01/01/2021 | Brexit (decoupling of GB) |
| | GB4 | 01/01/2021 | 31/12/2021 | end of sample |
| HU | HU1 | 14/09/2010 | 11/09/2012 | Coupling of CZ, HU and SK |
| | HU2 | 11/09/2012 | 18/11/2014 | Romania joins (4MC) |
| | HU3 | 18/11/2014 | 17/06/2021 | 4MC and CWE are coupled (SDAC) |
| | HU4 | 17/06/2021 | 31/12/2021 | end of sample |
| IT | IT1 | 01/06/2010 | 01/01/2011 | IT-SI coupling |
| | IT2 | 01/01/2011 | 24/02/2015 | IT joins CWE |
| | IT3 | 24/02/2015 | 19/06/2018 | HR joins |
| | IT4 | 19/06/2018 | 31/12/2021 | end of sample |
| NL | NL1 | 01/01/2008 | 01/04/2011 | coupling of GB and CWE markets |
| | NL2 | 01/04/2011 | 03/02/2014 | launch of the NWE Price Coupling |
| | NL3 | 03/02/2014 | 01/01/2021 | Brexit (decoupling of GB) |
| | NL4 | 01/01/2021 | 31/12/2021 | end of sample |

Table 2. Descriptive Statistics for Day ahead Prices

| Country | Sample | Data Points | Mean | Standard Deviation | Minimum | Maximum | Range | Skewness | Kurtosis | Standard Error |
|---|---|---|---|---|---|---|---|---|---|---|
| BE | All | 5114 | 49.86 | 29.63 | 1 | 432.99 | 431.99 | 4.68 | 34.49 | 0.41 |
| | BE1 | 1187 | 52.32 | 19.3 | 13.28 | 206.1 | 192.83 | 1.29 | 4.3 | 0.56 |
| | BE2 | 3564 | 43.47 | 15.35 | 1 | 207.92 | 206.92 | 1.56 | 10.53 | 0.26 |
| | BE3 | 365 | 104.18 | 73.69 | 1 | 432.99 | 431.99 | 1.53 | 2.32 | 3.86 |
| CH | All | 5114 | 51.91 | 32.43 | -12.67 | 435.51 | 448.18 | 4.75 | 34.43 | 0.45 |
| CZ | All | 5114 | 64.93 | 27.11 | 0.9 | 439.89 | 438.98 | 4.86 | 39.46 | 0.38 |
| | CZ1 | 1716 | 68.15 | 15.5 | 22.68 | 140.44 | 117.76 | 1 | 1.82 | 0.37 |
| | CZ2 | 799 | 55.89 | 10.91 | 1 | 89.34 | 88.34 | -0.4 | 1.2 | 0.39 |
| | CZ3 | 2404 | 58.06 | 13.77 | 0.9 | 111.8 | 110.9 | 0.32 | 0.91 | 0.28 |
| | CZ4 | 198 | 157.31 | 68.02 | 45.43 | 439.89 | 394.46 | 1.41 | 2.34 | 4.83 |
| DE | All | 5114 | 74.13 | 27.44 | 1 | 461.97 | 460.97 | 4.77 | 40.11 | 0.38 |
| | DE1 | 1043 | 79.56 | 18.04 | 1 | 161.4 | 160.4 | 0.87 | 1.34 | 0.56 |
| | DE2 | 1183 | 74.04 | 12.15 | 1 | 128.98 | 127.98 | -0.71 | 2.6 | 0.3 |
| | DE3 | 2691 | 65.46 | 13.81 | 1 | 131.92 | 130.92 | 0.08 | 2.05 | 0.27 |
| | DE4 | 198 | 164.08 | 70.85 | 35.63 | 461.97 | 426.34 | 1.39 | 2.44 | 5.03 |
| ES | All | 5114 | 71.08 | 28.88 | 20.13 | 403.67 | 383.54 | 4.53 | 30.91 | 0.4 |
| | ES1 | 2325 | 65.58 | 14.55 | 20.13 | 113.11 | 92.98 | -0.33 | 0.79 | 0.3 |
| | ES2 | 2425 | 67.19 | 12.9 | 21.94 | 111.88 | 89.94 | -0.48 | 0.44 | 0.26 |
| | ES3 | 365 | 131.94 | 72.45 | 21.42 | 403.67 | 382.25 | 1.05 | 0.67 | 3.79 |
| FR | All | 5114 | 48.91 | 32.78 | 1 | 612.77 | 611.77 | 5.66 | 52.04 | 0.46 |
| | FR1 | 1043 | 52.99 | 25.64 | 13.28 | 612.77 | 599.49 | 10.25 | 215.6 | 0.79 |
| | FR2 | 1184 | 46.72 | 16.63 | 1 | 367.6 | 366.6 | 6.15 | 117.38 | 0.48 |
| | FR3 | 2524 | 39.54 | 15.03 | 1 | 125.67 | 124.67 | 0.91 | 2.46 | 0.3 |
| | FR4 | 365 | 109.18 | 80.19 | 1 | 452.94 | 451.94 | 1.63 | 2.45 | 4.2 |
| GB | All | 4300 | 80.94 | 30.65 | 30 | 455.47 | 425.47 | 5.83 | 45.42 | 0.47 |
| | GB1 | 375 | 76.51 | 8.49 | 30 | 104.86 | 74.86 | -3.19 | 17.2 | 0.44 |
| | GB2 | 2738 | 75.39 | 8.06 | 57.93 | 199.65 | 141.72 | 2.59 | 26.66 | 0.15 |
| | GB3 | 825 | 71.84 | 12.4 | 30 | 108.23 | 78.23 | 0.34 | 0.1 | 0.43 |
| | GB4 | 365 | 147.79 | 72.54 | 54.86 | 455.47 | 400.61 | 1.67 | 3.15 | 3.8 |
| HU | All | 4127 | 51.81 | 32.18 | 1 | 420.46 | 419.46 | 4.59 | 29.63 | 0.5 |
| | HU1 | 729 | 54.16 | 13.52 | 18.22 | 145.05 | 126.83 | 1.09 | 4.34 | 0.5 |
| | HU2 | 799 | 41.99 | 11.55 | 1 | 81.69 | 80.69 | -0.05 | 0.78 | 0.41 |
| | HU3 | 2404 | 45.4 | 14.98 | 6.25 | 150.02 | 143.77 | 0.82 | 2 | 0.31 |
| | HU4 | 198 | 160.75 | 69.97 | 58.74 | 420.46 | 361.72 | 0.97 | 0.84 | 4.97 |
| IT | All | 4231 | 62.86 | 33.21 | 10.66 | 437.94 | 427.28 | 4.62 | 29.99 | 0.51 |
| | IT1 | 215 | 65.71 | 8.23 | 44.49 | 91.34 | 46.84 | 0.81 | 0.86 | 0.56 |
| | IT2 | 1516 | 65.23 | 12.96 | 24.61 | 136.67 | 112.05 | 0.2 | 1.03 | 0.33 |
| | IT3 | 1211 | 50.08 | 11.97 | 24.99 | 127.46 | 102.47 | 1.28 | 3.87 | 0.34 |
| | IT4 | 1292 | 71.58 | 55.08 | 10.66 | 437.94 | 427.28 | 2.86 | 9.28 | 1.53 |
| NL | All | 5114 | 49.16 | 26.89 | 1 | 429.84 | 428.84 | 5.22 | 42.24 | 0.38 |
| | NL1 | 1187 | 51.69 | 17.46 | 18.63 | 118.59 | 99.96 | 0.9 | 0.67 | 0.51 |
| | NL2 | 1040 | 50.24 | 7.6 | 23.13 | 98.98 | 75.85 | 0.19 | 2.86 | 0.24 |
| | NL3 | 2524 | 39.75 | 10.61 | 1 | 88.98 | 87.98 | 0.44 | 1.26 | 0.21 |
| | NL4 | 365 | 102.97 | 68.39 | 7.24 | 429.84 | 422.6 | 1.6 | 2.92 | 3.58 |

Table 3. Descriptive Statistics for Month Ahead Futures Prices

| Country | Sample | Data Points | Mean | Standard Deviation | Minimum | Maximum | Range | Skewness | Kurtosis | Standard Error |
|---|---|---|---|---|---|---|---|---|---|---|
| BE | All | 2735 | 53.01 | 35.08 | 2.88 | 441 | 438.12 | 5.15 | 35.67 | 0.67 |
| | BE1 | 617 | 48.58 | 14.13 | 30.52 | 116.65 | 86.13 | 1.89 | 4.94 | 0.57 |
| | BE2 | 1870 | 46.2 | 15.73 | 2.88 | 192 | 189.12 | 2.33 | 15.49 | 0.36 |
| | BE3 | 248 | 115.29 | 83.42 | 36.79 | 441 | 404.21 | 1.52 | 1.99 | 5.3 |
| CH | All | 1937 | 48.1 | 44.95 | 1.9 | 443 | 441.1 | 4.38 | 23.06 | 1.02 |
| CZ | All | 2783 | 46.51 | 31.99 | 18.2 | 414.91 | 396.71 | 5.83 | 43.35 | 0.61 |
| | CZ1 | 678 | 46.61 | 6.8 | 32 | 62.5 | 30.5 | 0.01 | -0.68 | 0.26 |
| | CZ2 | 369 | 37.55 | 6.29 | 28.7 | 51.35 | 22.65 | 0.55 | -0.9 | 0.33 |
| | CZ3 | 1603 | 39.07 | 10.6 | 18.2 | 76.65 | 58.45 | 0.92 | 0.58 | 0.26 |
| | CZ4 | 136 | 158.16 | 77.34 | 74.88 | 414.91 | 340.03 | 1.19 | 1.12 | 6.63 |
| DE | All | 3237 | 45.48 | 29.55 | 16.66 | 410.91 | 394.25 | 6.1 | 49.16 | 0.52 |
| | DE1 | 518 | 45.08 | 11.16 | 31 | 94.95 | 63.95 | 1.91 | 4.9 | 0.49 |
| | DE2 | 772 | 46.18 | 8.02 | 29.9 | 63.75 | 33.85 | 0.04 | -0.93 | 0.29 |
| | DE3 | 1812 | 37.13 | 9.77 | 16.66 | 73.57 | 56.91 | 1.08 | 1.21 | 0.23 |
| | DE4 | 136 | 154.57 | 76.67 | 72.19 | 410.91 | 338.72 | 1.22 | 1.23 | 6.57 |
| ES | All | 3126 | 53.27 | 30.99 | 1.01 | 403.67 | 402.66 | 5.56 | 37.39 | 0.55 |
| | ES1 | 1283 | 46.4 | 8.45 | 24 | 73.7 | 49.7 | -0.01 | 0.2 | 0.24 |
| | ES2 | 1597 | 48.48 | 9.87 | 1.01 | 81.14 | 80.13 | -0.14 | 0.76 | 0.25 |
| | ES3 | 246 | 120.13 | 79.75 | 36.7 | 403.67 | 366.97 | 1.09 | 0.34 | 5.08 |
| FR | All | 3224 | 52.47 | 42 | 15.15 | 673.86 | 658.71 | 7.24 | 69.89 | 0.74 |
| | FR1 | 518 | 50.11 | 15.7 | 30.75 | 116 | 85.25 | 1.54 | 2.99 | 0.69 |
| | FR2 | 768 | 48.9 | 9.2 | 26.5 | 66 | 39.5 | -0.59 | -0.48 | 0.33 |
| | FR3 | 1690 | 43.06 | 14.45 | 15.15 | 132 | 116.85 | 1.35 | 3.44 | 0.35 |
| | FR4 | 249 | 132.34 | 116.89 | 42.6 | 673.86 | 631.26 | 1.99 | 4.26 | 7.41 |
| GB | All | 3144 | 52.05 | 34.14 | 15.53 | 532.5 | 516.97 | 5.75 | 42.26 | 0.61 |
| | GB1 | 256 | 44.17 | 5.37 | 33.25 | 56.1 | 22.85 | 0.13 | -0.61 | 0.34 |
| | GB2 | 1696 | 46.02 | 7.96 | 30.38 | 82.3 | 51.92 | 0.79 | 1.47 | 0.19 |
| | GB3 | 556 | 44.23 | 11.87 | 15.53 | 72.71 | 57.18 | 0.4 | -0.35 | 0.5 |
| | GB4 | 248 | 125.57 | 85.14 | 50.55 | 532.5 | 481.95 | 1.45 | 1.75 | 5.41 |
| HU | All | 2562 | 54.18 | 35.77 | 4.77 | 430.67 | 425.9 | 5.43 | 35.89 | 0.71 |
| | HU1 | 330 | 55.48 | 5.2 | 43.6 | 68.75 | 25.15 | -0.18 | -0.29 | 0.29 |
| | HU2 | 484 | 43.58 | 5.97 | 30 | 58 | 28 | 0.14 | -0.67 | 0.27 |
| | HU3 | 1616 | 46.9 | 11.07 | 4.77 | 82.6 | 77.83 | 0.55 | 0.12 | 0.28 |
| | HU4 | 135 | 176.39 | 81.81 | 82.6 | 430.67 | 348.07 | 0.9 | 0.28 | 7.04 |
| IT | All | 3079 | 63.76 | 32.16 | 16 | 417.78 | 401.78 | 5.02 | 32.61 | 0.58 |
| | IT1 | 147 | 67.87 | 2.23 | 62.63 | 72.8 | 10.17 | 0.07 | -0.62 | 0.18 |
| | IT2 | 874 | 65.61 | 10.1 | 43.3 | 91.6 | 48.3 | -0.32 | -0.77 | 0.34 |
| | IT3 | 789 | 49.51 | 8.65 | 31.26 | 108.28 | 77.02 | 0.52 | 2.5 | 0.31 |
| | IT4 | 880 | 73.67 | 55.87 | 16 | 417.78 | 401.78 | 2.84 | 8.46 | 1.88 |
| NL | All | 3062 | 50.14 | 31.61 | 6.51 | 416 | 409.49 | 5.8 | 42.88 | 0.57 |
| | NL1 | 614 | 47.01 | 11.7 | 31.4 | 100.5 | 69.1 | 1.69 | 4.28 | 0.47 |
| | NL2 | 568 | 51.74 | 4.71 | 42.72 | 64 | 21.28 | 0.15 | -0.66 | 0.2 |
| | NL3 | 1632 | 40.73 | 9.64 | 6.51 | 74.64 | 68.13 | 0.7 | 1.34 | 0.24 |
| | NL4 | 248 | 116.16 | 79.91 | 44.15 | 416 | 371.85 | 1.42 | 1.6 | 5.07 |

We apply stationarity tests to each of the return series prior to the application of other statistical tests. Augmented Dickey-Fuller's (1979) ADF test results presented in Table 4 indicate that the null hypothesis of non-stationarity is rejected for all return series at significant levels. We can state that price return series for all day ahead and future markets are stationary.

Table 4. Augmented Dickey - Fuller Test

| Day Ahead Price Returns | | | | M+1 Future Price Returns | | | |
|---|---|---|---|---|---|---|---|
| Market | Dickey-Fuller | Lag order | p-value | Market | Dickey-Fuller | Lag order | p-value |
| BE | -17.04 | 17 | 0.01 | BE | -12.25 | 13 | 0.01 |
| CH | -18.42 | 17 | 0.01 | CH | -12.52 | 12 | 0.01 |
| CZ | -17.01 | 17 | 0.01 | CZ | -12.56 | 14 | 0.01 |
| DE | -17.04 | 17 | 0.01 | DE | -14.30 | 14 | 0.01 |
| ES | -18.12 | 17 | 0.01 | ES | -14.24 | 14 | 0.01 |
| FR | -16.98 | 17 | 0.01 | FR | -13.37 | 14 | 0.01 |
| GB | -16.23 | 16 | 0.01 | GB | -12.57 | 14 | 0.01 |
| HU | -15.37 | 16 | 0.01 | HU | -13.31 | 13 | 0.01 |
| IT | -16.16 | 14 | 0.01 | IT | -14.35 | 14 | 0.01 |
| NL | -15.09 | 17 | 0.01 | NL | -15.65 | 14 | 0.01 |

# CHAPTER 6

# DATA ANALYSIS AND RESULTS

## 6.1 Entropy measure

We have applied ApEn (Approximate Entropy) measure to the price returns for each price sample. We used the R programming tool to implement the function discussed in the previous section. The selection of r for the approximate entropy calculation has been an issue in the literature. Castiglioni and di Rienzo (2008) defend that the most reasonable approach for choosing “r” is to select the value which maximises ApEn, as this would help detect more of the irregularity in the times series. However, Delgado-Bonal and Marshak (2019) refuse this approach and states that ApEn can provide more regularity than it should only if the selected value of r is before the maximum of ApEn. Similarly, Yentes et al. (2013) support that choosing a higher r multiplicator value of 0.25 or 0.3 might lead to unstable relationships as the data length changes. On the other hand, selecting a small “r” can cause to capture more number of self-matches.

Under the light of such assumptions, we have chosen r as 0.2 times the standard deviation of the time series following the general practice in the literature. Finally, we rescaled the results by dividing them by as performed by Kristoufek and Vosvrda (2013). On the other hand, using ApEn test results to compare different commodities can produce erroneous results. Because products with different characters have different properties, entropy scores will also be formed differently. Therefore, it would be a correct approach to compare different periods of the same product in electricity markets. Table 5 demonstrates the approximate entropy measure for each subset of day ahead market returns.

Table 5. Approximate Entropy for Day ahead Price Returns

| Country | Sample | ApEn |
|---|---|---|
| BE | BE1 | 0.40 |
|  | BE2 | 0.32 |
|  | BE3 | 0.24 |
| CH | CH0 | 0.34 |
| CZ | CZ1 | 0.40 |
|  | CZ2 | 0.24 |
|  | CZ3 | 0.22 |
|  | CZ4 | 0.30 |
| DE | DE1 | 0.10 |
|  | DE2 | 0.12 |
|  | DE3 | 0.14 |
|  | DE4 | 0.31 |
| ES | ES1 | 0.31 |
|  | ES2 | 0.37 |
|  | ES3 | 0.28 |
| FR | FR1 | 0.36 |
|  | FR2 | 0.32 |
|  | FR3 | 0.40 |
|  | FR4 | 0.19 |

| Country | Sample | ApEn |
|---|---|---|
| GB | GB1 | 0.13 |
|  | GB2 | 0.30 |
|  | GB3 | 0.29 |
|  | GB4 | 0.27 |
| HU | HU1 | 0.25 |
|  | HU2 | 0.38 |
|  | HU3 | 0.39 |
|  | HU4 | 0.40 |
| IT | IT1 | 0.25 |
|  | IT2 | 0.38 |
|  | IT3 | 0.39 |
|  | IT4 | 0.40 |
| NL | NL1 | 0.40 |
|  | NL2 | 0.36 |
|  | NL3 | 0.33 |
|  | NL4 | 0.35 |

In Table 6 calculated approximate entropy is presented for continuous return data of month ahead futures for each subset. Additionally, for a better graphical representation and to detect the volatility regime changes, 250-days rolling calculations are also presented for each market in Appendix C. The futures markets are open only in business days, so for ease of comparison 250 days period is chosen to represent one year period. Furthermore, as suggested by Papaioannou et al. (2019) using a rolling window facilitates the representative power of the metric. Again, Figure 2 shows the ApEn results for the white noise we have simulated in R for comparative purposes.

Table 6. Approximate Entropy for Month Ahead Future Price Returns

| Country | Sample | ApEn |
|---|---|---|
| BE | BE1 | 0.24 |
|  | BE2 | 0.13 |
|  | BE3 | 0.19 |
| CH | CH0 | 0.11 |
| CZ | CZ1 | 0.23 |
|  | CZ2 | 0.21 |
|  | CZ3 | 0.28 |
|  | CZ4 | 0.17 |
| DE | DE1 | 0.22 |
|  | DE2 | 0.24 |
|  | DE3 | 0.23 |
|  | DE4 | 0.15 |
| ES | ES1 | 0.24 |
|  | ES2 | 0.05 |
|  | ES3 | 0.20 |
| FR | FR1 | 0.22 |
|  | FR2 | 0.25 |
|  | FR3 | 0.28 |
|  | FR4 | 0.21 |
| GB | GB1 | 0.17 |
|  | GB2 | 0.26 |
|  | GB3 | 0.25 |
|  | GB4 | 0.17 |
| HU | HU1 | 0.21 |
|  | HU2 | 0.23 |
|  | HU3 | 0.11 |
|  | HU4 | 0.16 |
| IT | IT1 | 0.16 |
|  | IT2 | 0.22 |
|  | IT3 | 0.22 |
|  | IT4 | 0.23 |
| NL | NL1 | 0.23 |
|  | NL2 | 0.22 |
|  | NL3 | 0.19 |
|  | NL4 | 0.20 |

All markets are distant from the entropy levels represented by the White noise data. It is observable that the complexities of day ahead prices are more volatile than those of futures.

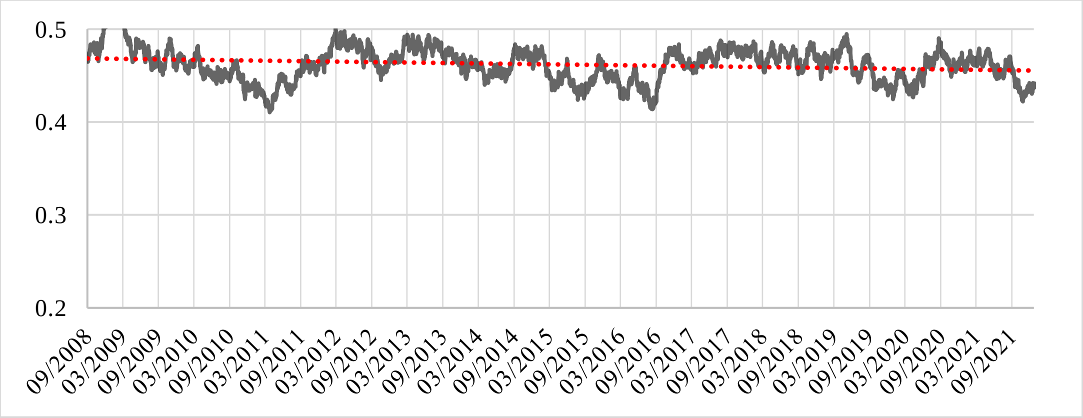

Figure 2. White noise 250 days rolling ApEn

## 6.2 Long term memory measure

We apply the GPH estimator shown in equation (2) and the Local Whittle estimator as indicated in equation (3) to the price return data for all samples. Accordingly, an H measure is calculated by taking the mean of two measurements for each data point. Table 7 and 8 exhibit the spot and futures market results, respectively for each country.

Table 7. Hurst Exponents for Day ahead Price Returns

| Country | Sample | GPH Estimator | Local Whittle Estimator | H |
|---|---|---|---|---|
| BE | BE1 | 0.533 | 0.476 | 0.505 |
| | BE2 | 0.639 | 0.642 | 0.640 |
| | BE3 | 0.503 | 0.462 | 0.483 |
| CH | CH0 | 0.499 | 0.493 | 0.496 |
| CZ | CZ1 | 0.414 | 0.508 | 0.461 |
| | CZ2 | 0.514 | 0.513 | 0.513 |
| | CZ3 | 0.509 | 0.503 | 0.506 |
| | CZ4 | 0.212 | 0.299 | 0.255 |
| DE | DE1 | 0.497 | 0.497 | 0.497 |
| | DE2 | 0.502 | 0.502 | 0.502 |
| | DE3 | 0.493 | 0.499 | 0.496 |
| | DE4 | 0.365 | 0.295 | 0.330 |
| ES | ES1 | 0.563 | 0.649 | 0.606 |
| | ES2 | 0.402 | 0.427 | 0.415 |
| | ES3 | 0.392 | 0.426 | 0.409 |
| FR | FR1 | 0.484 | 0.485 | 0.484 |
| | FR2 | 0.593 | 0.592 | 0.592 |
| | FR3 | 0.695 | 0.660 | 0.677 |
| | FR4 | 0.501 | 0.499 | 0.500 |
| GB | GB1 | 0.421 | 0.374 | 0.398 |
| | GB2 | 0.594 | 0.578 | 0.586 |
| | GB3 | 0.321 | 0.417 | 0.369 |
| | GB4 | 0.590 | 0.589 | 0.589 |
| HU | HU1 | 0.701 | 0.691 | 0.696 |
| | HU2 | 0.512 | 0.516 | 0.514 |
| | HU3 | 0.488 | 0.543 | 0.516 |
| | HU4 | 0.414 | 0.526 | 0.470 |
| IT | IT1 | 0.076 | 0.053 | 0.064 |
| | IT2 | 0.615 | 0.629 | 0.622 |
| | IT3 | 0.334 | 0.259 | 0.297 |
| | IT4 | 0.444 | 0.522 | 0.483 |
| NL | NL1 | 0.530 | 0.543 | 0.537 |
| | NL2 | 0.292 | 0.334 | 0.313 |
| | NL3 | 0.730 | 0.693 | 0.712 |
| | NL4 | 0.537 | 0.476 | 0.507 |

Additionally, for a better graphical representation and to detect the volatility regime changes 250-days rolling calculations are also presented for each market in Appendix D. For comparative purposes Figure 3 shows the Hurst exponent results for the white noise which we have simulated in R.

Table 8.  Hurst Exponents for Month Ahead Futures Returns

| Country | Sample | GPH Estimator | Local Whittle Estimator | H |
|---|---|---|---|---|
| BE | BE1 | 0.732 | 0.713 | 0.722 |
| | BE2 | 0.540 | 0.511 | 0.525 |
| | BE3 | 0.493 | 0.402 | 0.448 |
| CH | CH0 | 0.528 | 0.519 | 0.524 |
| CZ | CZ1 | 0.421 | 0.428 | 0.425 |
| | CZ2 | 0.686 | 0.614 | 0.650 |
| | CZ3 | 0.400 | 0.483 | 0.442 |
| | CZ4 | 0.508 | 0.429 | 0.469 |
| DE | DE1 | 0.753 | 0.652 | 0.702 |
| | DE2 | 0.429 | 0.455 | 0.442 |
| | DE3 | 0.532 | 0.493 | 0.513 |
| | DE4 | 0.547 | 0.459 | 0.503 |
| ES | ES1 | 0.414 | 0.434 | 0.424 |
| | ES2 | 0.498 | 0.499 | 0.499 |
| | ES3 | 0.575 | 0.463 | 0.519 |
| FR | FR1 | 0.641 | 0.615 | 0.628 |
| | FR2 | 0.379 | 0.426 | 0.402 |
| | FR3 | 0.483 | 0.571 | 0.527 |
| | FR4 | 0.498 | 0.467 | 0.483 |
| GB | GB1 | 0.576 | 0.617 | 0.596 |
| | GB2 | 0.588 | 0.573 | 0.581 |
| | GB3 | 0.557 | 0.541 | 0.549 |
| | GB4 | 0.323 | 0.411 | 0.367 |
| HU | HU1 | 0.411 | 0.378 | 0.395 |
| | HU2 | 0.497 | 0.522 | 0.510 |
| | HU3 | 0.495 | 0.490 | 0.492 |
| | HU4 | 0.328 | 0.298 | 0.313 |
| IT | IT1 | 0.561 | 0.483 | 0.522 |
| | IT2 | 0.660 | 0.590 | 0.625 |
| | IT3 | 0.506 | 0.426 | 0.466 |
| | IT4 | 0.492 | 0.486 | 0.489 |
| NL | NL1 | 0.699 | 0.624 | 0.661 |
| | NL2 | 0.467 | 0.497 | 0.482 |
| | NL3 | 0.474 | 0.437 | 0.455 |
| | NL4 | 0.536 | 0.493 | 0.514 |

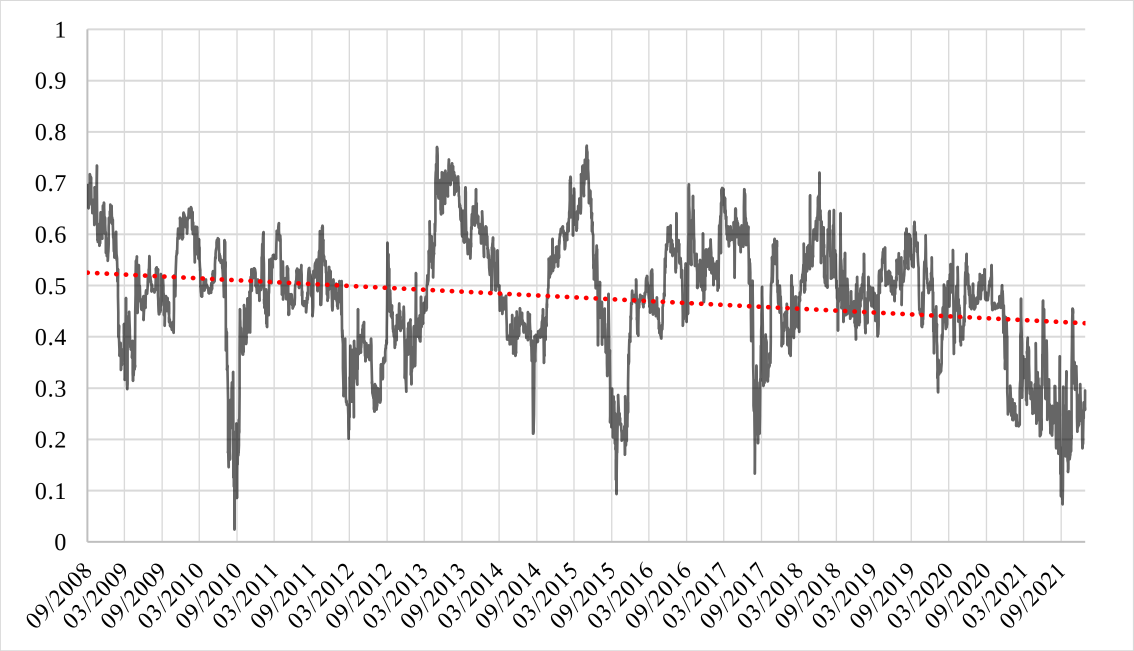

Figure 3.  White noise 250 days rolling Hurst exponent

Markets are generally distant from the efficiency levels represented by the White noise data. It is observable that long term memory characteristics of day ahead prices are more volatile than those of futures.

In parallel with the existing literature, none of the market prices is generated by entirely efficient processes. Instead, processes fluctuate between mean-reverting and persistent regimes in most markets. However, in the vast majority of the sample markets, it is observable that trendlines converge to the efficient state of H=0.5.

### 6.3 Fractal dimension measure

For measuring fractal dimension, two estimators, Genton and Hall-Wood, are derived in equations (4) and (5), respectively. Like the Hurst exponent, values are calculated for each sample, and a fractal dimension measure of (D) is derived using the mean of two estimators. We must note that price data are used instead of price returns due to the nature of the statistics. Table 9 and 10 exhibit the spot and futures market results, respectively for each country.

Additionally, for a better graphical representation and detecting the volatility regime changes 250 days rolling calculations are also presented for each market in Appendix E.

For comparative purposes Figure 4 shows the fractal dimension results for the 250 days rolling random walk we simulated in R.

Table 9. Fractal Dimensions for Day ahead Prices

| Country | Sample | Genton Estimator | Hall-Wood Estimator | D |
|---|---|---|---|---|
| BE | BE1 | 1.383 | 1.502 | 1.443 |
| | BE2 | 1.442 | 1.566 | 1.504 |
| | BE3 | 1.453 | 1.555 | 1.504 |
| CH | CH0 | 1.369 | 1.476 | 1.423 |
| CZ | CZ1 | 1.448 | 1.524 | 1.486 |
| | CZ2 | 1.372 | 1.499 | 1.436 |
| | CZ3 | 1.426 | 1.537 | 1.482 |
| | CZ4 | 1.307 | 1.455 | 1.381 |
| DE | DE1 | 1.407 | 1.567 | 1.487 |
| | DE2 | 1.453 | 1.554 | 1.504 |
| | DE3 | 1.471 | 1.526 | 1.499 |
| | DE4 | 1.432 | 1.486 | 1.459 |
| ES | ES1 | 1.564 | 1.614 | 1.589 |
| | ES2 | 1.484 | 1.521 | 1.503 |
| | ES3 | 1.362 | 1.507 | 1.435 |
| FR | FR1 | 1.430 | 1.727 | 1.579 |
| | FR2 | 1.392 | 1.432 | 1.412 |
| | FR3 | 1.370 | 1.465 | 1.418 |
| | FR4 | 1.442 | 1.534 | 1.488 |

| Country | Sample | Genton Estimator | Hall-Wood Estimator | D |
|---|---|---|---|---|
| GB | GB1 | 1.535 | 1.718 | 1.627 |
| | GB2 | 1.662 | 1.584 | 1.623 |
| | GB3 | 1.557 | 1.627 | 1.592 |
| | GB4 | 1.402 | 1.436 | 1.419 |
| HU | HU1 | 1.667 | 1.678 | 1.673 |
| | HU2 | 1.668 | 1.739 | 1.704 |
| | HU3 | 1.504 | 1.584 | 1.544 |
| | HU4 | 1.583 | 1.547 | 1.565 |
| IT | IT1 | 1.715 | 1.922 | 1.819 |
| | IT2 | 1.641 | 1.744 | 1.693 |
| | IT3 | 1.531 | 1.543 | 1.537 |
| | IT4 | 1.532 | 1.497 | 1.515 |
| NL | NL1 | 1.395 | 1.478 | 1.437 |
| | NL2 | 1.505 | 1.583 | 1.544 |
| | NL3 | 1.519 | 1.599 | 1.559 |
| | NL4 | 1.458 | 1.602 | 1.530 |

In contrast to long term memory, we experience more volatility in fractal dimension measures of future prices than the spot prices. We note that all of the day ahead markets except Germany and Netherlands have fractality closer to the random walk state than pre-coupling samples. However, the case is exactly the opposite for the M+1 futures market. We can see that the distances from the efficiency case are increased for Belgium, France, Hungary, Italy and Spain futures markets.

Table 10. Fractal Dimensions for Month Ahead Future Prices

| Country | Sample | Genton Estimator | Hall-Wood Estimator | D |
|---|---|---|---|---|
| BE | BE1 | 1.419 | 1.533 | 1.476 |
| | BE2 | 1.219 | 1.569 | 1.394 |
| | BE3 | 1.391 | 1.514 | 1.453 |
| CH | CH0 | 1.261 | 1.435 | 1.348 |
| CZ | CZ1 | 1.475 | 1.582 | 1.529 |
| | CZ2 | 1.313 | 1.423 | 1.368 |
| | CZ3 | 1.357 | 1.446 | 1.402 |
| | CZ4 | 1.515 | 1.444 | 1.480 |
| DE | DE1 | 1.355 | 1.371 | 1.363 |
| | DE2 | 1.420 | 1.351 | 1.386 |
| | DE3 | 1.324 | 1.350 | 1.337 |
| | DE4 | 1.408 | 1.341 | 1.375 |
| ES | ES1 | 1.260 | 1.396 | 1.328 |
| | ES2 | 1.370 | 1.698 | 1.534 |
| | ES3 | 1.393 | 1.523 | 1.458 |
| FR | FR1 | 1.422 | 1.357 | 1.390 |
| | FR2 | 1.197 | 1.309 | 1.253 |
| | FR3 | 1.210 | 1.288 | 1.249 |
| | FR4 | 1.468 | 1.451 | 1.460 |

| Country | Sample | Genton Estimator | Hall-Wood Estimator | D |
|---|---|---|---|---|
| GB | GB1 | 1.461 | 1.404 | 1.433 |
| | GB2 | 1.368 | 1.464 | 1.416 |
| | GB3 | 1.441 | 1.427 | 1.434 |
| | GB4 | 1.552 | 1.583 | 1.568 |
| HU | HU1 | 1.313 | 1.324 | 1.319 |
| | HU2 | 1.422 | 1.340 | 1.381 |
| | HU3 | 1.324 | 1.473 | 1.399 |
| | HU4 | 1.674 | 1.435 | 1.555 |
| IT | IT1 | 1.491 | 1.473 | 1.482 |
| | IT2 | 1.197 | 1.314 | 1.256 |
| | IT3 | 1.400 | 1.508 | 1.454 |
| | IT4 | 1.337 | 1.593 | 1.465 |
| NL | NL1 | 1.354 | 1.341 | 1.348 |
| | NL2 | 1.292 | 1.381 | 1.337 |
| | NL3 | 1.339 | 1.537 | 1.438 |
| | NL4 | 1.432 | 1.368 | 1.400 |

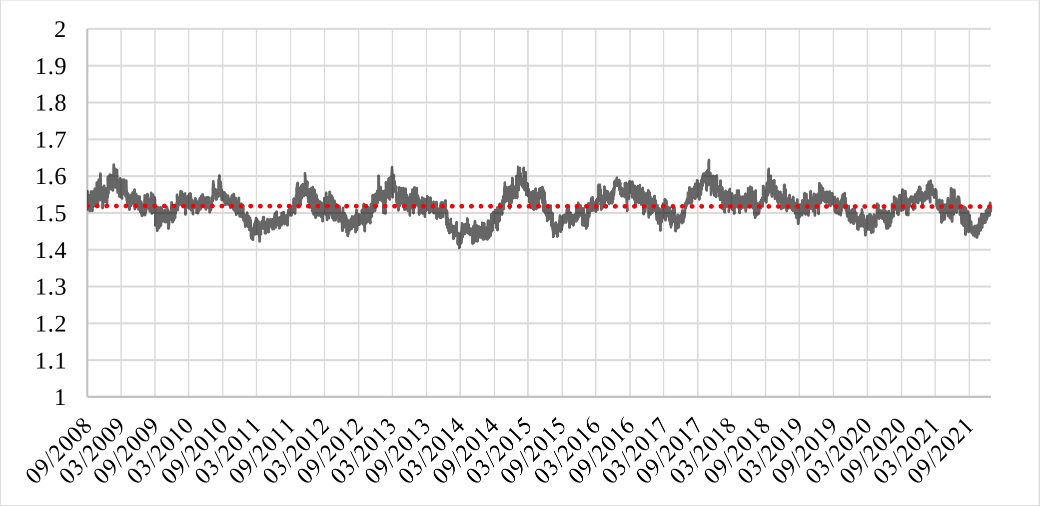

Figure 4. Random walk 250 days rolling fractal dimension

### 6.4. Ex-post risk premium

We applied the formulation (6) to the monthly futures data and monthly averages of the realized day ahead prices for the corresponding month to apply the risk premium calculation. We removed the months with non-available data.

We have tested if the risk premiums are different from zero under a given level of significance or not. We used a one-sample T-test by choosing the expected premium as zero. The results in Table 11 show mixed effects when ex-post risk premiums are compared according to structural breaks.

Table 11. Ex-post Risk Premiums of Month Ahead Futures

| Country | Sample | Premium (%) | p value |
|---|---|---|---|
| BE | BE1 | -5.58% | 0.04 |
| | BE2 | -5.82% | 0.00 |
| | BE3 | 9.35% | 0.04 |
| CH | CH0 | 12.95% | 0.00 |
| CZ | CZ1 | -2.70% | 0.14 |
| | CZ2 | -3.28% | 0.12 |
| | CZ3 | -2.07% | 0.24 |
| | CZ4 | 10.95% | 0.09 |
| DE | DE1 | -5.60% | 0.01 |
| | DE2 | -4.55% | 0.01 |
| | DE3 | -4.17% | 0.01 |
| | DE4 | 11.38% | 0.07 |
| ES | ES1 | -10.99% | 0.00 |
| | ES2 | -3.52% | 0.03 |
| | ES3 | 8.89% | 0.30 |
| FR | FR1 | -7.18% | 0.07 |
| | FR2 | -4.73% | 0.09 |
| | FR3 | -8.12% | 0.00 |
| | FR4 | 7.30% | 0.14 |

| Country | Sample | Premium (%) | p value |
|---|---|---|---|
| GB | GB1 | 6.90% | 0.04 |
| | GB2 | -0.74% | 0.41 |
| | GB3 | -6.53% | 0.01 |
| | GB4 | 13.25% | 0.05 |
| HU | HU1 | -0.73% | 0.83 |
| | HU2 | -4.10% | 0.16 |
| | HU3 | -3.34% | 0.08 |
| | HU4 | 15.52% | 0.01 |
| IT | IT1 | -2.79% | 0.08 |
| | IT2 | -1.48% | 0.21 |
| | IT3 | 1.43% | 0.45 |
| | IT4 | 0.42% | 0.85 |
| NL | NL1 | -4.41% | 0.07 |
| | NL2 | -2.46% | 0.12 |
| | NL3 | -2.25% | 0.08 |
| | NL4 | 7.09% | 0.08 |

Especially the sample groups with the most recent data tend to create bias since the observations are not as much as desired. However, one can experience the tendency to fail to state that average premiums are different from zero—a sign of the move towards efficiency.

Figure 5 shows all countries' average ex-post risk premiums between 2008-2021. One can easily observe that countries behave similarly even though the magnitude of the ex-post risk premiums are different for each country.

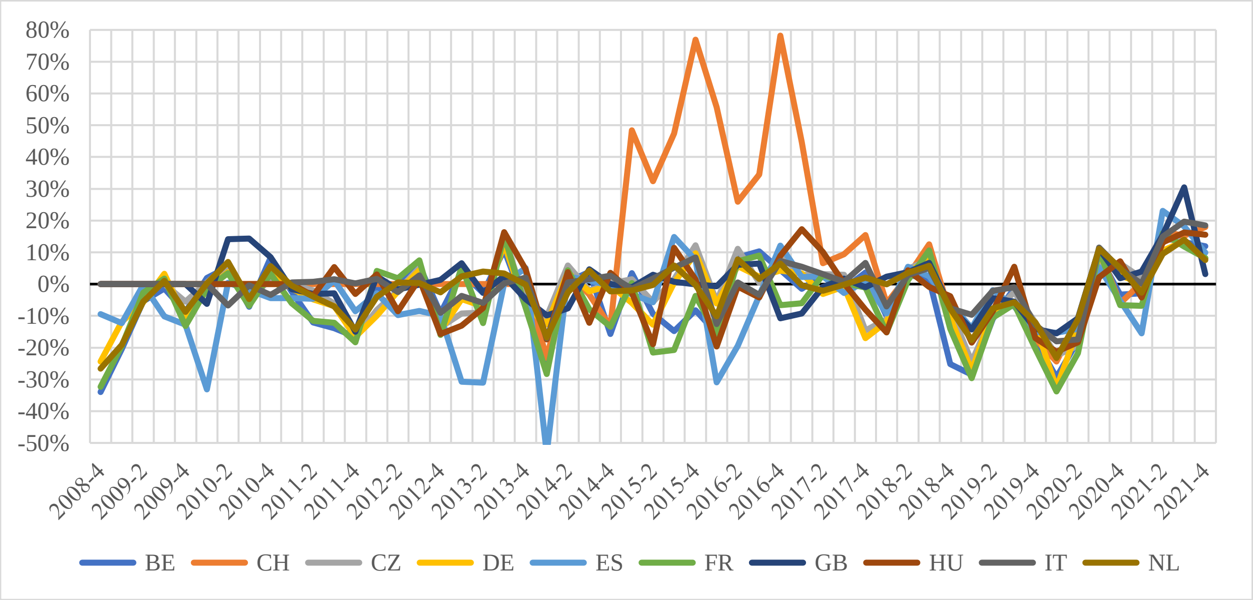

Figure 5. Monthly ex-post risk premium for sample countries

Correlation tables (Tables 12-14) comprehensively show the relations among ex-post risk premiums in other markets. The last column (AVG) in each table indicates the mean of the correlation coefficients of each country.

Table 12. Monthly Ex-post Risk Premium Correlations Between the Countries in year 2011-2015

| | BE | CZ | DE | ES | FR | GB | HU | IT | NL | AVG |
|---|---|---|---|---|---|---|---|---|---|---|
| BE | | 65% | 71% | 9% | 88% | 62% | 35% | 41% | 87% | 57% |
| CZ | 65% | | 96% | 22% | 75% | 37% | 66% | 43% | 59% | 58% |
| DE | 71% | 96% | | 20% | 80% | 45% | 60% | 43% | 66% | 60% |
| ES | 9% | 22% | 20% | | 21% | 6% | 41% | 48% | 9% | 22% |
| FR | 88% | 75% | 80% | 21% | | 61% | 54% | 56% | 77% | 64% |
| GB | 62% | 37% | 45% | 6% | 61% | | 11% | 28% | 76% | 41% |
| HU | 35% | 66% | 60% | 41% | 54% | 11% | | 62% | 31% | 45% |
| IT | 41% | 43% | 43% | 48% | 56% | 28% | 62% | | 48% | 46% |
| NL | 87% | 59% | 66% | 9% | 77% | 76% | 31% | 48% | | 57% |

Table 13. Monthly Ex-post Risk Premium Correlations Between the Countries in year 2015-2021

| | BE | CZ | DE | ES | FR | GB | HU | IT | NL | AVG |
|---|---|---|---|---|---|---|---|---|---|---|
| BE | | 80% | 81% | 54% | 92% | 73% | 60% | 71% | 84% | 74% |
| CZ | 80% | | 95% | 54% | 82% | 66% | 75% | 74% | 84% | 76% |
| DE | 81% | 95% | | 54% | 84% | 68% | 71% | 72% | 87% | 76% |
| ES | 54% | 54% | 54% | | 55% | 53% | 62% | 69% | 62% | 58% |
| FR | 92% | 82% | 84% | 55% | | 74% | 63% | 73% | 82% | 76% |
| GB | 73% | 66% | 68% | 53% | 74% | | 39% | 63% | 75% | 64% |
| HU | 60% | 75% | 71% | 62% | 63% | 39% | | 78% | 66% | 64% |
| IT | 71% | 74% | 72% | 69% | 73% | 63% | 78% | | 80% | 72% |
| NL | 84% | 84% | 87% | 62% | 82% | 75% | 66% | 80% | | 77% |

Table 14. Monthly Ex-post Risk Premium Correlations Between the Countries in year 2021-2022

| | BE | CZ | DE | ES | FR | GB | HU | IT | NL | AVG |
|---|---|---|---|---|---|---|---|---|---|---|
| BE | | 92% | 96% | 80% | 92% | 77% | 71% | 85% | 95% | 86% |
| CZ | 92% | | 94% | 74% | 83% | 73% | 65% | 78% | 90% | 81% |
| DE | 96% | 94% | | 69% | 82% | 79% | 59% | 77% | 95% | 81% |
| ES | 80% | 74% | 69% | | 87% | 76% | 79% | 83% | 75% | 78% |
| FR | 92% | 83% | 82% | 87% | | 72% | 84% | 88% | 86% | 84% |
| GB | 77% | 73% | 79% | 76% | 72% | | 46% | 64% | 80% | 71% |
| HU | 71% | 65% | 59% | 79% | 84% | 46% | | 95% | 74% | 72% |
| IT | 85% | 78% | 77% | 83% | 88% | 64% | 95% | | 88% | 82% |
| NL | 95% | 90% | 95% | 75% | 86% | 80% | 74% | 88% | | 85% |

Table 15 shows the corelation between skewness of day ahead market prices and ex-post month ahead futures risk premiums. p values show the significance of the skewness variable when analysis of variance (ANOVA) applied to the data.

Table 15. Skewness of Day ahead Prices and Correlation with Ex-post Risk Premiums

| | BE | CH | CZ | DE | ES | FR | GB | HU | IT | NL |
|---|---|---|---|---|---|---|---|---|---|---|
| Correlation | -8% | 22% | 26% | 23% | 16% | 10% | 18% | 14% | 20% | 16% |
| p value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

### 6.5 Spread analysis

Using Roll (1984)'s method as the equation (7) we made the assumptions for the average bid-ask spreads for each sample period for eight countries. First, the values are calculated as percentages of the prices. Then, under the assumption that the bid-ask spreads would converge to zero in the efficient market, we evaluated the predicted spreads using prices of M+1 future contracts. We should note that day ahead prices are not occurring in an exchange method but in an auction method in there is no bid and ask spread for those prices.

To measure the consistency of the method, we used a similar T-test to Roll's with uninterrupted market prices. For robustness, it was expected that five-day spreads should be significantly more than one-day spreads, which are also compliant with our results. Even though we expected to examine a tendency to decrease in spreads following the market couplings, it is impossible to come to such a conclusion. (Table 16) Initial structural changes had an increasing effect in efficiency. However, the following samples had larger expected spreads. Once the samples are analyzed in line with probability distribution charts in appendix B, we observe that samples with thinner data distribution have smaller expected spreads. Twenty-one days rolling spread calculations are also made to identify outliers affecting the average expected bid-ask spreads in the chosen periods. One can note that the first half of 2020 contains spikes in results leading to increases in the averages in related terms. The effect on the 5-day spread is mixed.

Table 16. Expected Bid-Ask Spreads for Month Ahead Futures

| Country | Sample | 1 day Spread | 5 days Spread |
|---|---|---:|---:|
| BE | BE1 | 3.3% | 256.1% |
|  | BE2 | 20.8% | 237.0% |
|  | BE3 | 2.0% | 25.9% |
| CH | CH0 | 11.8% | 19.4% |
| CZ | CZ1 | 3.1% | 9.8% |
|  | CZ2 | 0.9% | 8.7% |
|  | CZ3 | 2.9% | 11.6% |
|  | CZ4 | 4.9% | 30.9% |
| DE | DE1 | 1.3% | 11.5% |
|  | DE2 | 1.2% | 8.2% |
|  | DE3 | 5.6% | 11.0% |
|  | DE4 | 4.9% | 31.1% |
| ES | ES1 | 0.9% | 11.9% |
|  | ES2 | 18.9% | 14.1% |
|  | ES3 | 3.2% | 21.5% |
| FR | FR1 | 1.9% | 15.2% |
|  | FR2 | 0.5% | 13.9% |
|  | FR3 | 1.8% | 17.1% |
|  | FR4 | 1.9% | 28.4% |
| GB | GB1 | 0.6% | 6.8% |
|  | GB2 | 1.5% | 8.0% |
|  | GB3 | 6.0% | 11.4% |
|  | GB4 | 11.2% | 22.9% |
| HU | HU1 | 0.7% | 10.1% |
|  | HU2 | 1.2% | 9.5% |
|  | HU3 | 11.2% | 13.2% |
|  | HU4 | 3.5% | 26.5% |
| IT | IT1 | 1.0% | 4.7% |
|  | IT2 | 1.0% | 5.5% |
|  | IT3 | 5.3% | 14.7% |
|  | IT4 | 8.9% | 14.5% |
| NL | NL1 | 1.6% | 10.7% |
|  | NL2 | 0.7% | 6.4% |
|  | NL3 | 7.2% | 12.8% |
|  | NL4 | 4.0% | 23.4% |

## 6.6 Discussion

Considering the period analyzed (2008-2021), we experience considerable fluctuations in most measures. This is because there have been significant changes in production and consumption structure and market regulations the period. However, one can state a tendency to drift away from the inefficiency in all markets.

Our findings support Uritskaya and Serletis (2008) and Morales and Hanly (2018) that electricity markets are inefficient as they do not follow a random walk. However, similar to Morales and Hanly (2018) we can also point out that there is progress towards less inefficiency in the markets, especially after introducing structural and regulatory changes.

Approximate Entropy results indicate inefficiency for all the market samples analyzed. When subsets are compared, Belgium (BE) and Czechia(CZ) show a decrease in entropy in day ahead price returns and month ahead future returns. However, both countries' day ahead returns have had the highest entropy levels in earlier samples, along with the Netherlands (NL). Italy (IT) has shown an increase in the entropy level for both markets. While Spain (ES) and NL maintain their entropy levels for both markets, the United Kingdom (GB) exhibits the most noticeable changes with the market coupling. For future and spot markets, the level of entropy dramatically increases for GB following the initial market coupling with CWE. However, a decrease in entropy level is observable following the Brexit for both markets. Obviously, all markets face high volatility, especially in the 2020 and 2021 periods.

Our results comply with the findings of Papaioannou et al. (2019) that IT day ahead market has higher entropy than ES day ahead market.

We observe falling entropy levels in first half of 2020 in all of the markets. Especially NL and IT futures show the sharpest fall in ApEn results. However, markets adapt to the new standards, and entropy levels begin increasing, leading to convergence to efficiency afterwards. For all countries, entropy indices revert to pre-Covid levels both in the day ahead and futures market. We also note that price shocks in post-vaccination time have similar effects. That complies with Lee and Lee (2009)since they suggest that price shocks in energy markets are temporary. However, our sample is not recent enough to measure the recovery effects in the markets.

Futures markets fluctuate around H=0.5 through the examined period, however we can state that the trend is towards to the less inefficient state in terms of long-term memory. Germany (DE)'s futures market is the least inefficient when most recent samples are compared with long-term memory. However, drastic changes are observable during the analyzed period. Most recent samples from the NL and France (FR) spot markets show the least inefficiency along with Switzerland (CH). After three market couplings, Hungary (HU)'s spot market shows the most significant change from the persistent state to a less inefficient but mean-reverting state. Another most considerable change in long term memory exponent is in Italy's spot market while remaining as mean-reverting.

It's also observable that none of the day ahead market samples except GB's after Brexit sample (GB4) remained in persistent state even though markets switch regimes between mean reverting to persistence through the periods.[2] It's also compliant with Papaioannou et al. (2019) article that spot electricity markets carry an anti-persistent character. Moreover, our result is also compliant with Kristoufek and Lunackova (2013)'s result which found that CZ day ahead market is mean reverting between 2009 -2012.

Once the samples are analyzed separately, we can state that BE, DE and NL spot markets are almost in random walk state in terms of fractal dimension through the analyzed period. When the rolling results are examined, we note fractal dimension above 1.5 for all of the day ahead market indicating an anti-persistence. While BE and GB day ahead market remains in the same level of fractality in the observed period, CH, ES, FR, HU and IT have a trend towards less inefficient states. We also observe that CZ, DE, and NL day ahead markets move towards more anti-persistent nature through the analyzed period.

Characteristics of futures markets in terms of fractal dimension in all of the analyzed countries is opposite of the day ahead markets. We observe that future markets show less degree of inefficiency, however they have fractal dimension below 1.5 indicating local persistence, or in other words short term trends, in the prices. Temporary fluctuations above 1.5 level are observable through the analyzed period. Except CH and CZ which have a stable fractal dimension of 1.4 all of the futures market has a fractal dimension very close to 1.5 as of 2021 year end.

Even though, in principle, the local property of fractal dimension and global characteristic of long-term memory, Hurst estimates are independent factors, numerous

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[2] $H<0$ or $H>1$ results are observable due to the finite sample

studies link each other(Gneiting and Schlather, 2001). We can witness the same phenomenon in our results as well. As stated in Krištoufek (2010), we witness D=2-H as the measures converge to efficient points.

Even though a convergence towards efficient state of D=1.5 is common behaviour in the majority of the analyzed markets, markets tend to keep their characteristics through the analyzed period. One can observe that, unlike to the Hurst measures, fractal dimension of the markets has less fluctuations through the time.

Country specific graphs in Appendix F show that the linear trendlines for all countries except CH show positive slopes for the ex-post risk premiums. Even though this phenomenon could be a sign of convergence to the efficient state, it might be showing distancing from hypothesis of  Bessembinder and Lemmon (2002) regarding the expected negative premium in electricity futures

CH is excluded from the correlations stated in Tables 12-14 since it has never been a part of market coupling and carries a different character in terms of production regime. CH is a hydro dominated country where the power is indirectly storable via the reservoirs. In parallel with Bessembinder and Lemmon (2002)'s assumption which Botterud, Kristiansen, and Ilic (2010) supported, high hydro reservoirs lead to a positive risk premium. We can interpret it as the producers are eager to sell as much as possible, accepting lower prices than expected.

The most outstanding observation is that ex-post risk premiums are positively correlated between the markets in the observed time periods. The average correlation among the analyzed markets increased from 50% in 2011-2015 period to 71% in 2015-

2021, and finally, in 2021 average is more than 80%. 2021 has been the year with record-high gas and oil prices. Abnormal behaviour is visible also with other measures.

It is observable that ex-post risk premiums in ES, GB and HU are the least correlated with other countries. However, it is still interesting that ES's correlation increased to 78% from 22% between 2011-2015. That can be interpreted as the convergence towards standard behaviour for European power markets. On the other hand, this phenomenon also brings exposure risk to the market participants. In extreme events in the markets, traders and market participants would face difficulties taking positions as the majority of the markets are willing to take similar positions. That would make hedging more difficult and increase transaction costs and margin requirements.

Moreover, Weron and Zator underlined in 2014 that the observed risk premium is positively related to the expected variance of the spot price but negatively associated with its expected skewness. In other words, when there is a high possibility of price spikes (high skewness), the prices of futures contracts rise, leading to smaller risk premiums. The average ex-post risk premiums support the argument when price spikes are more likely to occur in the first quarters of the year, consumers are afraid of high prices and are eager to pay more for future contracts for hedging purposes. (Figure 6)

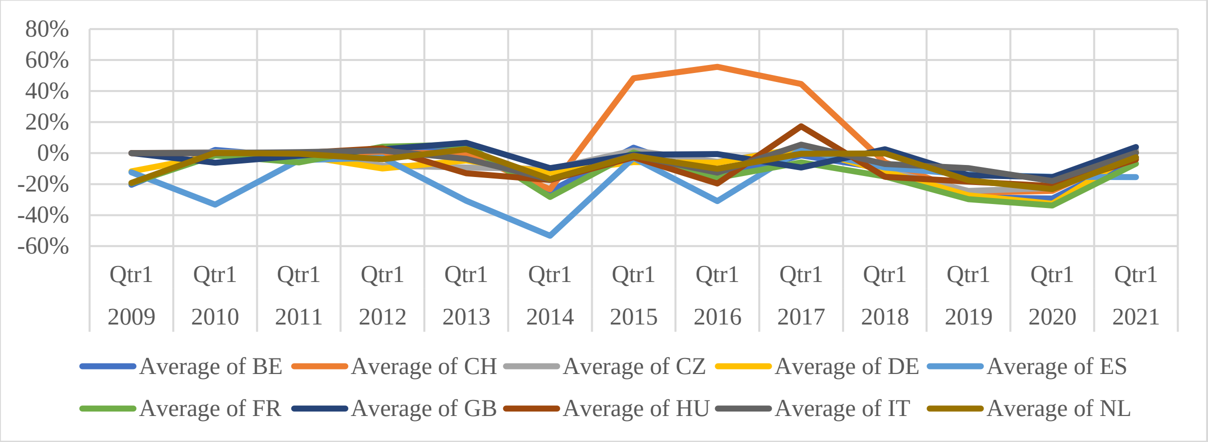

Figure 6. Average quarterly ex-post risk premiums for 1st quarters

However, contradictorily to the above argument, the relation between skewness and risk premium is not negative when the whole sample is analysed. Only BE has a negative correlation. That can be interpreted as the producers need to hedge their sales as well. Another argument can be the increased amount of speculative trading activities in the markets, which are not directly related to marginal cost fundamentals.

We also observe the effects of Covid-19 lockdowns during 2020. Unexpectedly low prices have been observed on day ahead market throughout Europe. Marginal costs were also record low levels as surplus of commodities experienced. The ambiguity for the opening date for economies can be considered as boosting factor for decreasing risk premiums on the month ahead futures. On the other hand, the economic recovery in post-vaccination and high demand for commodities caused sudden increases in the prices. Accordingly, most of the futures contracts have been in the money as the prices kept on rising.

The disruptive moves during 2020 and 2021 are also observable in long term memory, fractal dimension and entropy measures. According to Arciniegas et al. (2003)

the California energy crisis was not connected to a lack of efficiency in the markets. That would be a defendable argument for European markets as well. Furthermore, our findings support the authors that as the markets mature, efficiency in the electricity markets improves as well. Moreover, our results support Yang et al. (2009) that the addition of new countries to the pricing mechanism improves the efficiency of the markets.

Even though we face mixed results for the changes in the expected spreads, we can state that the increasing spreads can be considered as a sign of lacking liquidity in the markets. That is an observable phenomenon during the crisis periods. Therefore, it is not surprising to experience such market behavior in 2020 and 2021.

We can have different approaches for analyzing the reasons behind the changes in efficiency levels. There have been ongoing energy efficiency policies to decrease the primary energy consumption and heat demand in buildings.  Moreover, the share of renewables is rapidly increasing in all EU countries. (More than doubled in the last decade.)

One would admit that the Fukushima Nuclear Disaster in 2011 had a considerable effect on the incentives for renewable energy investments, which have a more volatile production regime than conventional production facilities such as nuclear, natural gas or coal. The European Green Deal for deducting carbon emissions and promoting renewable energy investments is vitally connected with the market developments. Well performing physical and financial electricity exchanges not only provide price signals for the investors but also gives the transparency for reducing price risk for both producers and consumers.

Thanks to the increased level of integration relatively less developed markets can attract investors for renewable productions as well.

European market integration aims to minimize the transmission grid constraints, consequently leading to price convergence through the markets as supported with this study. However, introduction of more renewable resources to the systems inevitably leads to more congestions. That would increase the importance of short-term markets. Integration of intraday markets which was not discussed under this study carries importance as well. Real time optimisation with demand and supply participation in the markets will be more crucial. Recently developing technologies like storage systems, hydrogen fuel cells and increased efficiency of production facilities carry potential to replace conventional carbon-based fuels. However, until then, it is anticipated that the supply security would keep on carrying importance as wider integration of renewable sources could not take over the role of system flexibility provided by on demand power plants.

Even though we intend to measure the results of the structural changes in the markets, one cannot state that filtering out the other developments in the markets is very convenient. Therefore, we used CH market as the control group as its production composition has not shown notable changes during the analyzed period. Moreover, it has not been a part of EU directives or market couplings. However, we should claim that given the amount of cross border trade, we can isolate none of the countries from the developments in surrounding markets.

Another limitation is that since we have not analyzed the correlations between the market prices in sample countries, we can hardly pinpoint the changes' resources. One must note that increasing correlation between the analyzed markets is a natural consequence of market couplings as the ultimate target is to create one single European electricity market.

A new study analyzing the drawbacks of market integration can reach interesting outcomes in contrast to generally accepted presumptions about the benefits. Moreover, studies for calculating optimal cross-border transmission constraints can achieve different results for maximizing social welfare. Finally, we note that increasing renewable production leads the markets to move in the same direction, which can cause extreme price fluctuations.

# CHAPTER 7

# CONCLUSION

This study aimed to analyze the change in efficiency in spot and future electricity markets in selected European countries after structural changes through the measured period. Based on quantitative analysis, we can conclude that these markets carry some common characteristics and move towards a less inefficient state.

Our study has been adding to the existing literature by presenting results in financial terms that correspond with the intentions in market changes. Moreover, our results provide insight into the expected structures of other markets if they follow similar developments. We build the theoretical foundation based on Efficient Market Hypothesis, which has been considered as the benchmark for evaluating efficiencies in the financial markets. We reviewed the existing literature by putting the weak and semi-strong forms of efficiency in the scope. Differently from the current literature on efficiency tests in electricity markets, we have applied tests on five different domains.

First, we have used entropy measure to understand the disorder, or in other words, randomness in the markets. Our tests to calculate the Hurst measure has aimed to capture the long-term memory in the price series. Moreover, we used fractal dimension to measure the roughness and irregularity of price series. Additionally, ex-post risk premiums are calculated to understand the analysed countries' spot and future market relations. And finally, expected spread analysis has provided insight regarding the liquidity in the markets.

Even though we had limitations to filter out the changes such as production compositions in the markets, our study is an essential addition to the literature as it covers a relatively longer period (2008-2021) than the existing studies. Moreover, we have analysed ten different countries' spot and futures markets using five different efficiency measures. Application of moment statistics, as well as regularity statistics on such a data set, is helpful for making broader deductions.

Based on the conclusions from our work, policymakers can consider the applications of similar road maps for developing markets. Furthermore, to better understand the implications of our results, the relationships between trade capacities, supply and demand compositions and market efficiencies could be addressed by future research.

# APPENDIX A

# PRICE GRAPHS

For each price graph, vertical blue lines indicate the market coupling dates stated in Table 1, and red dashed lines indicate trend lines over the analyzed period. Y-Axis indicates EUR price per Mwh of electrical energy. X-Axis is the dates.

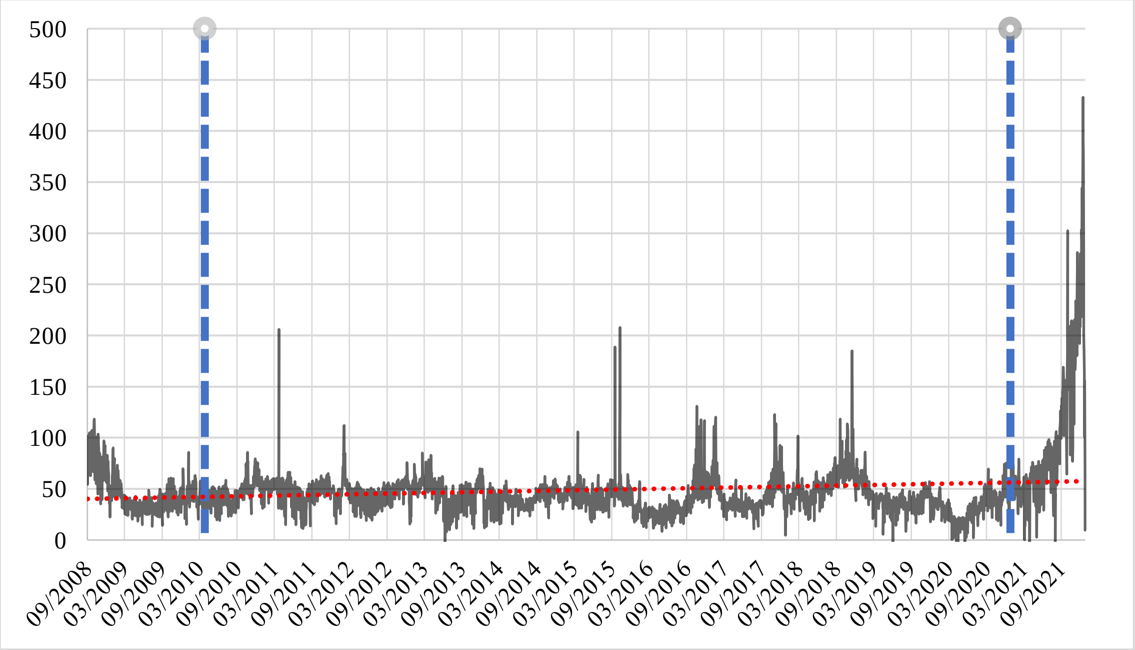

Figure A1. Belgium day ahead prices

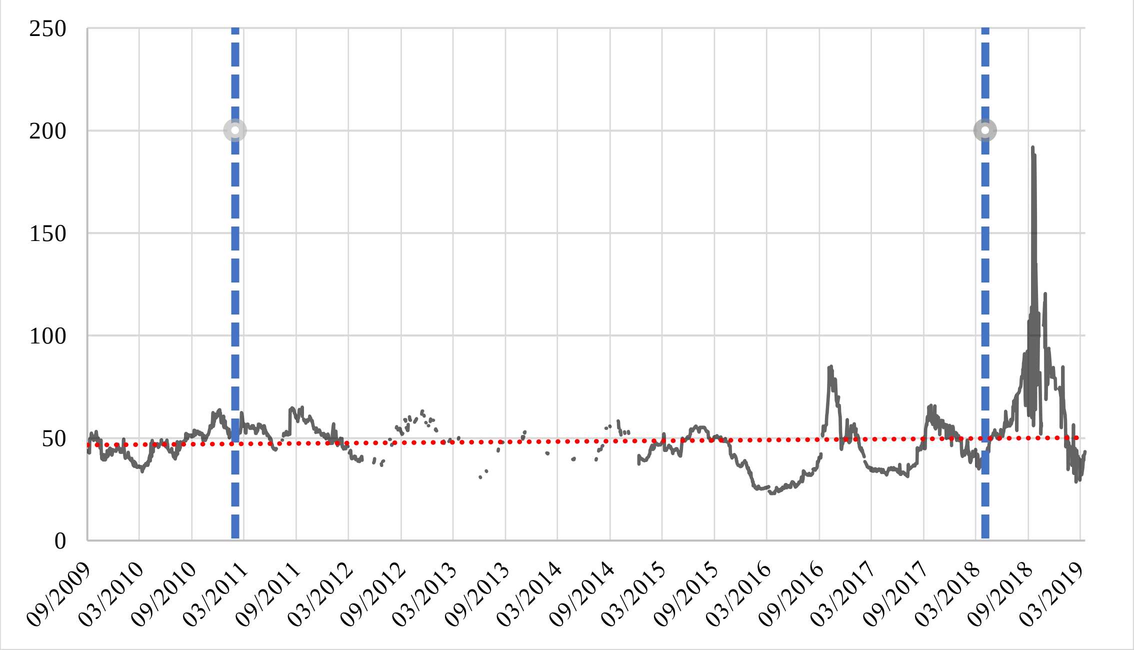

Figure A2. Belgium month ahead future prices

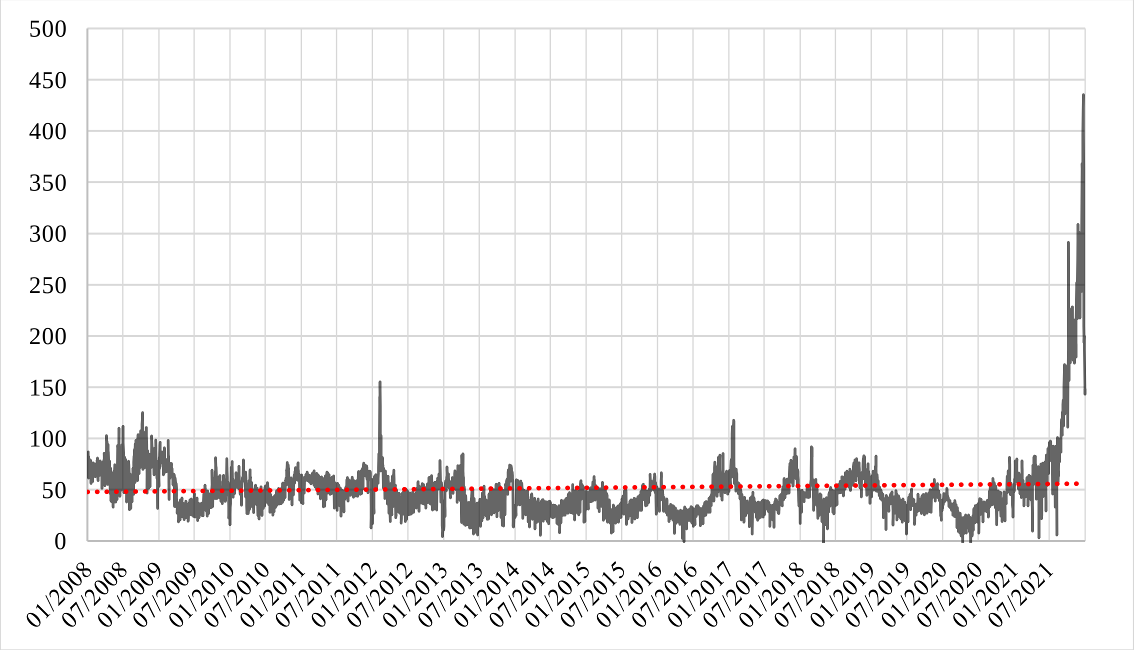

Figure A3. Switzerland day ahead prices

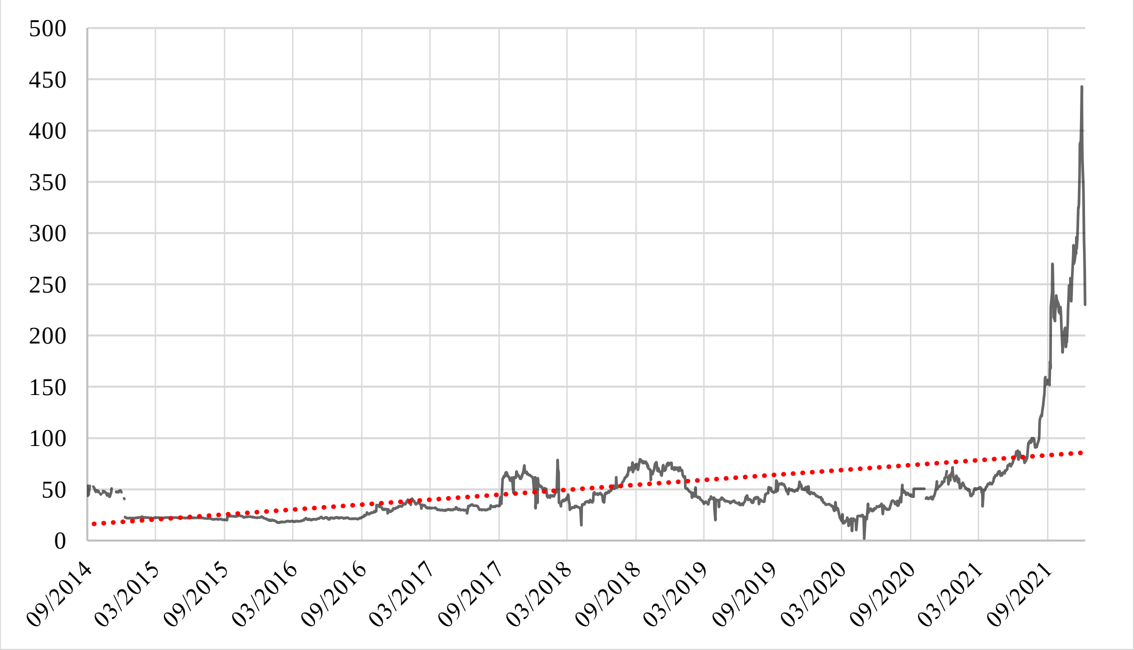

Figure A4. Switzerland month ahead future prices

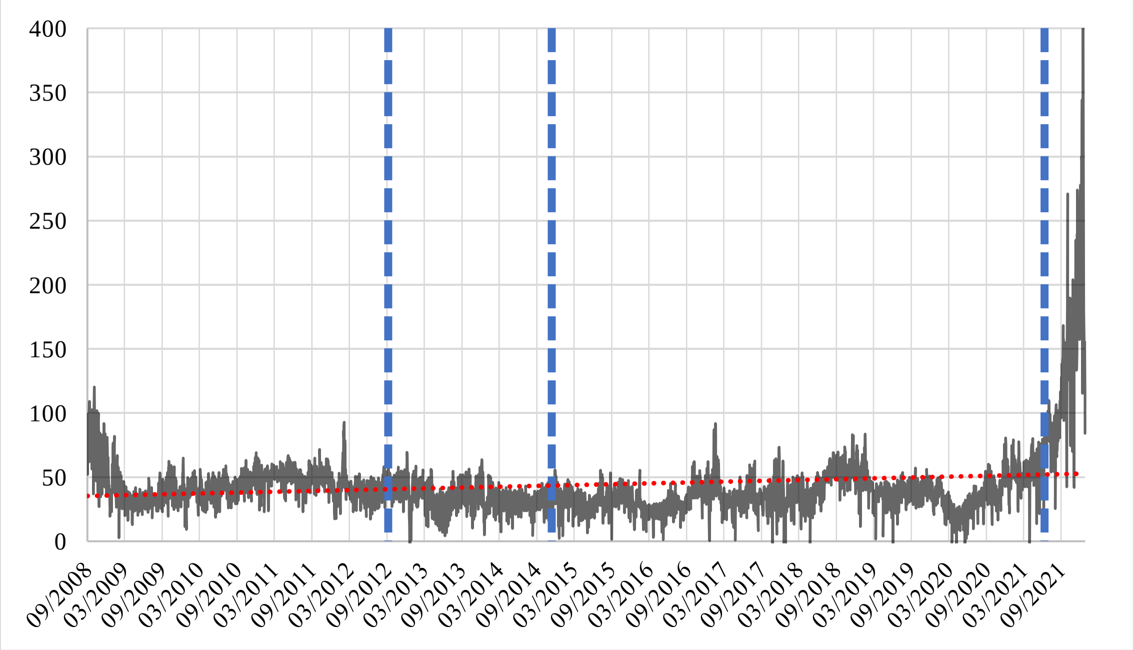

Figure A5. Czechia day ahead prices

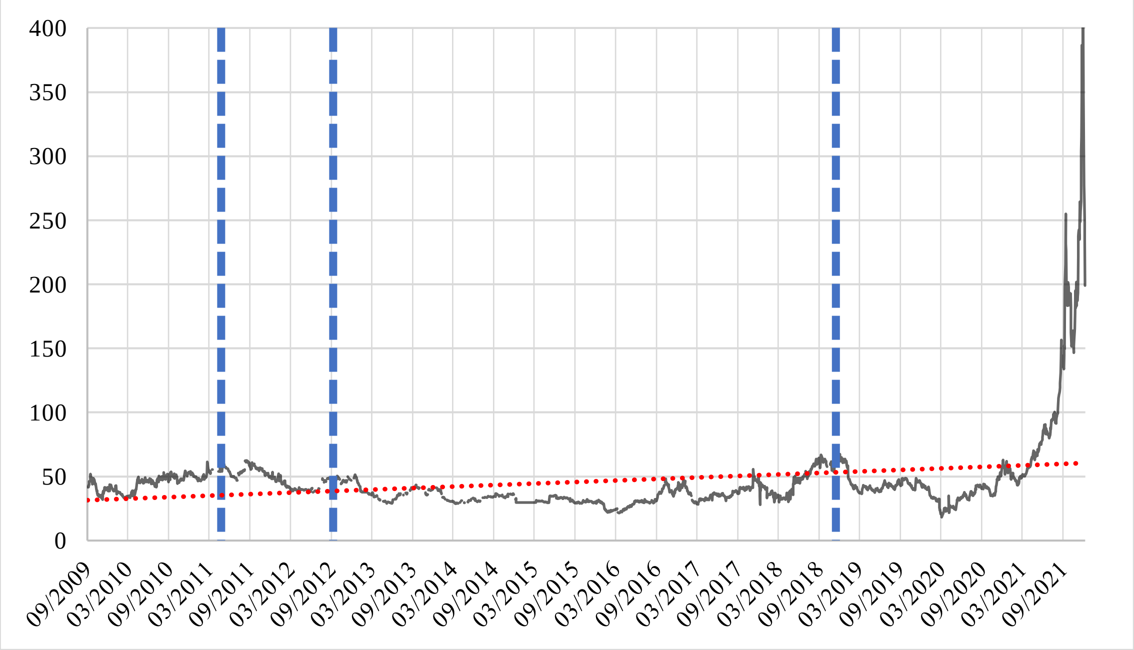

Figure A6. Czechia month ahead future prices

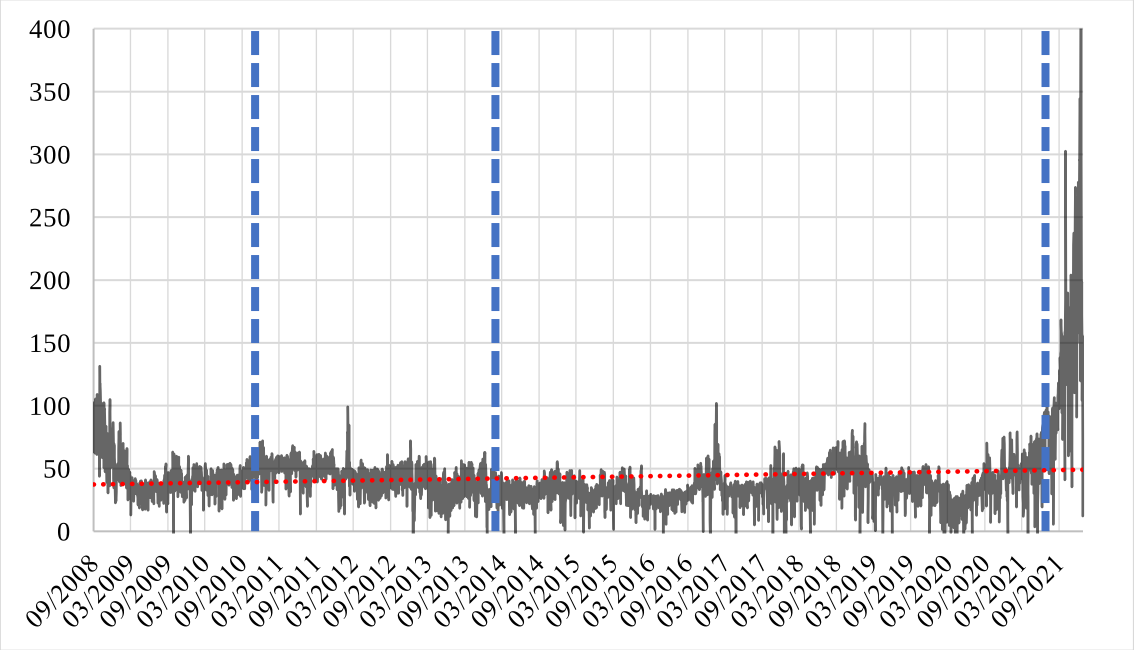

Figure A7. Germany day ahead prices

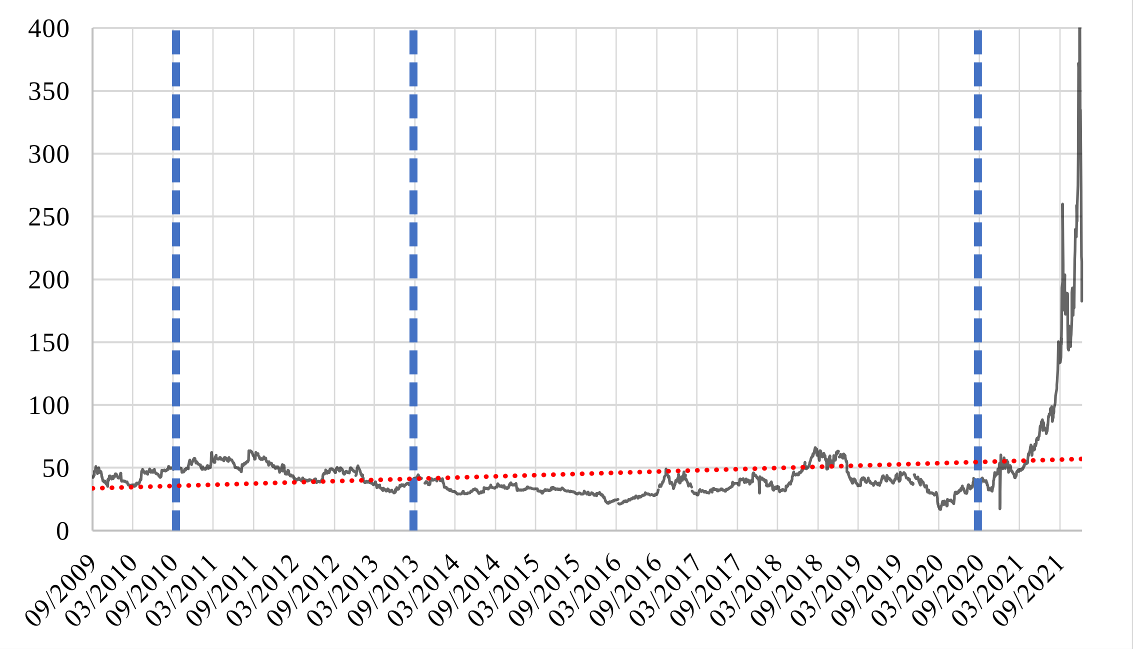

Figure A8. Germany month ahead future prices

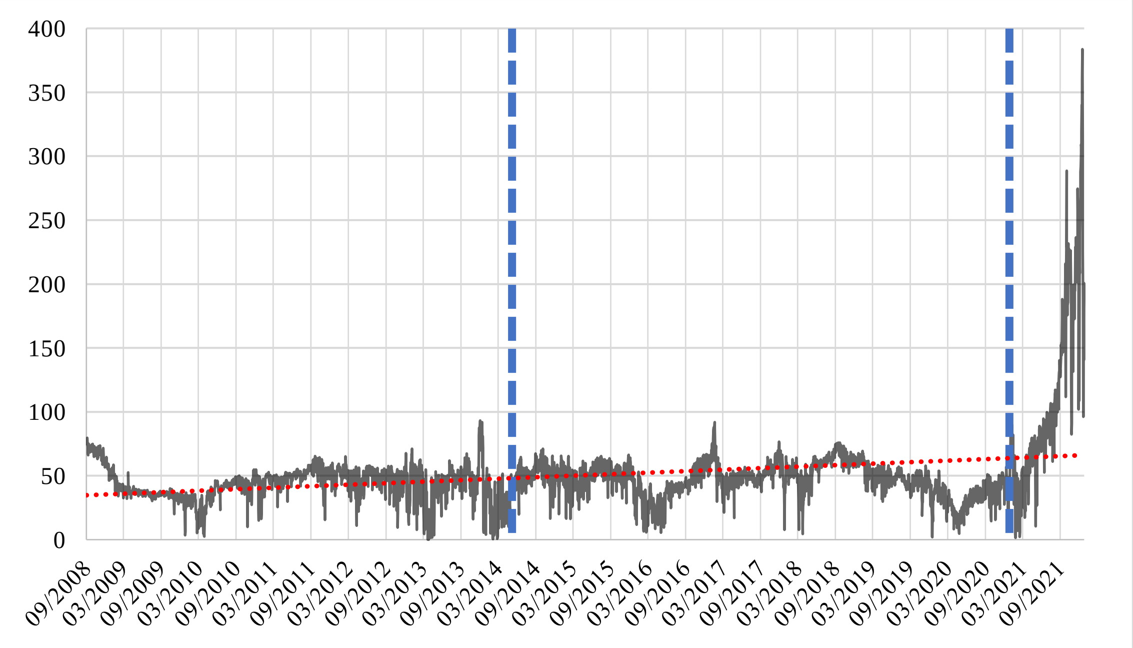

Figure A9. Spain day ahead prices

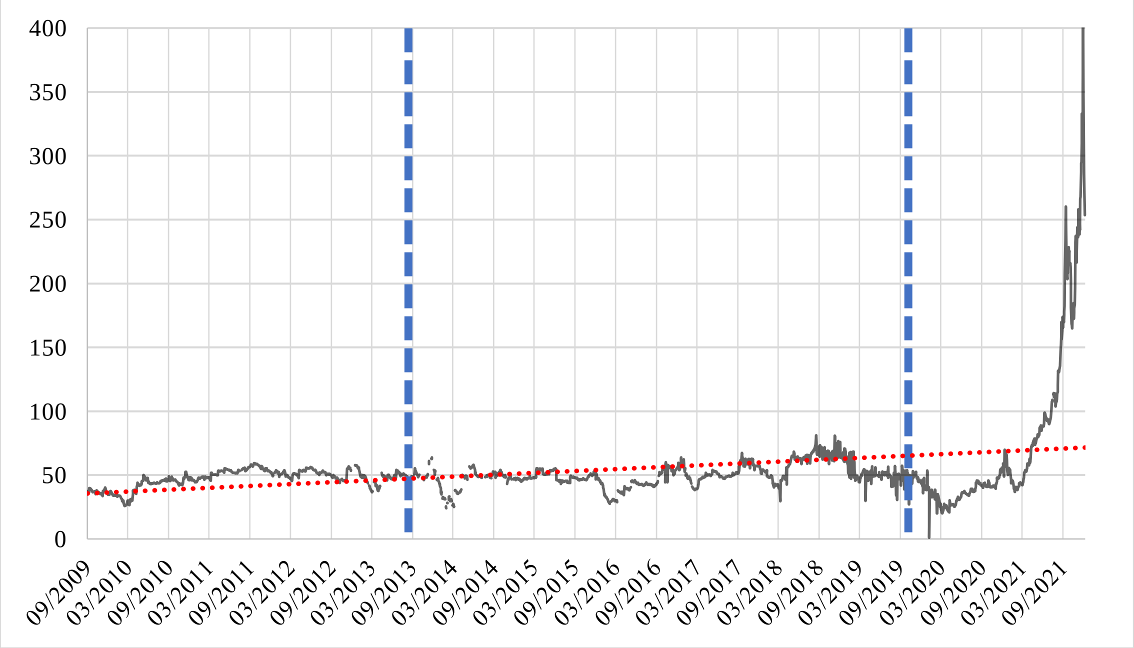

Figure A10. Spain month ahead future prices

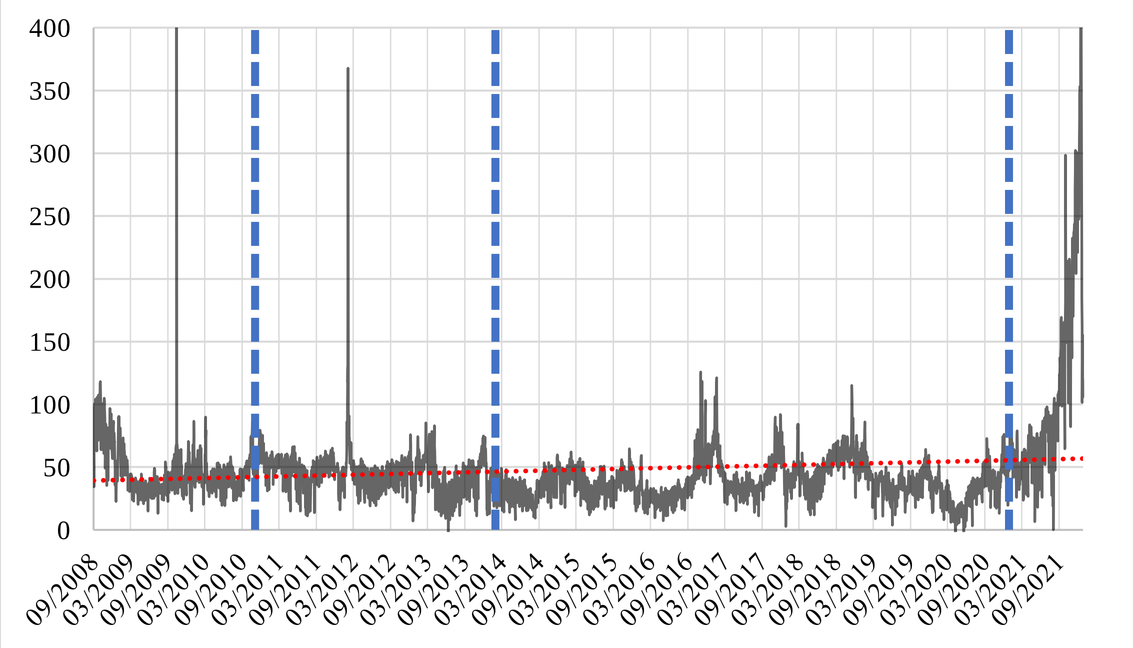

Figure A11. France day ahead prices

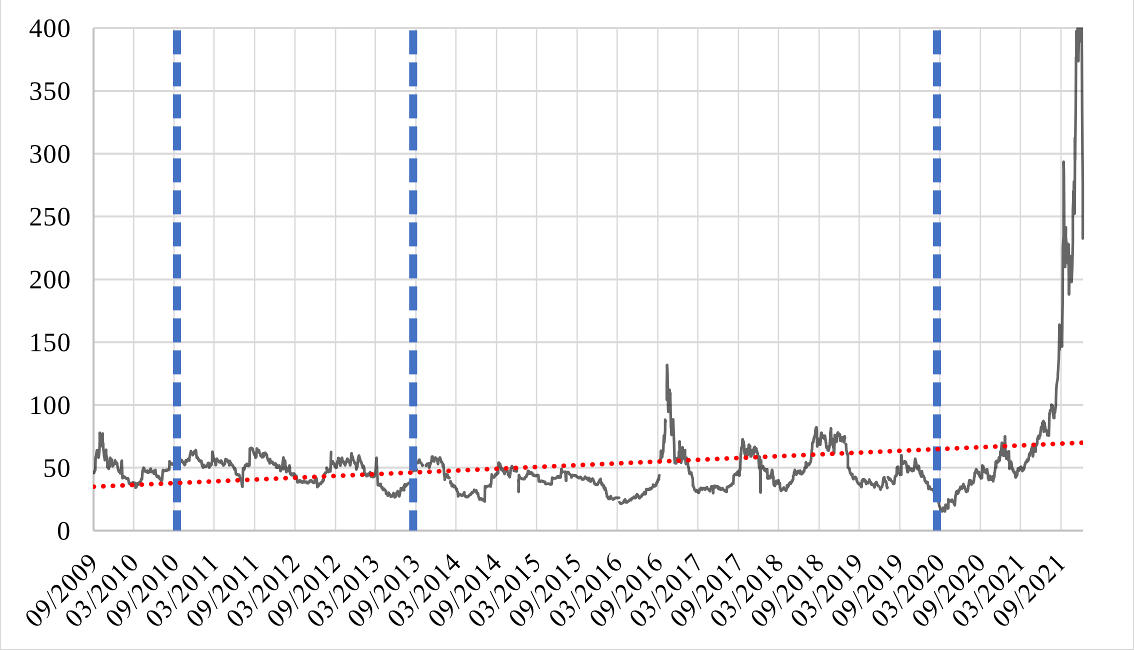

Figure A12. France month ahead future prices

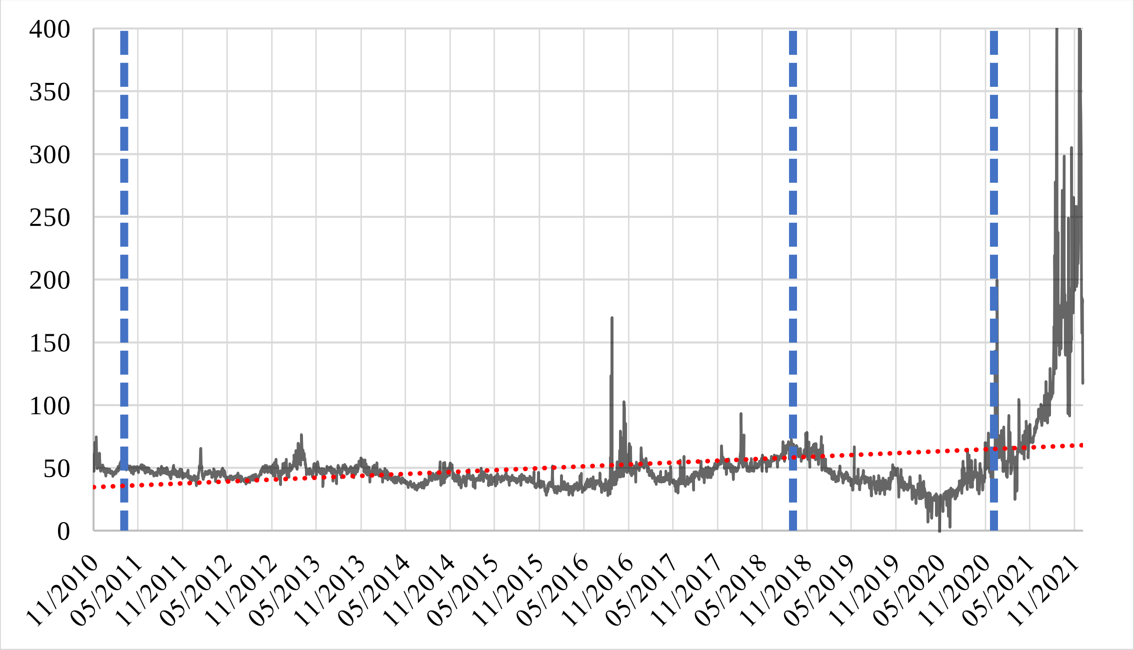

Figure A13. United Kingdom day ahead prices

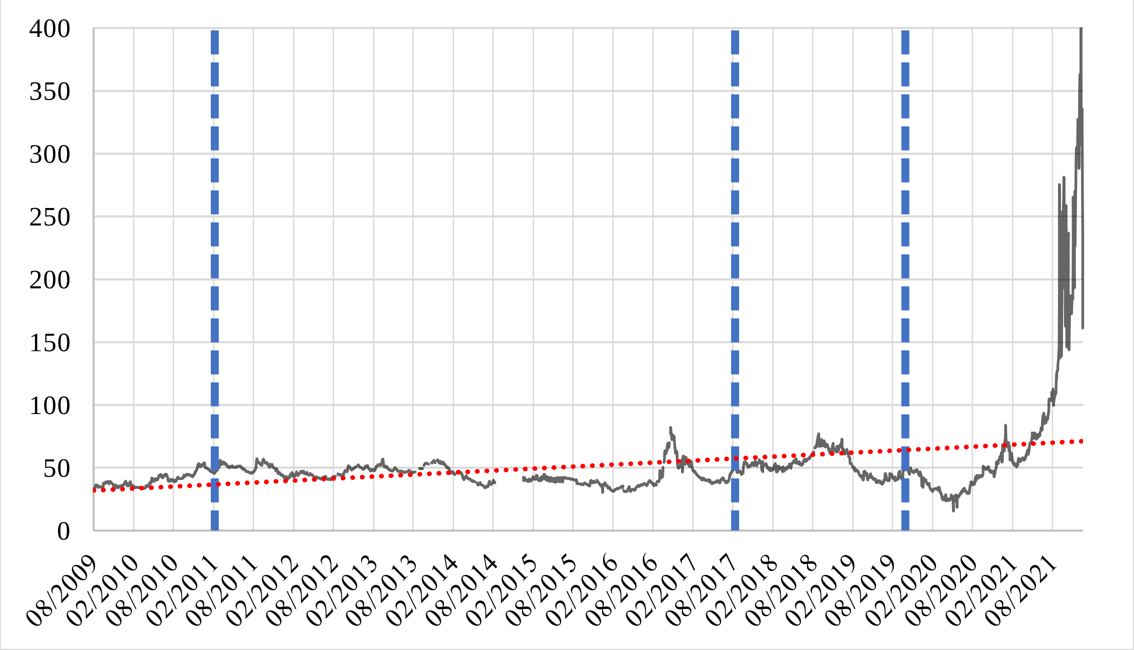

Figure A14. United Kingdom month ahead future prices

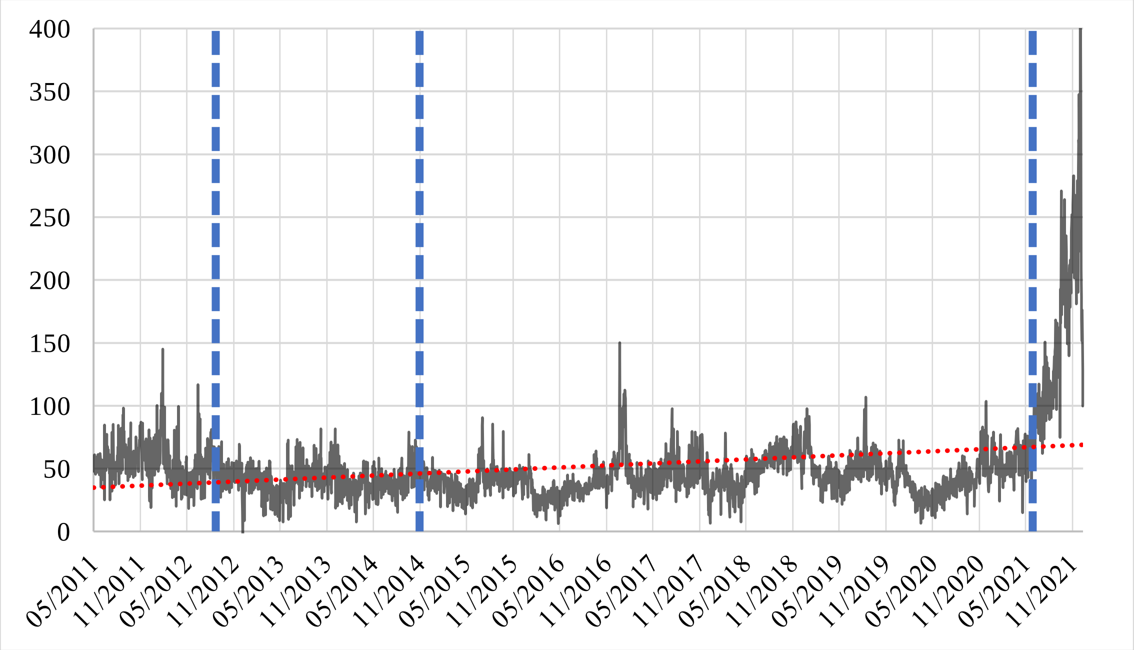

Figure A15. Hungary day ahead prices

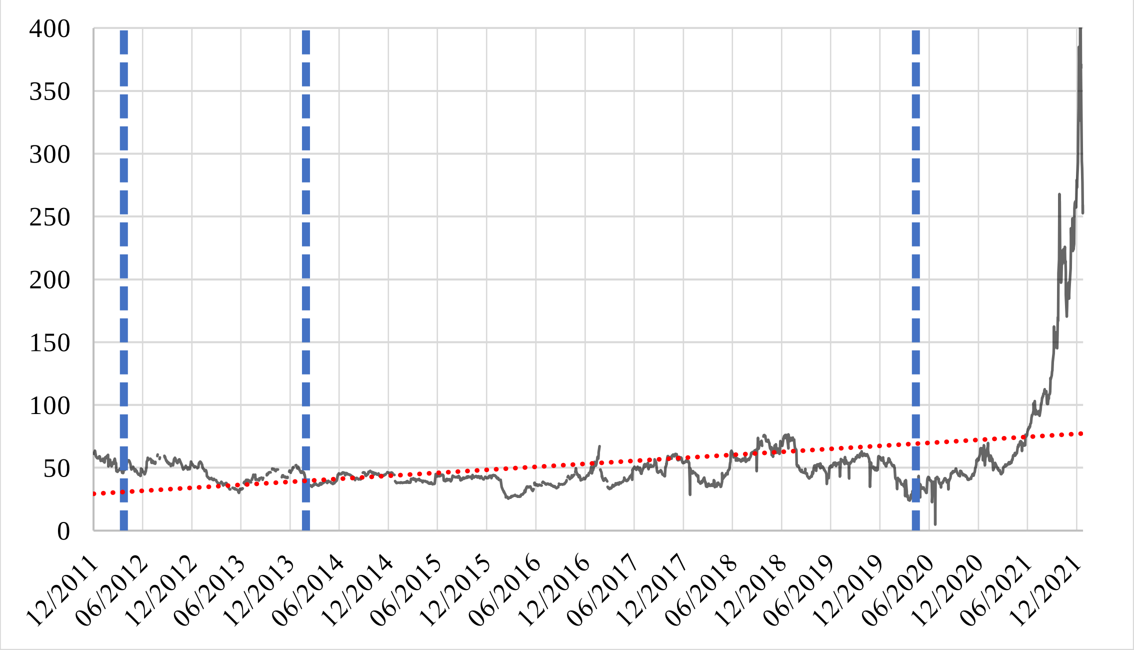

Figure A16. Hungary month ahead future prices

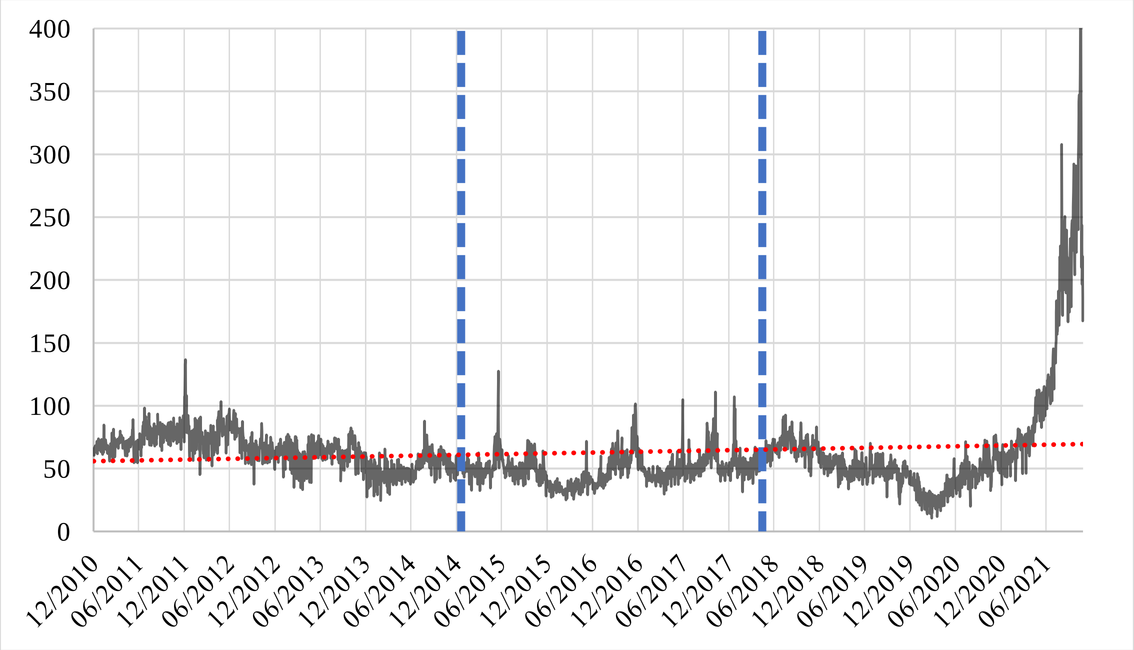

Figure A17. Italy day ahead prices

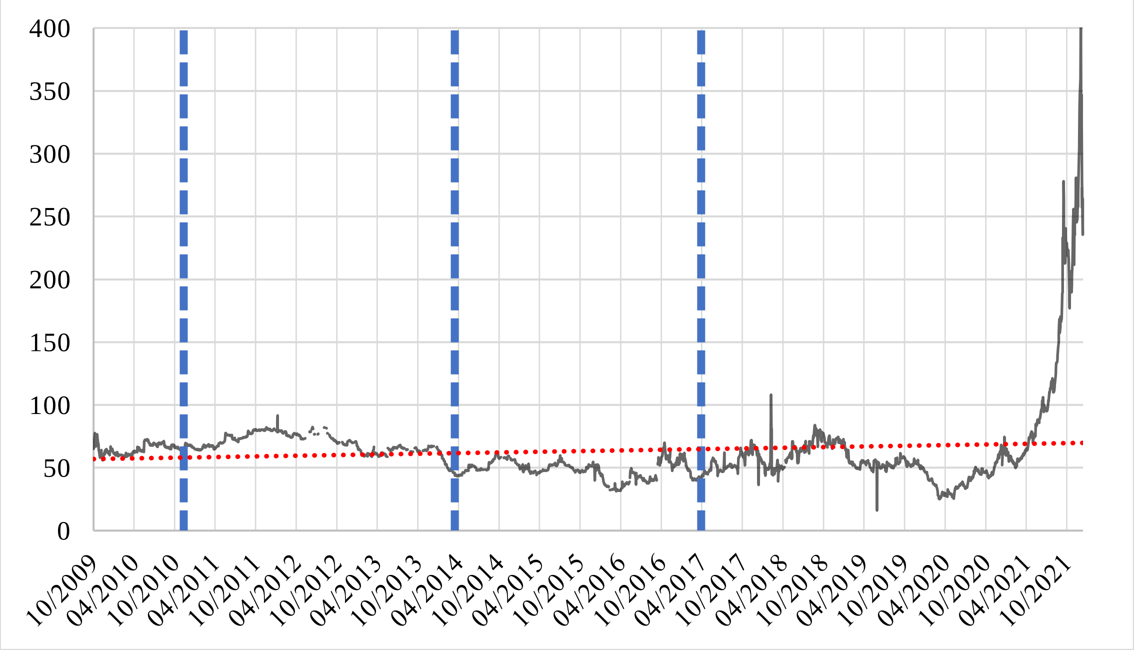

Figure A18. Italy month ahead future prices

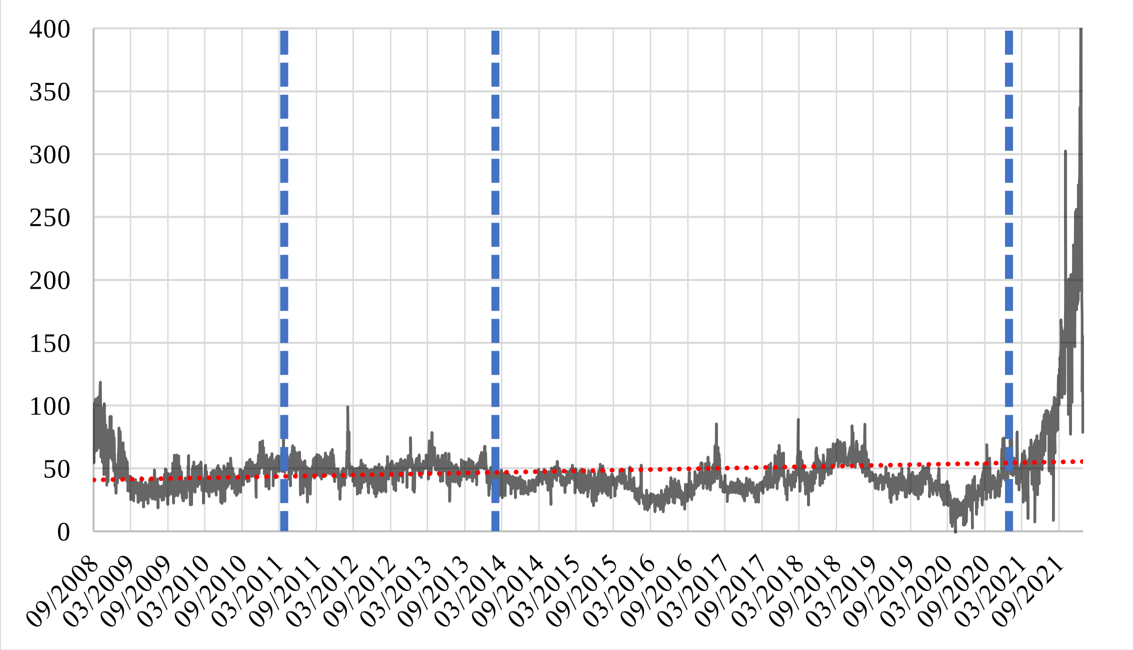

Figure A19. Netherlands day ahead prices

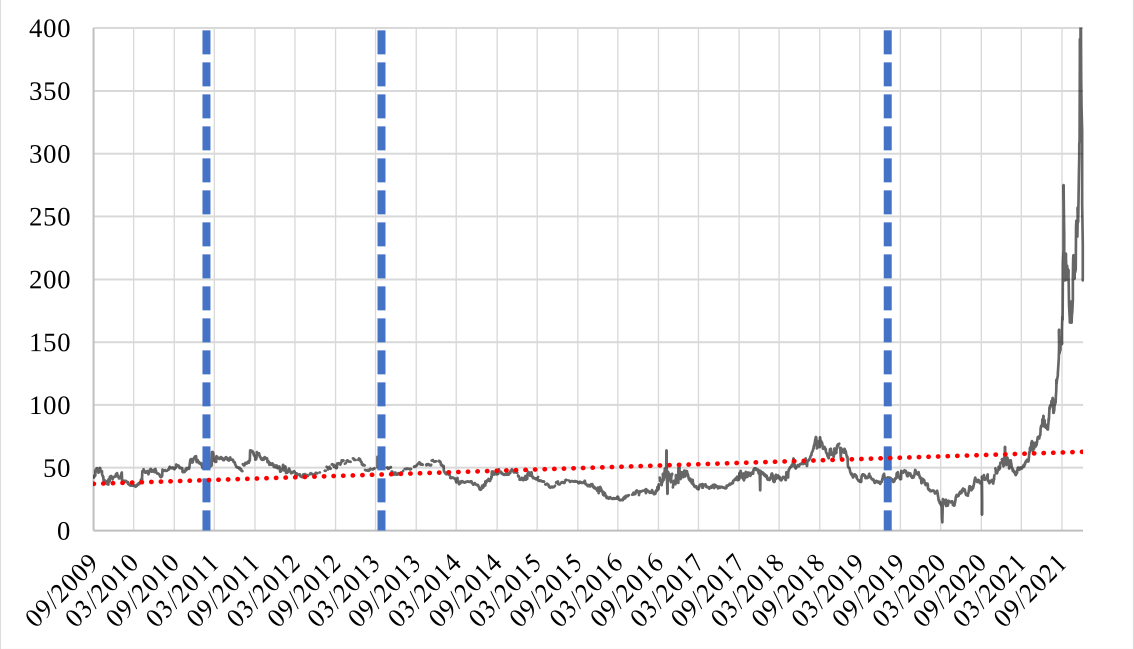

Figure A20. Netherlands month ahead future prices

# APPENDIX B

## PRICE SUBSETS

For each country, price data of day ahead markets and month ahead future markets are grouped according to market coupling dates, as indicated in Table 1 in Chapter 5. Each subset is represented with a violin shape which shows the density of data points in any price range. EUR price per Mwh of electrical energy in a given market is shown in Y-Axis.

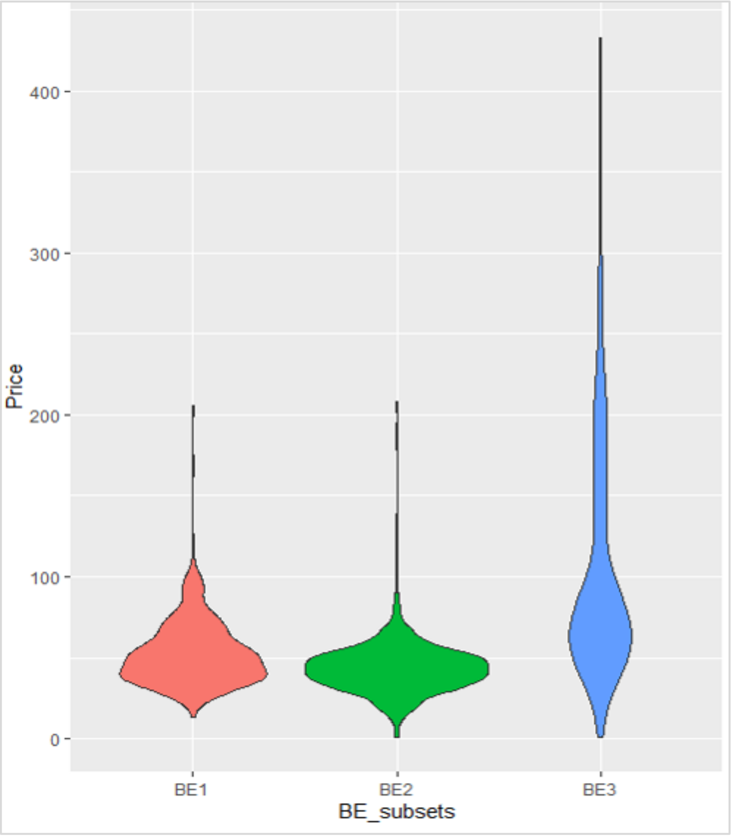

Figure B1. Belgium day ahead market subsets

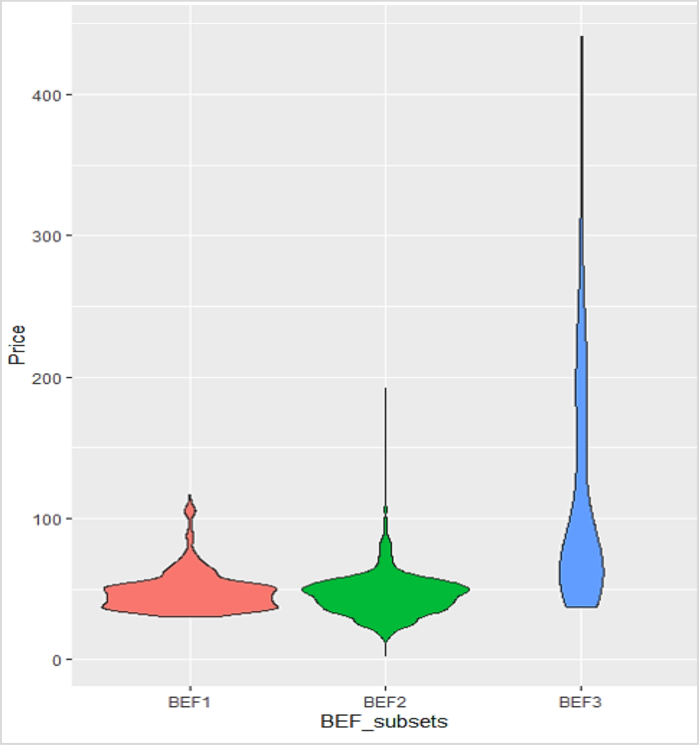

Figure B2.  Belgium month ahead future subsets

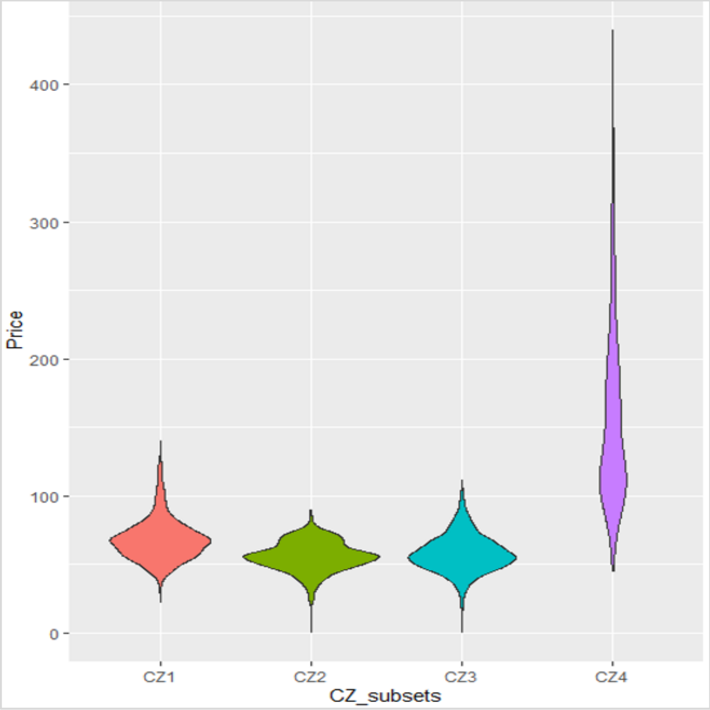

Figure B3.  Czechia day ahead market subsets

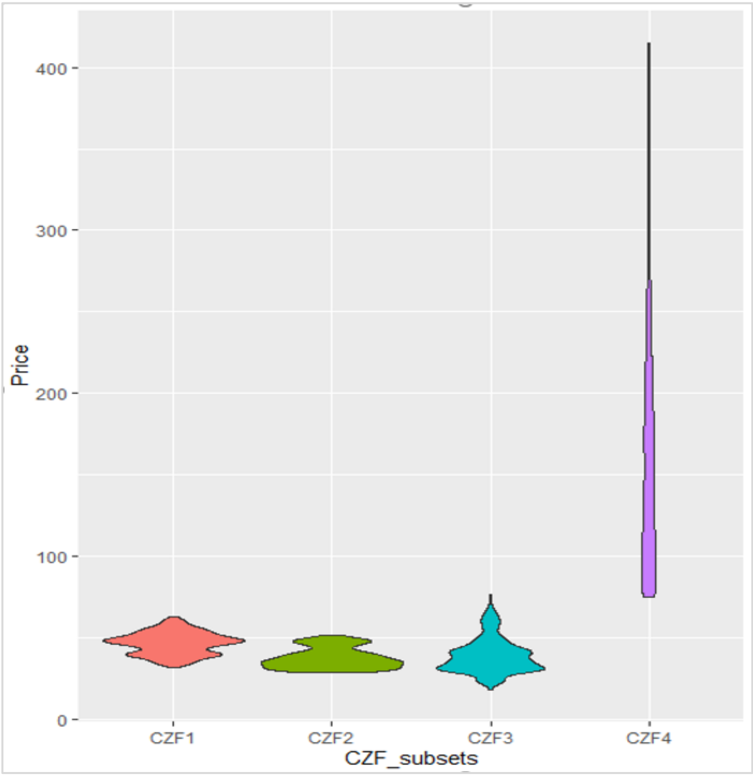

Figure B4. Czechia month ahead future subsets

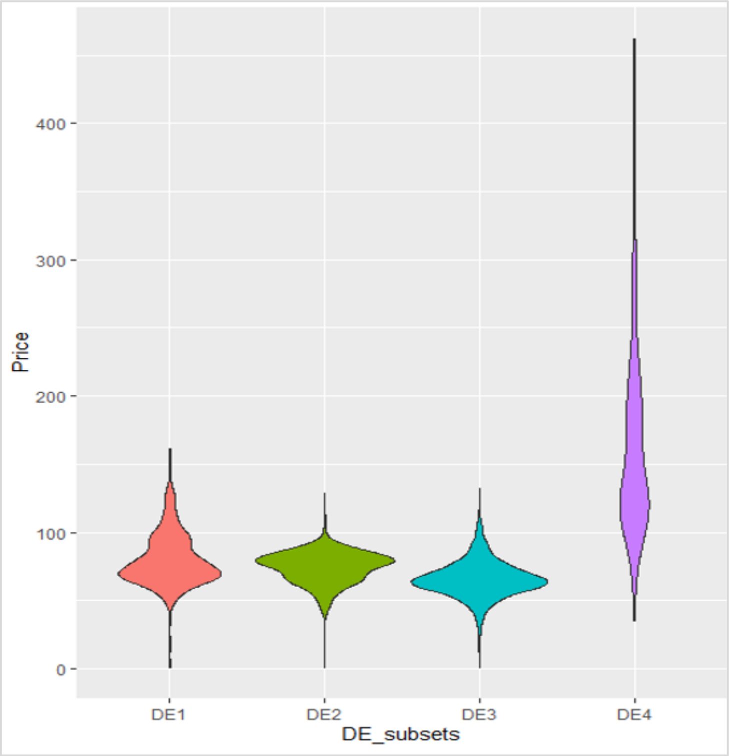

Figure B5. Germany day ahead market subsets

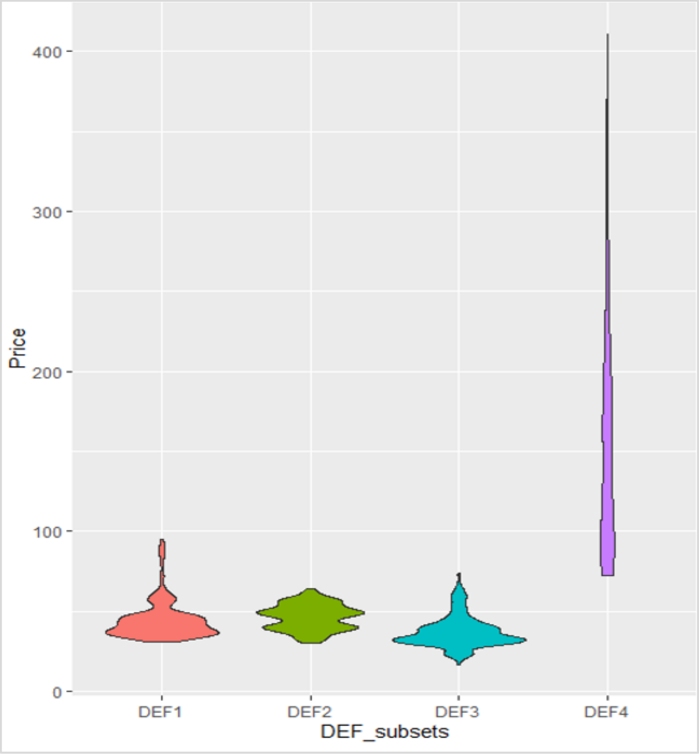

Figure B6. Germany month ahead future subsets

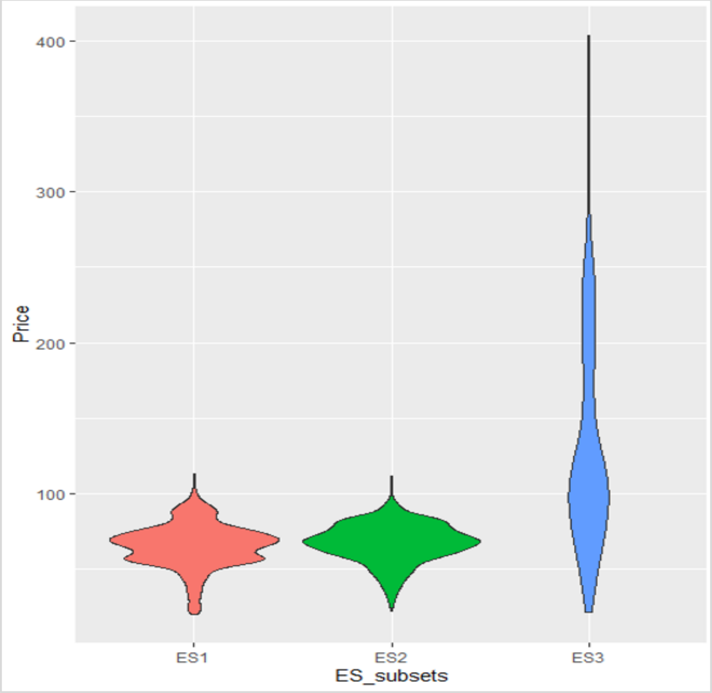

Figure B7. Spain day ahead market subsets

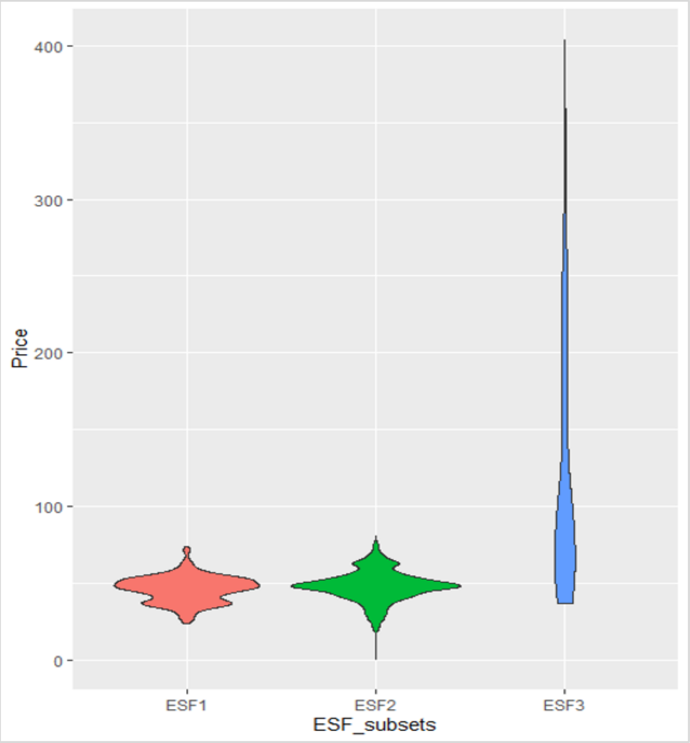

Figure B8. Spain month ahead future subsets

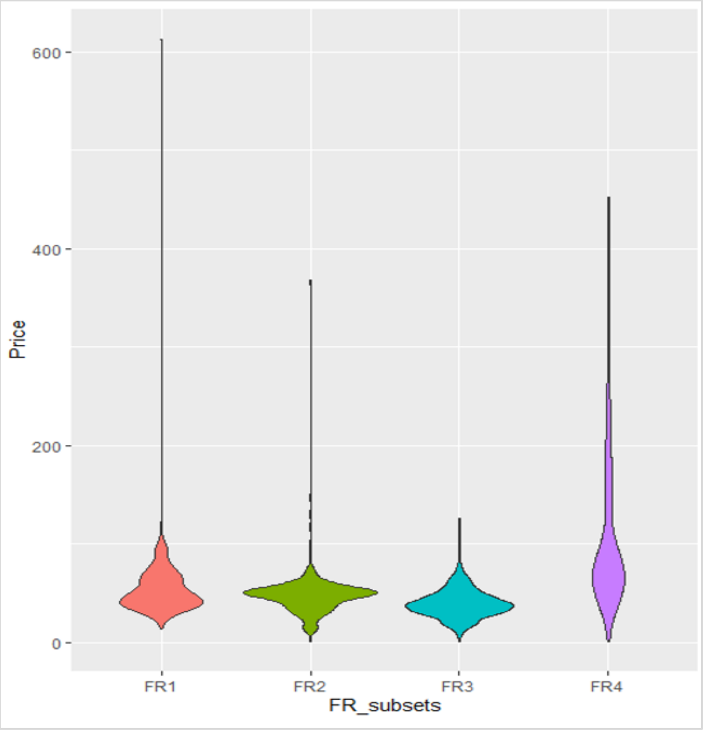

Figure B9. France day ahead market subsets

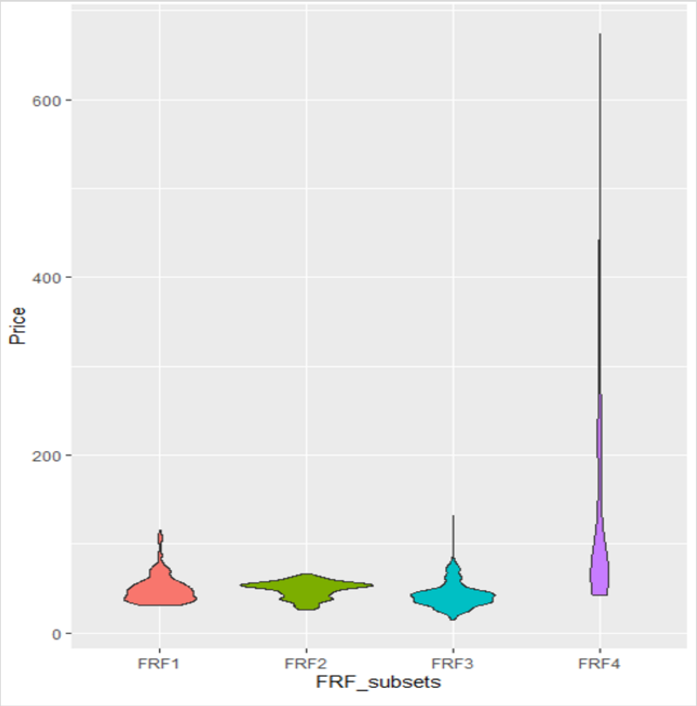

Figure B10. France month ahead future subsets

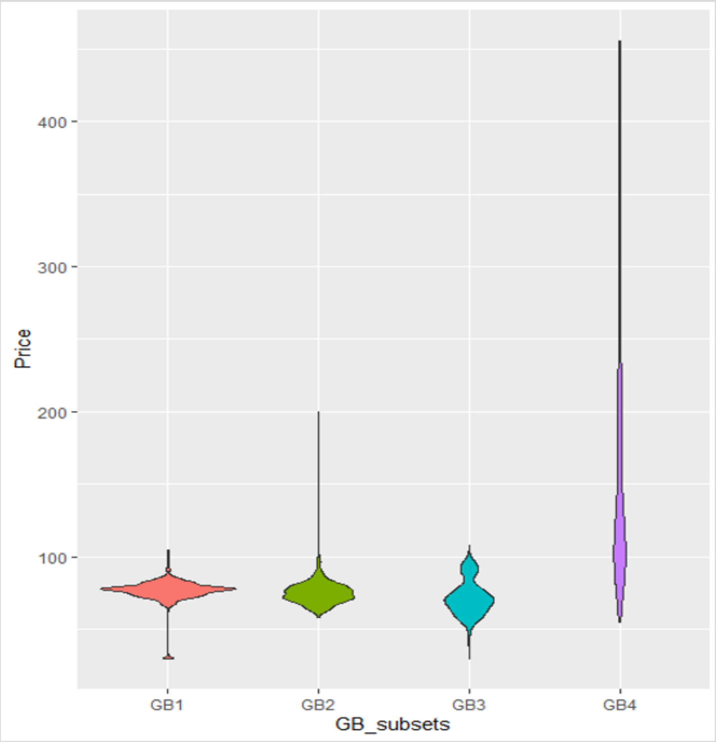

Figure B11. United Kingdom day ahead market subsets

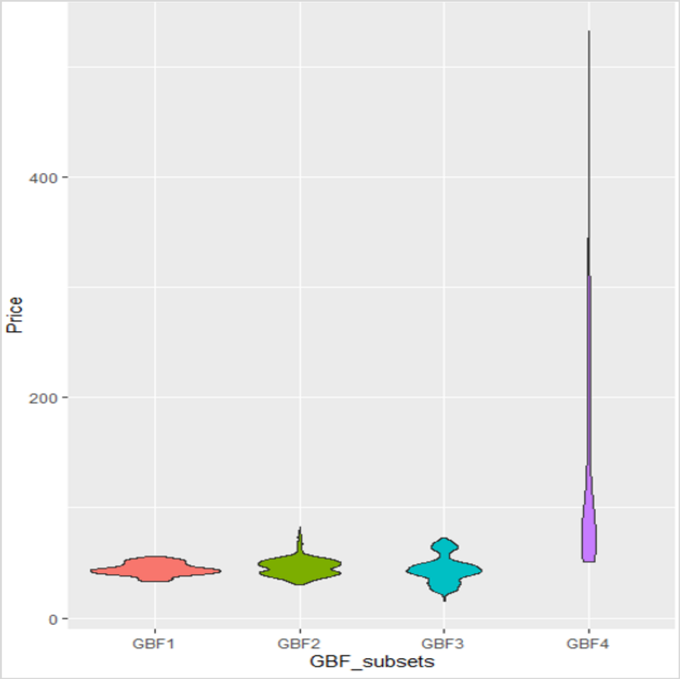

Figure B12. United Kingdom month ahead future subsets

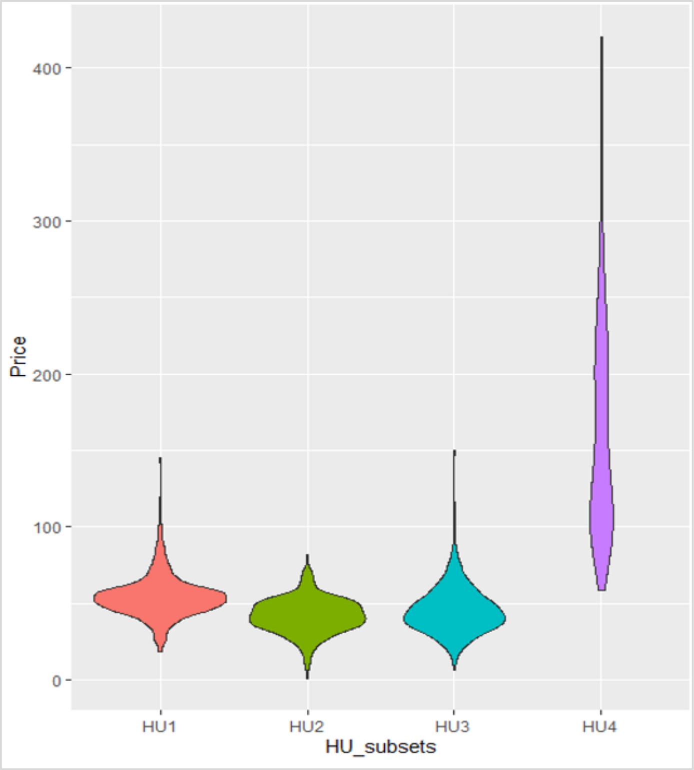

Figure B13. Hungary day ahead market subsets

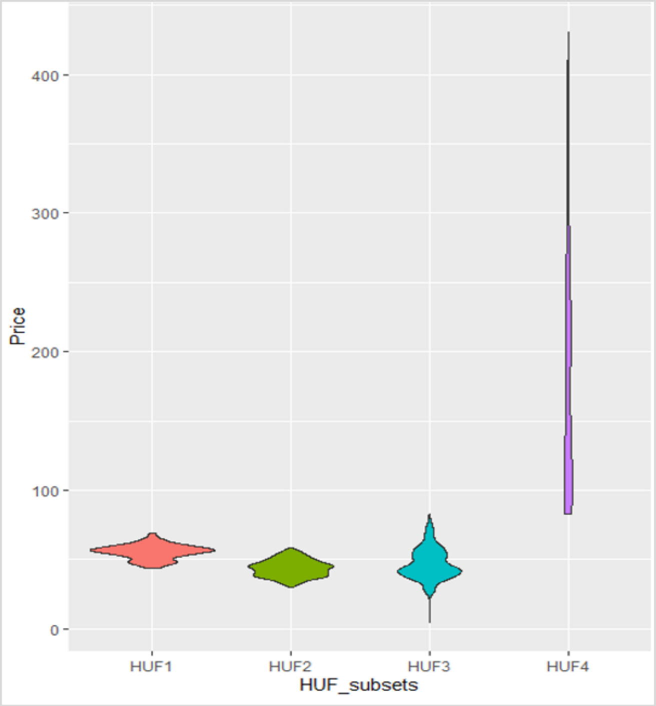

Figure B14. Hungary month ahead future subsets

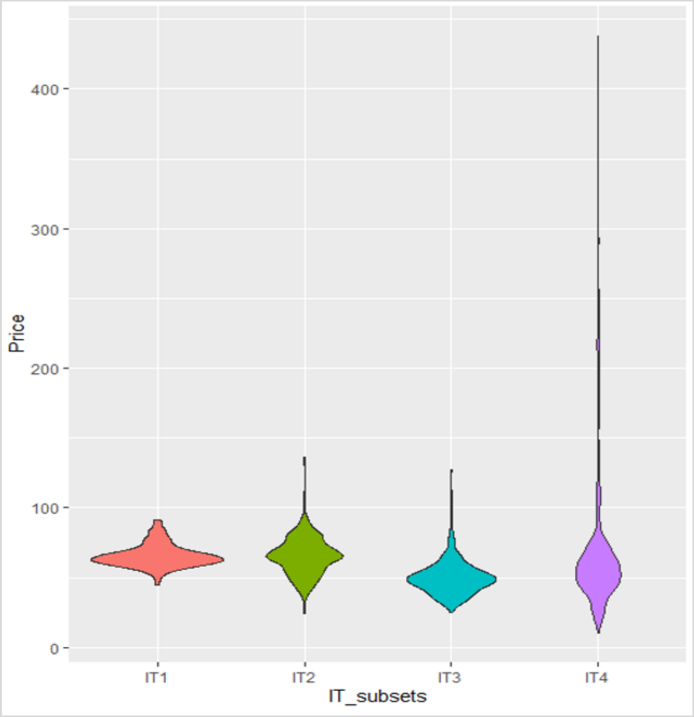

Figure B15. Italy day ahead market subsets

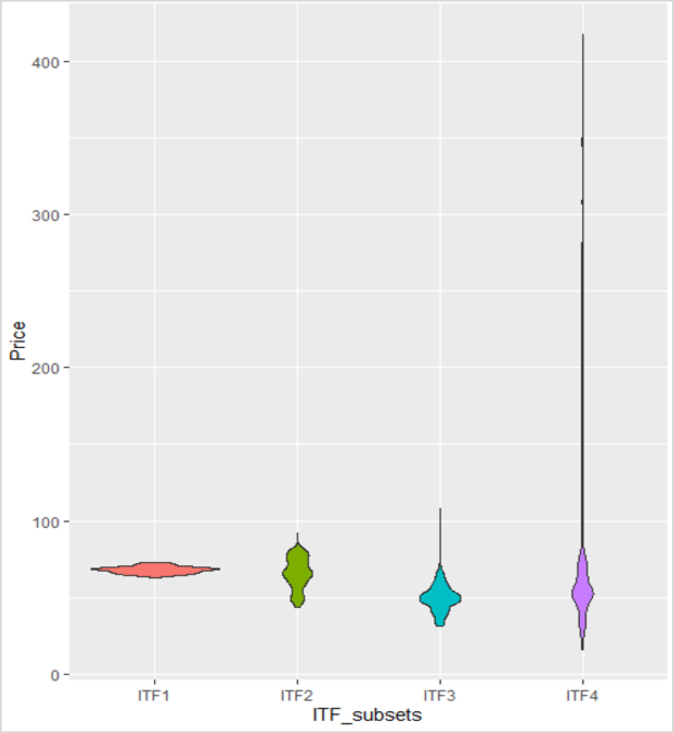

Figure B16. Italy month ahead future subsets

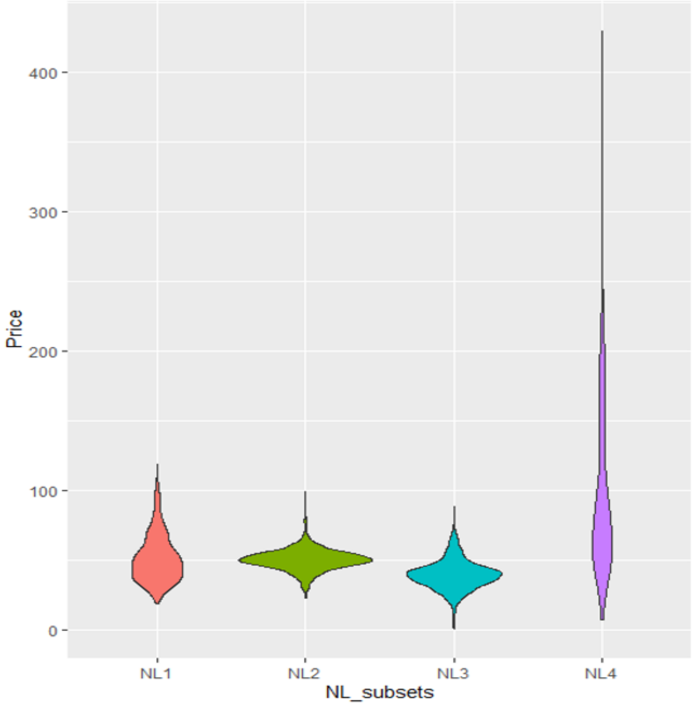

Figure B17. Netherlands day ahead market subsets

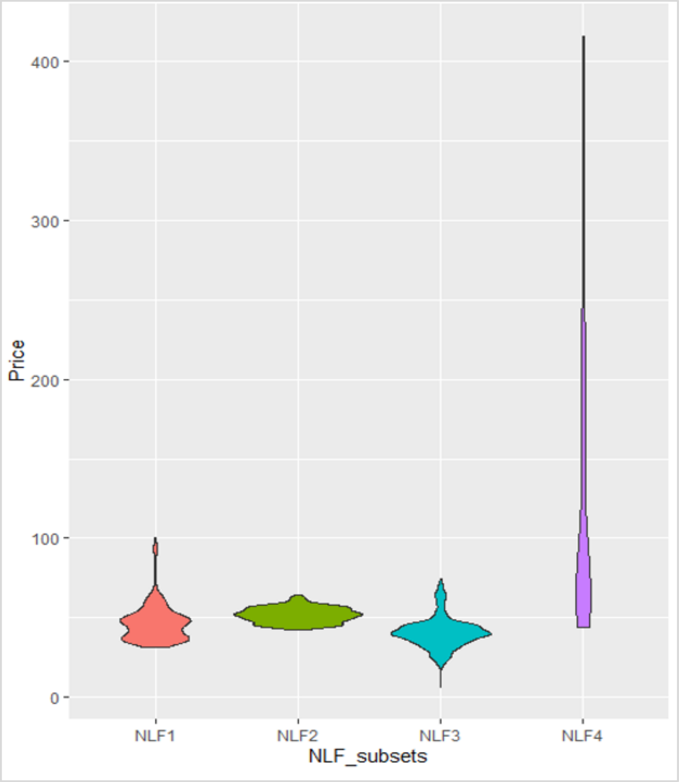

Figure B18. Netherlands month ahead future subsets

# APPENDIX C

## APPROXIMATE ENTROPY

For each graph, vertical blue lines indicate the market coupling dates stated in Table 1, and red dashed lines indicate trend lines over the analyzed period. Y-Axis indicates ApEn measure and X-Axis is the dates.

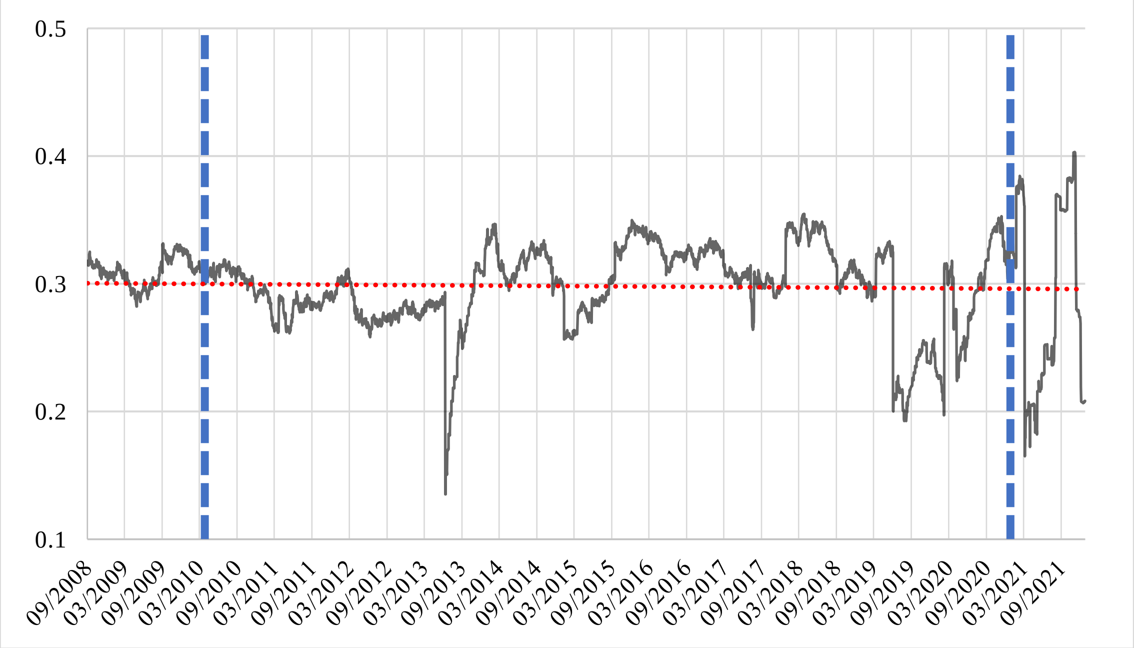

Figure C1. Belgium day ahead returns 250 days rolling ApEn results

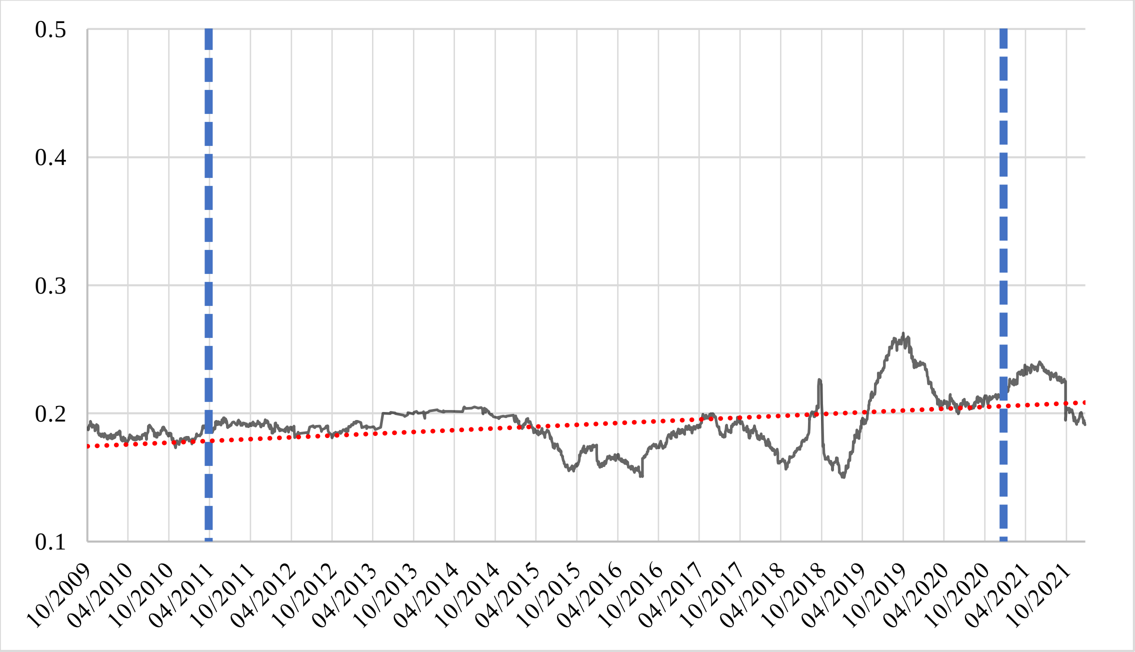

Figure C2. Belgium month ahead continuous returns 250 days rolling ApEn results

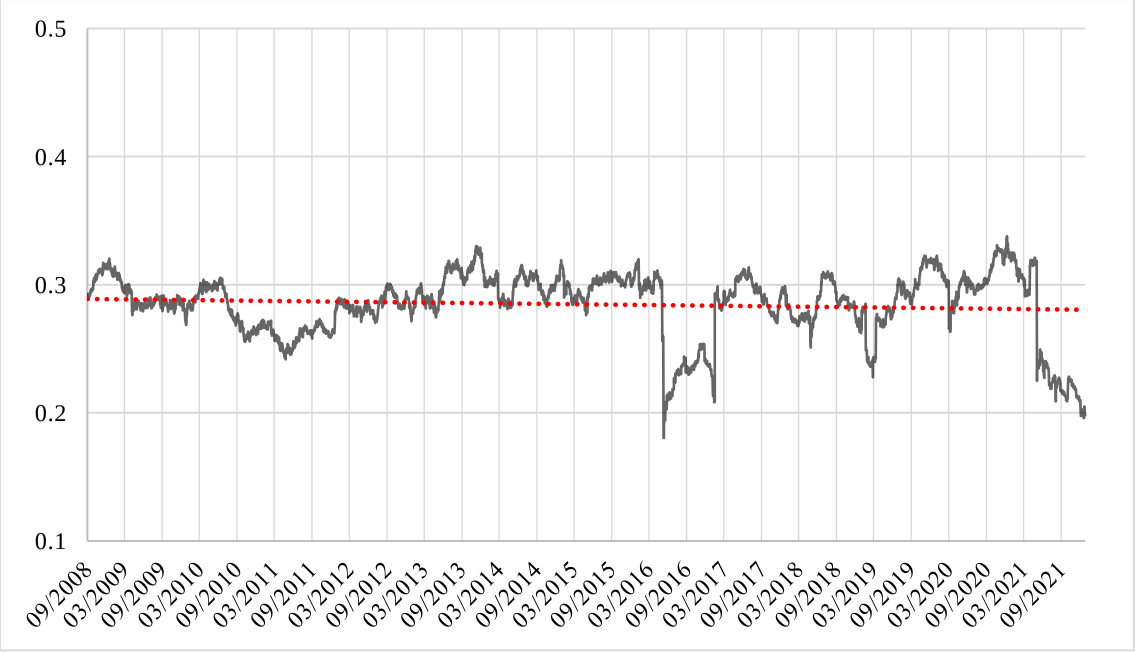

Figure C3. Switzerland day ahead returns 250 days rolling ApEn results

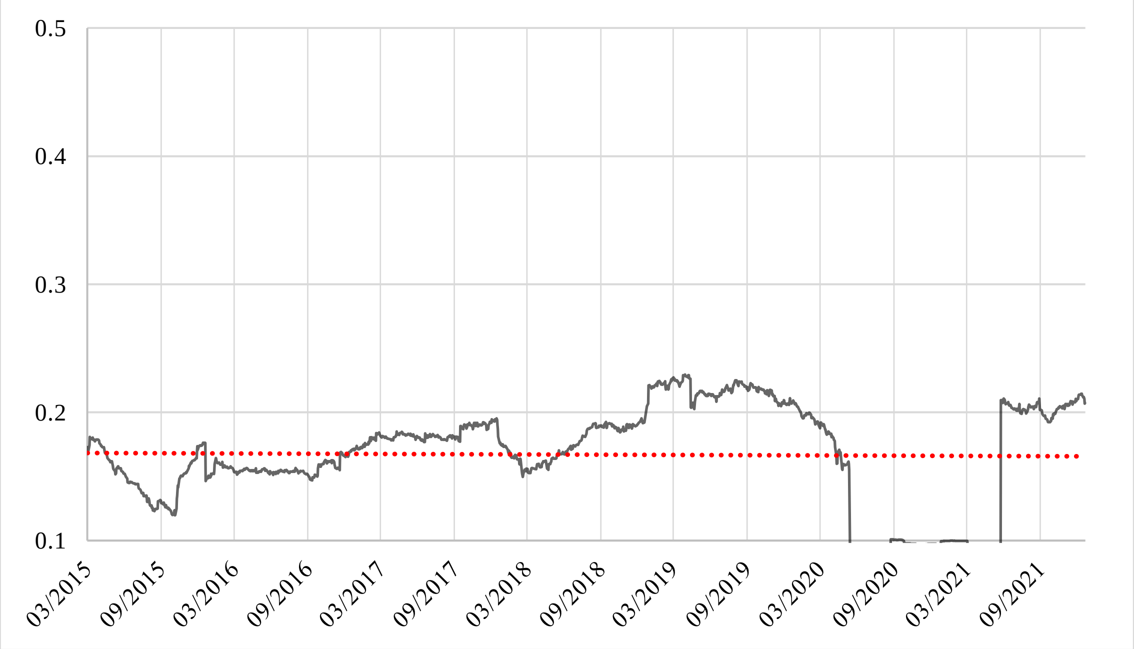

Figure C4. Switzerland month ahead continuous returns 250 days rolling ApEn results

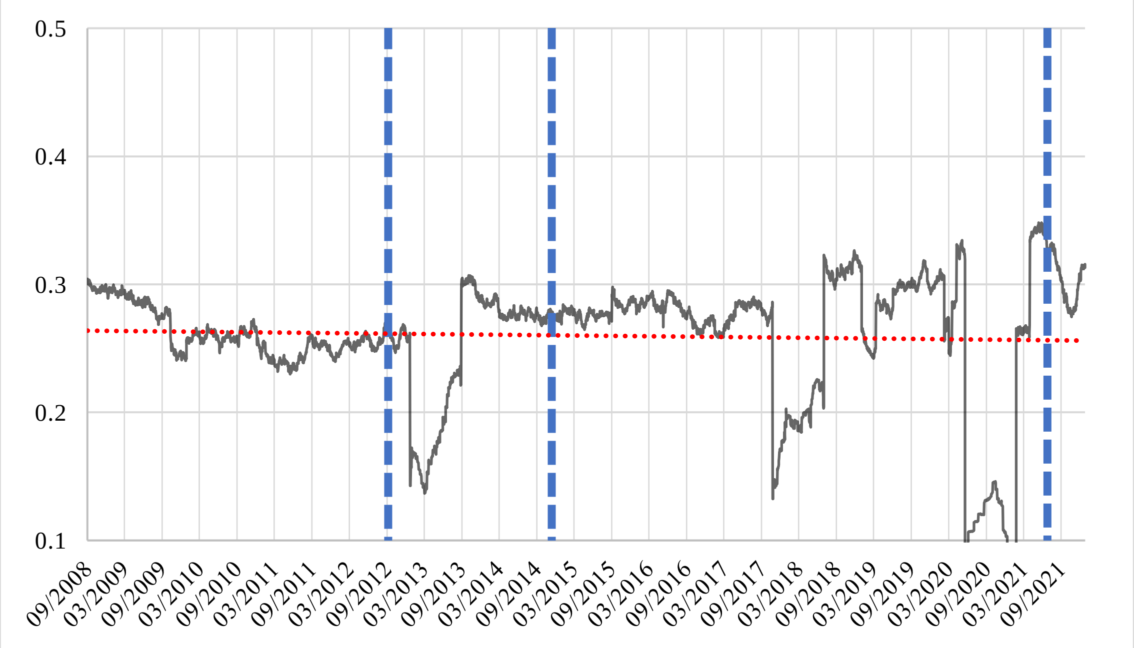

Figure C5. Czechia day ahead returns 250 days rolling ApEn results

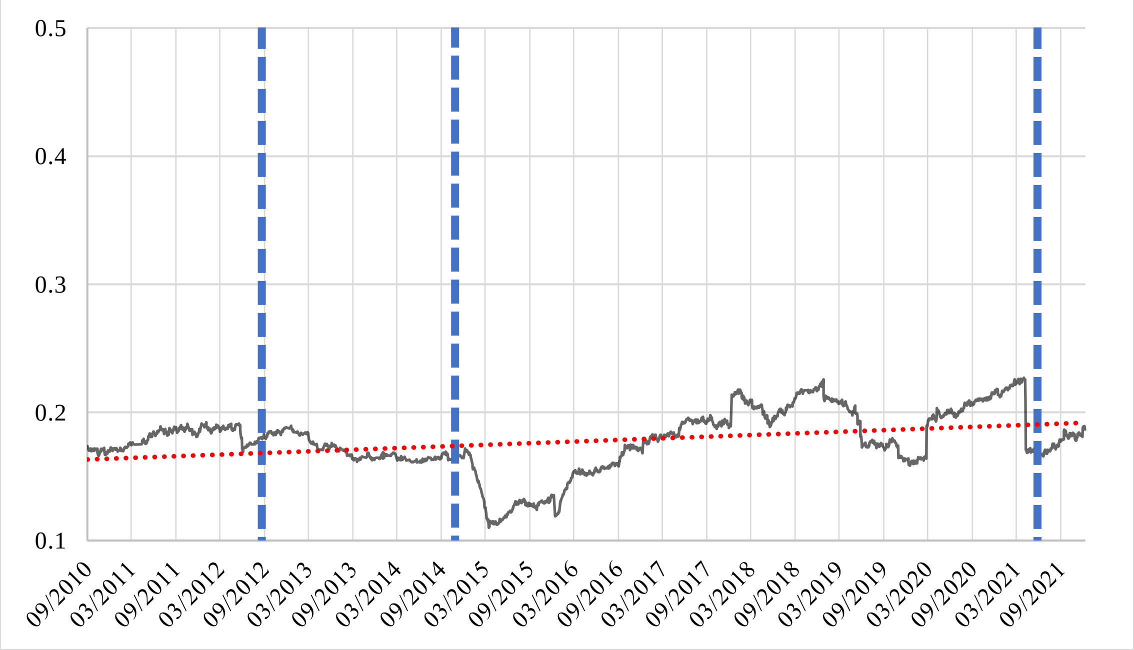

Figure C6. Czechia month ahead continuous returns 250 days rolling ApEn results

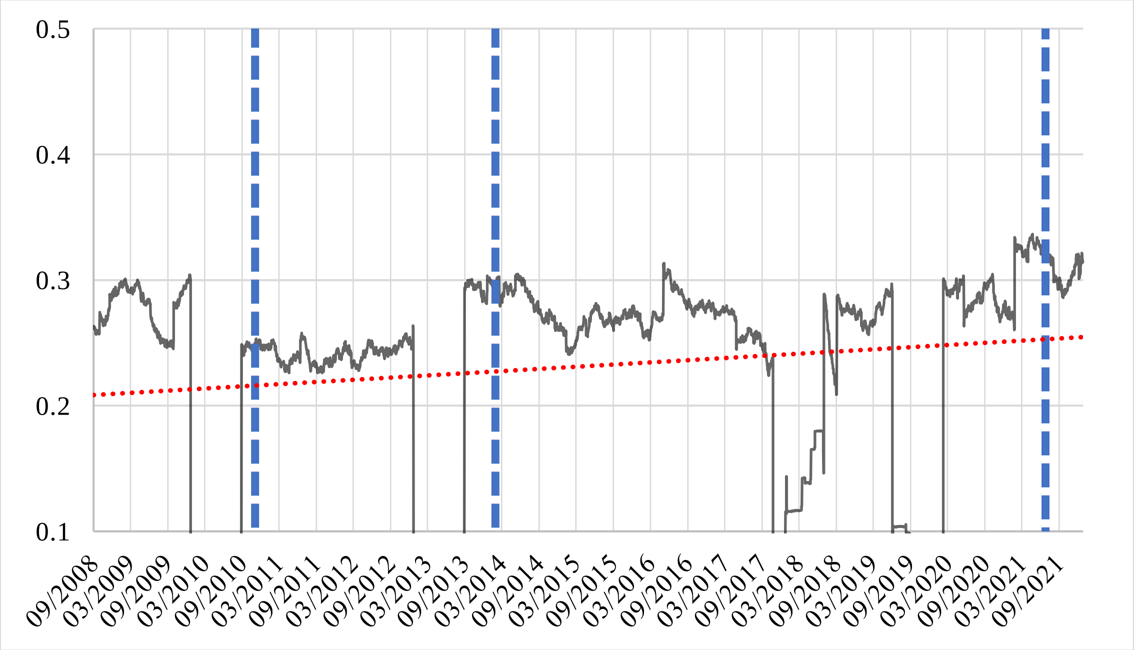

Figure C7. Germany day ahead returns 250 days rolling ApEn results

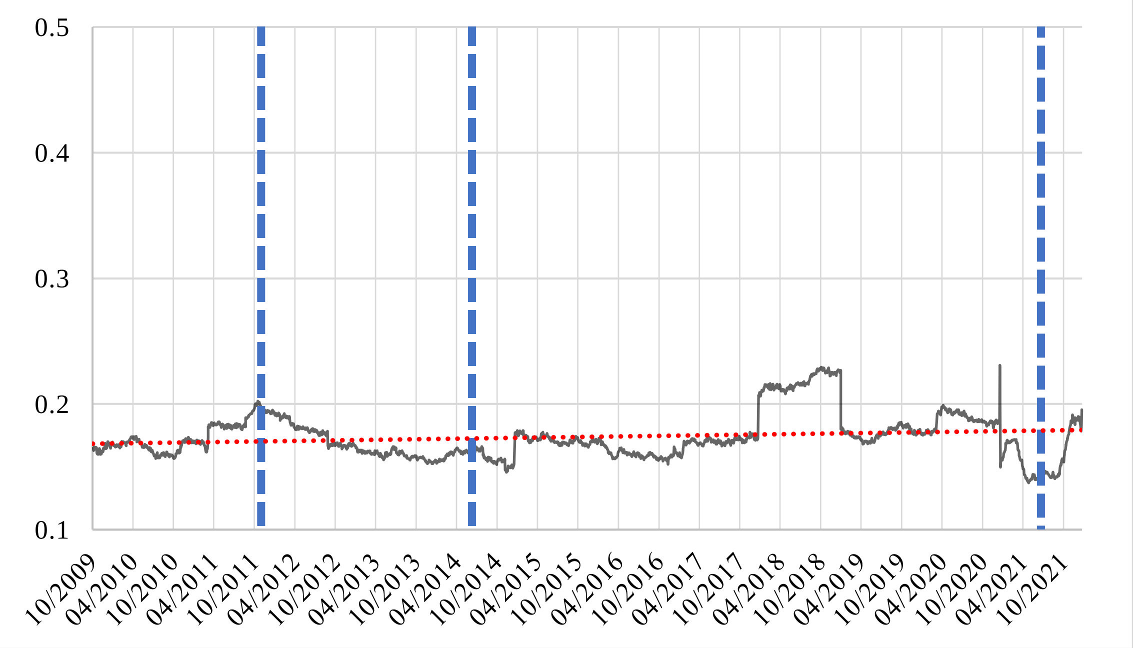

Figure C8. Germany month ahead continuous returns 250 days rolling ApEn results

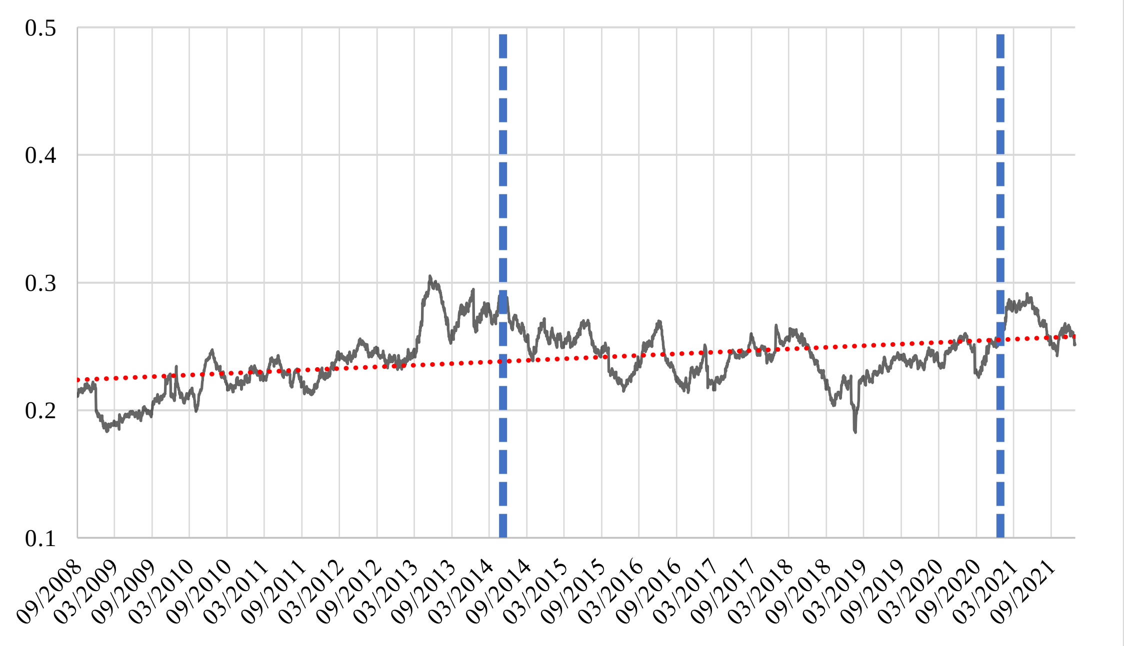

Figure C9. Spain day ahead returns 250 days rolling ApEn results

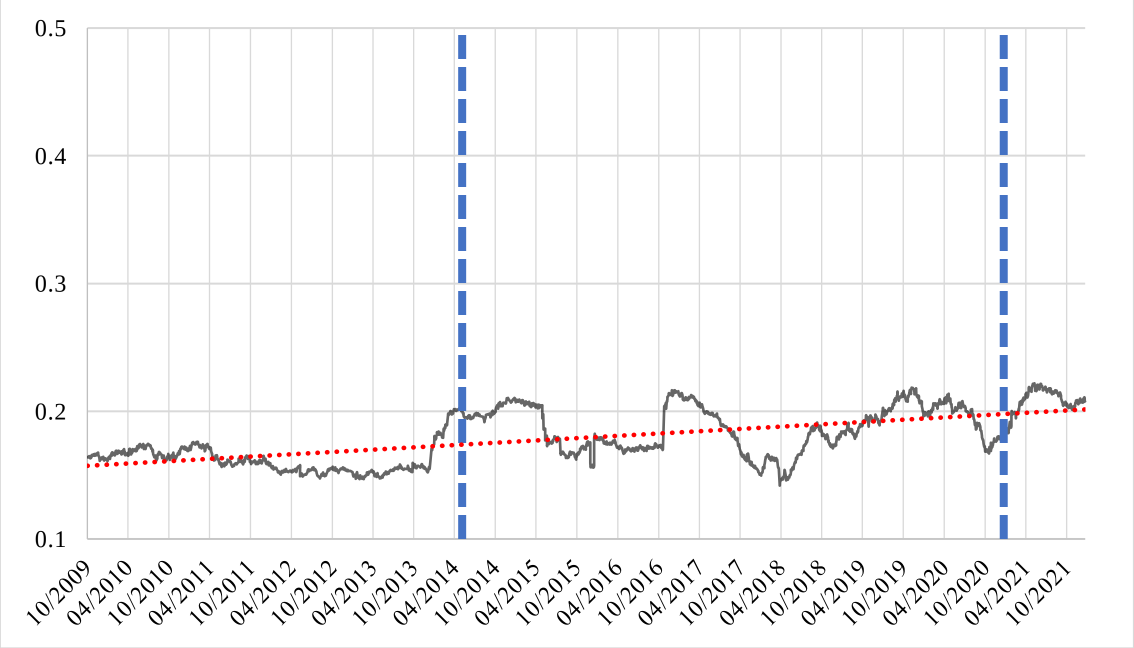

Figure C10. Spain month ahead continuous returns 250 days rolling ApEn results

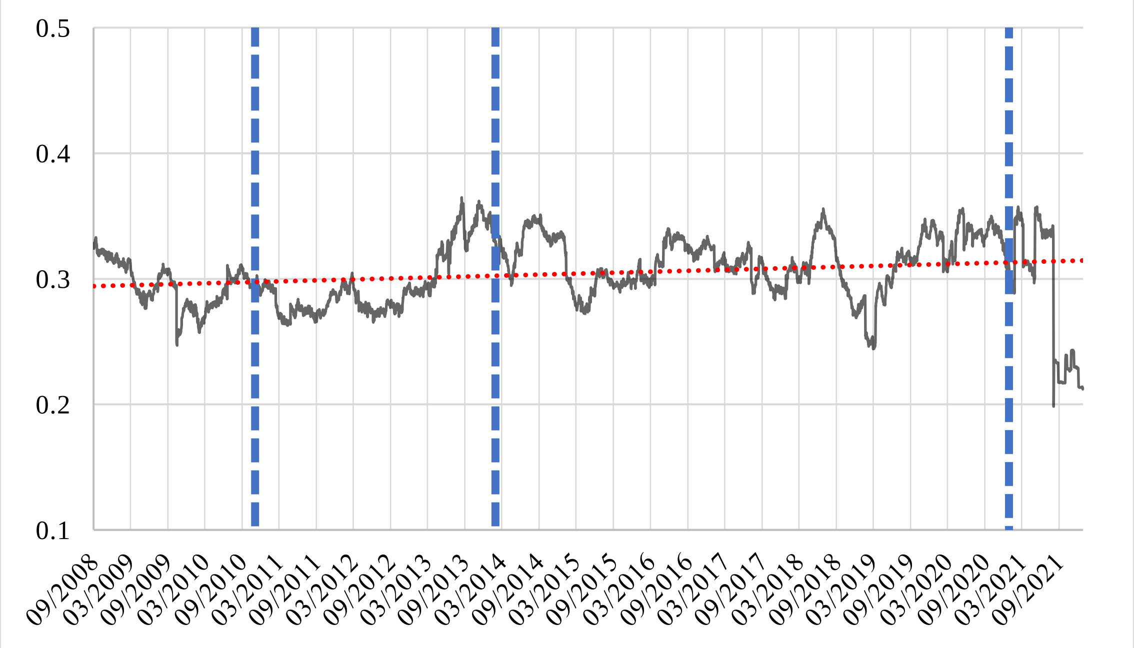

Figure C11. France day ahead returns 250 days rolling ApEn results

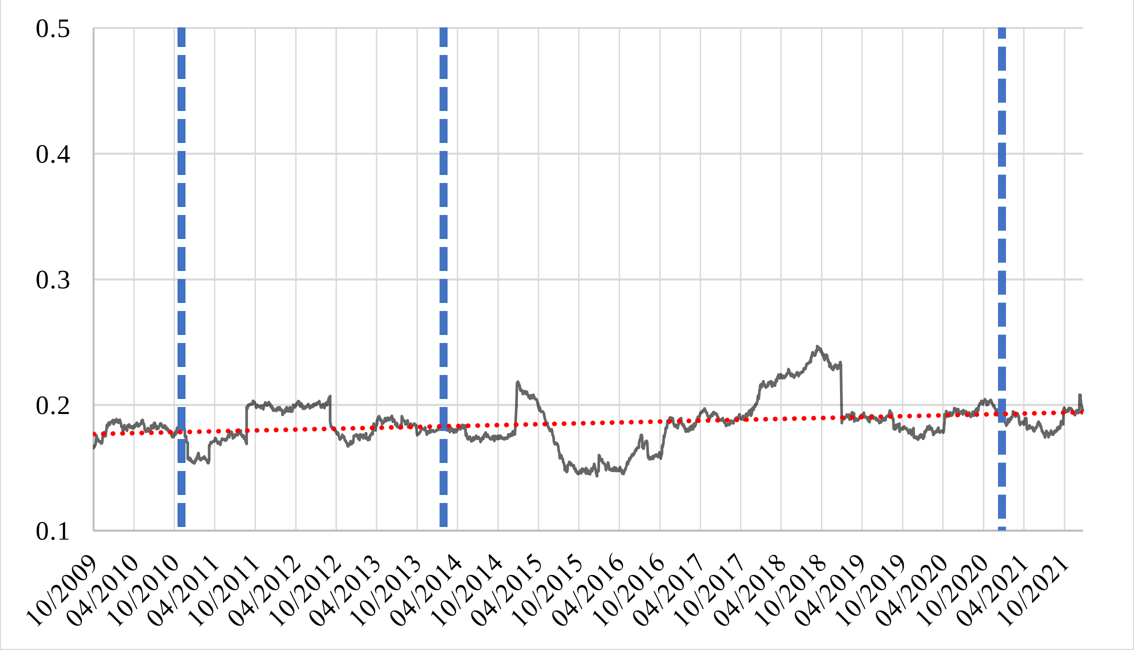

Figure C12. France month ahead continuous returns 250 days rolling ApEn results

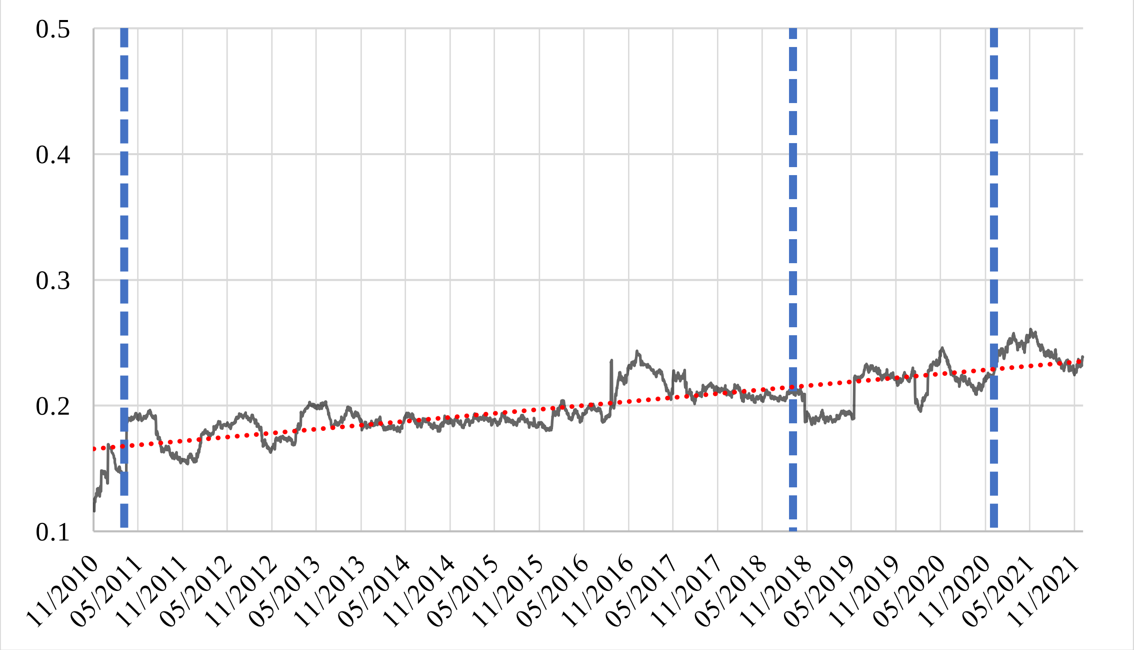

Figure C13. United Kingdom day ahead returns 250 days rolling ApEn results

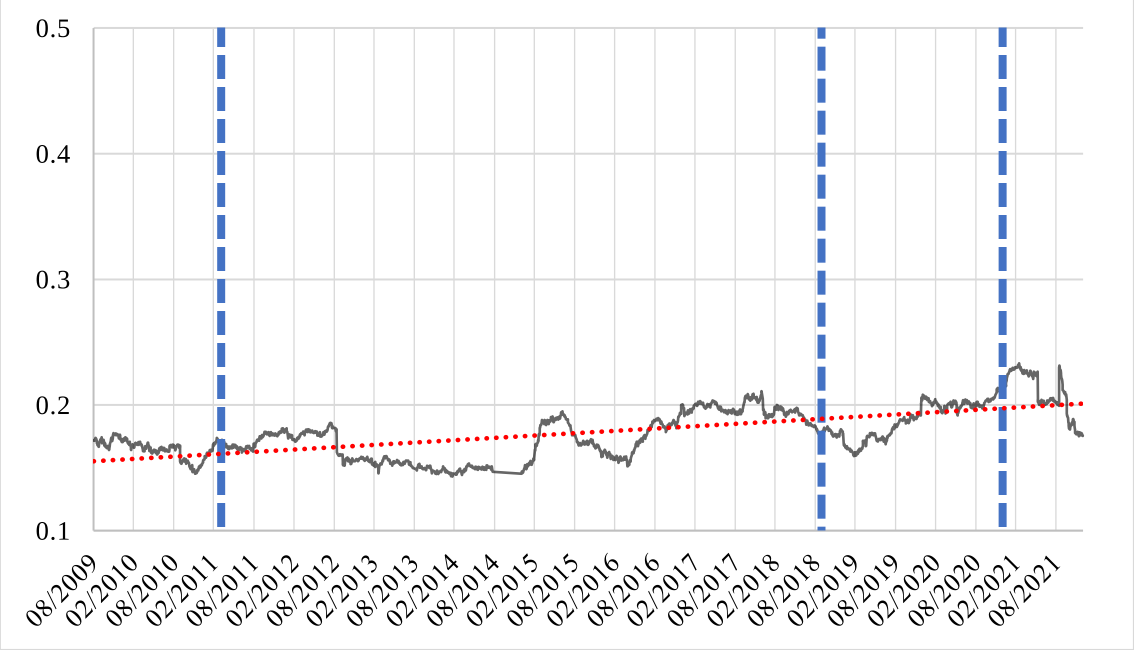

Figure C14. United Kingdom month ahead continuous returns 250 days rolling ApEn results

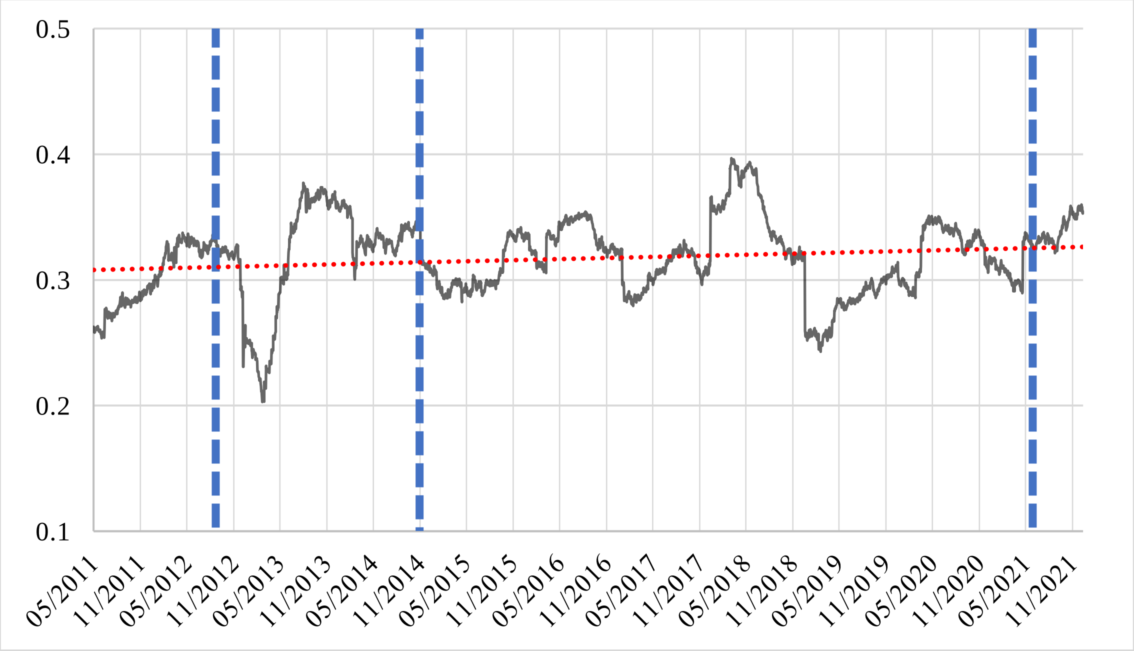

Figure C15. Hungary day ahead returns 250 days rolling ApEn results

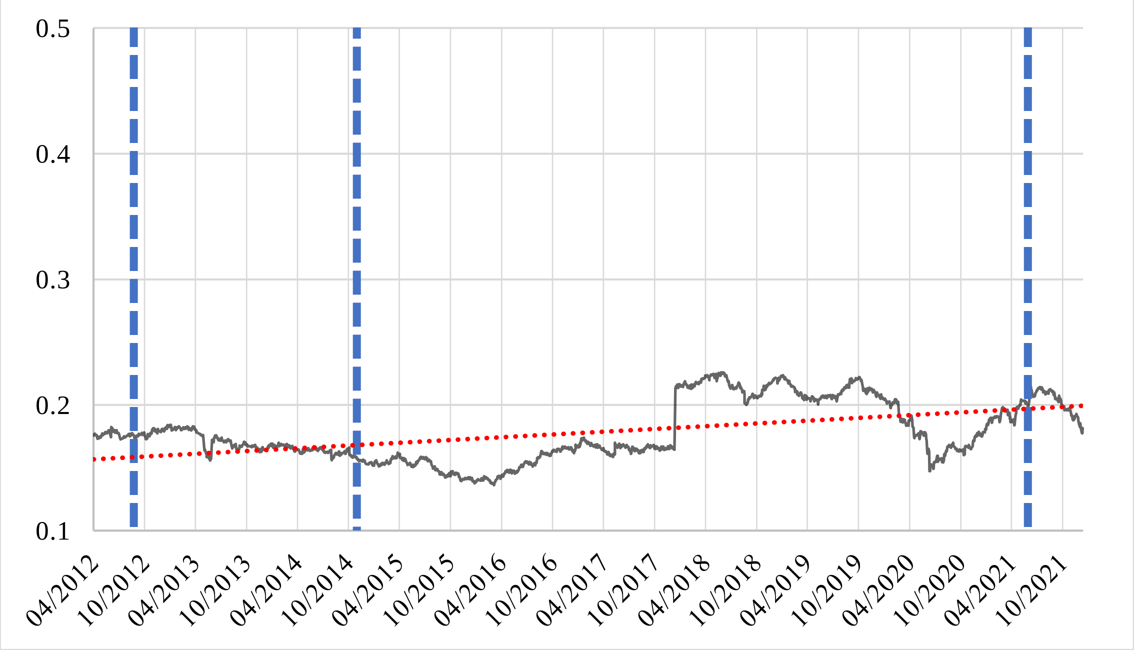

Figure C16. Hungary month ahead continuous returns 250 days rolling ApEn results

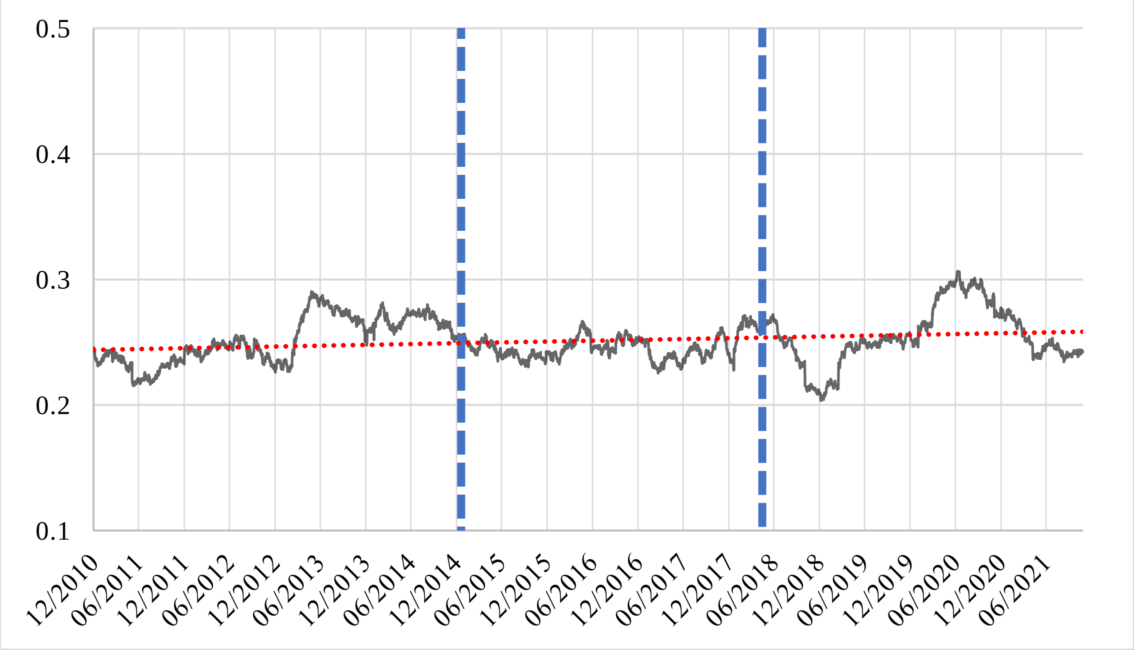

Figure C17. Italy day ahead returns 250 days rolling ApEn results

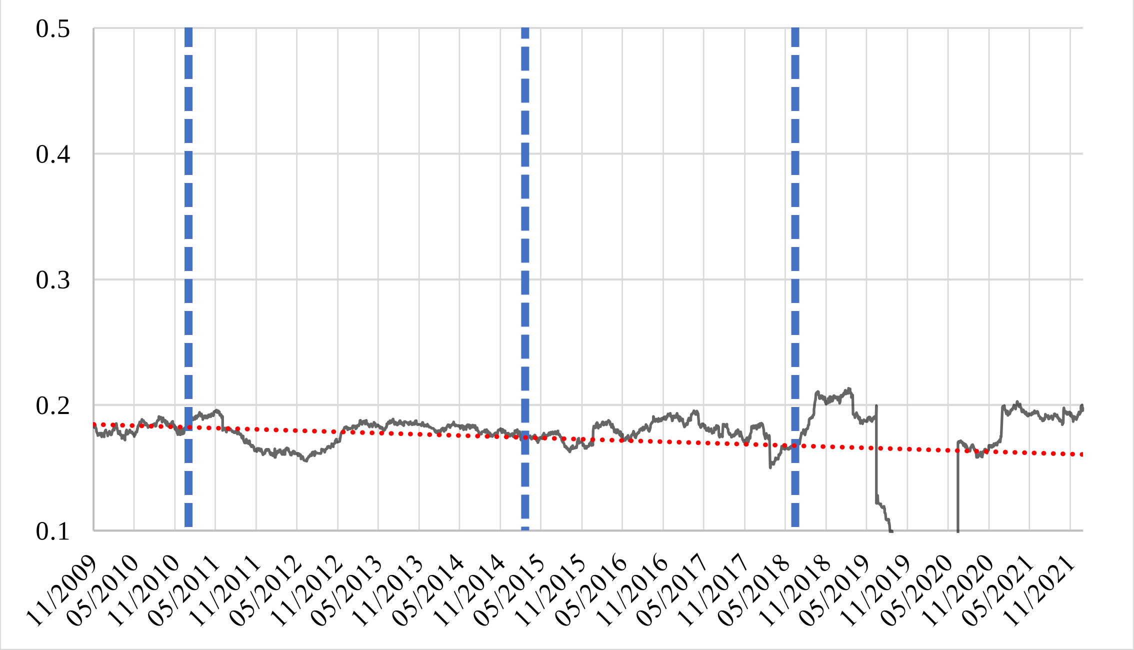

Figure C18. Italy month ahead continuous returns 250 days rolling ApEn results

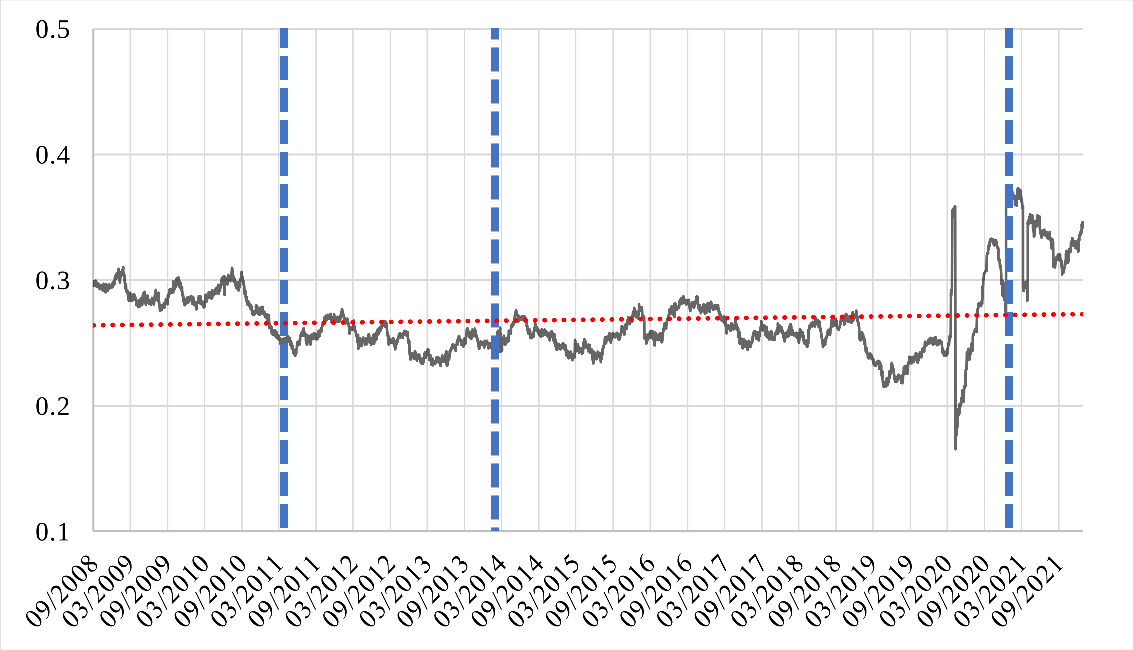

Figure C19. Netherlands day ahead returns 250 days rolling ApEn results

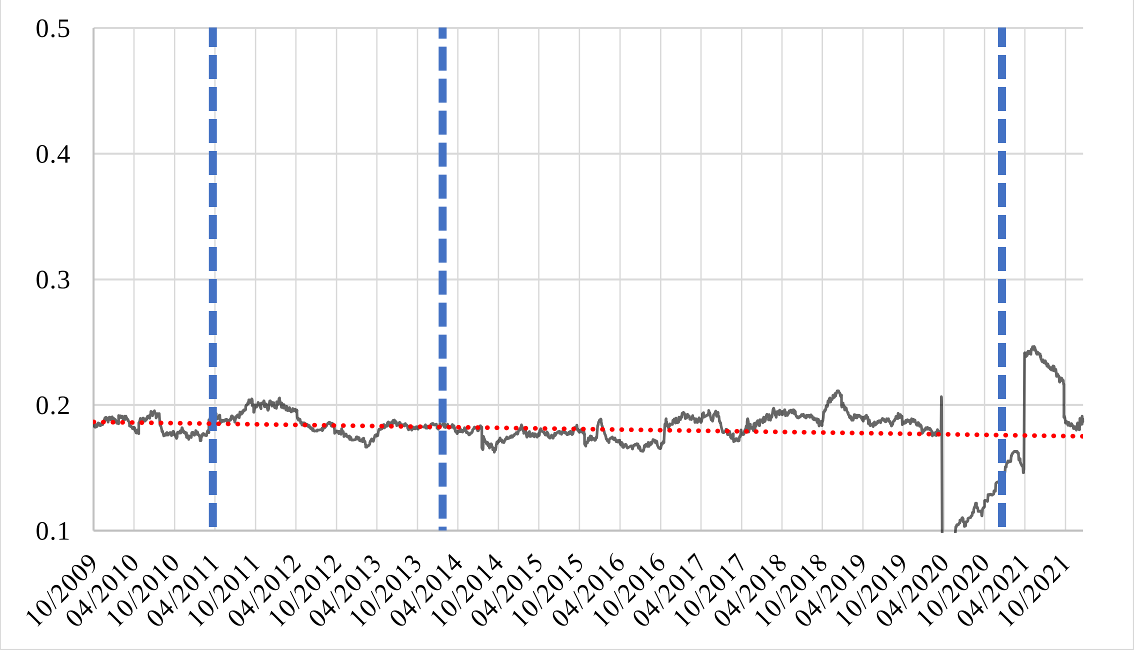

Figure C20. Netherlands month ahead continuous returns 250 days rolling ApEn results

# APPENDIX D

# HURST EXPONENTS

For each graph, vertical blue lines indicate the market coupling dates stated in Table 1, and red dashed lines indicate trend lines over the analyzed period. Y-Axis indicates average Hurst exponent measure and X-Axis is the dates.

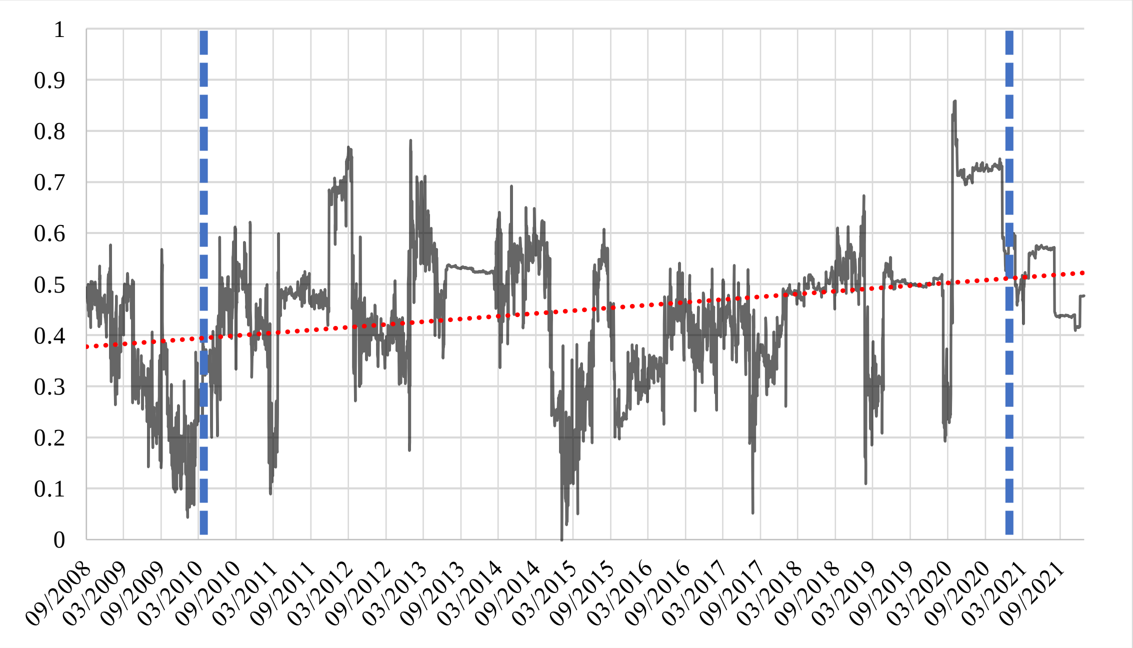

Figure D1. Belgium day ahead returns 250 days rolling Hurst exponents

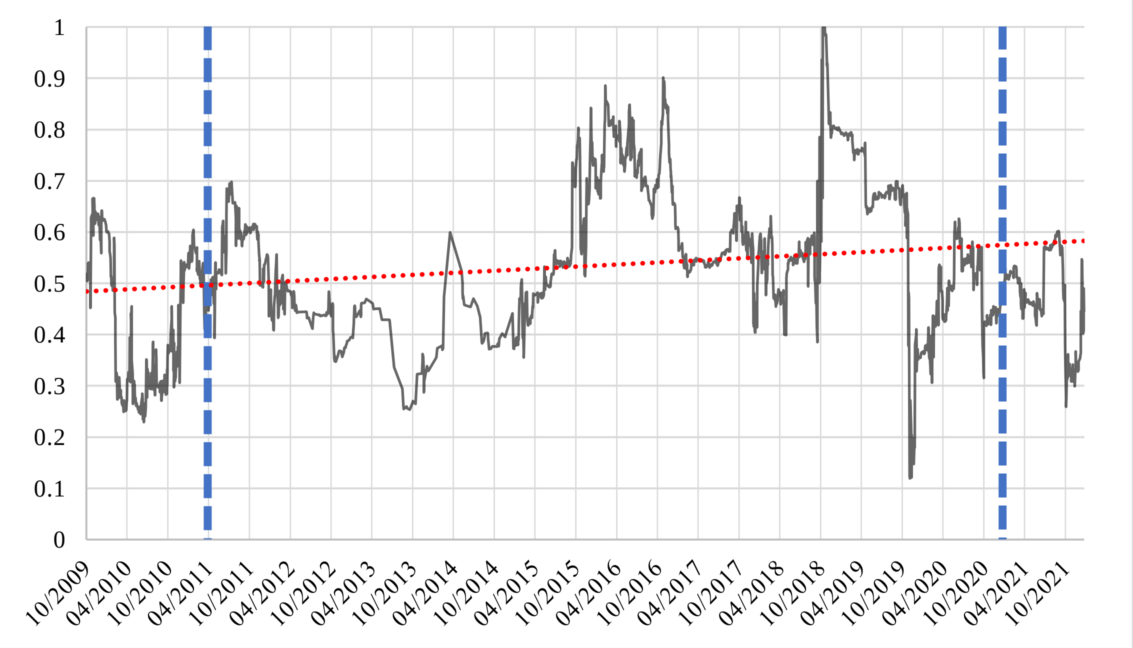

Figure D2. Belgium month ahead continuous returns 250 days rolling Hurst exponents

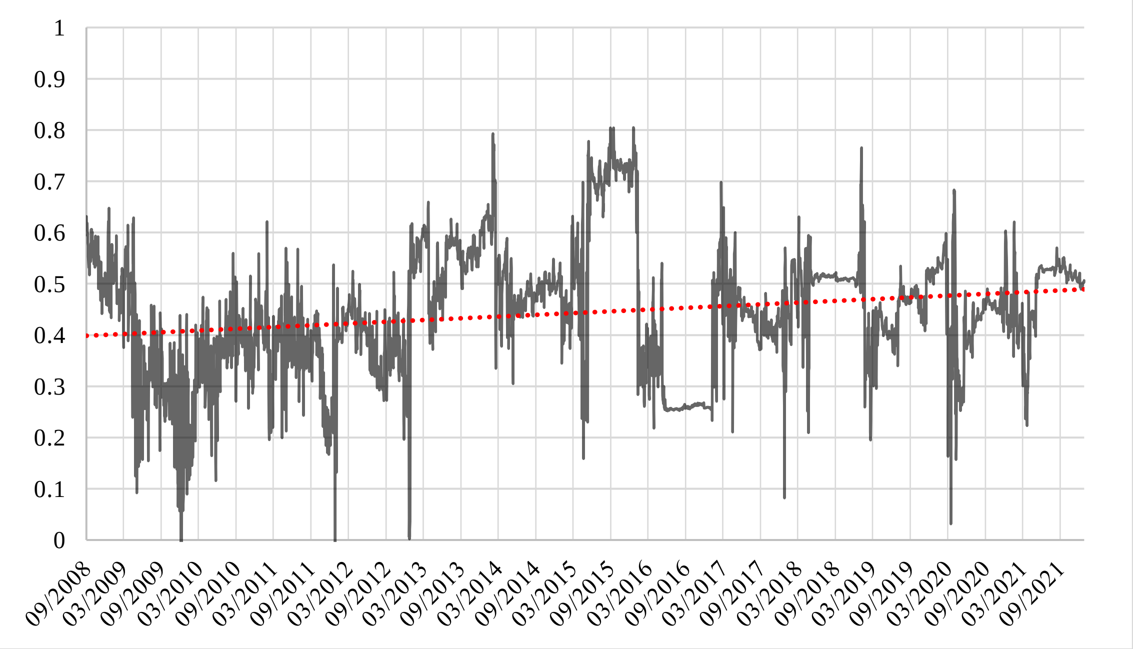

Figure D3. Switzerland day ahead returns 250 days rolling Hurst exponents

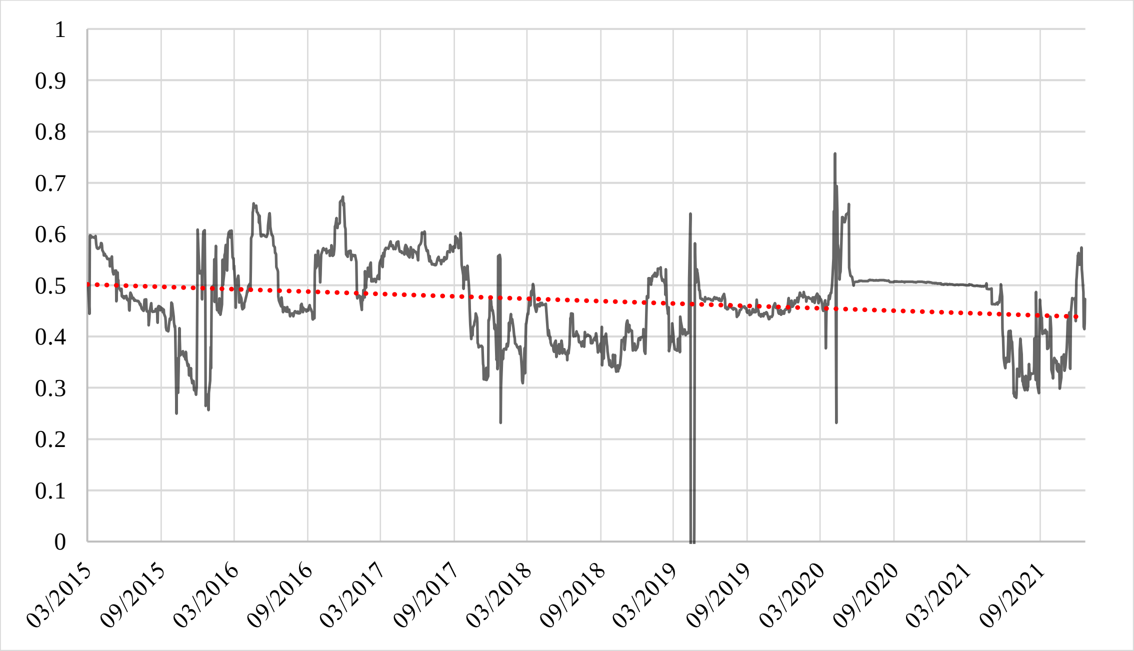

Figure D4. Switzerland month ahead continuous returns 250 days rolling Hurst exponents

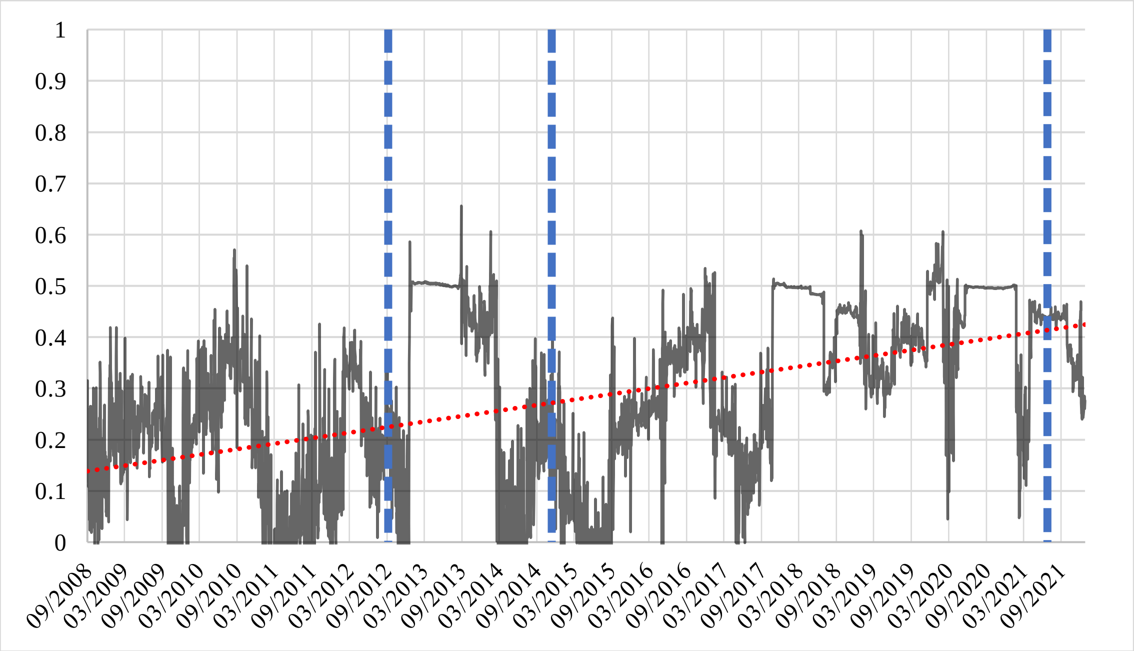

Figure D5. Czechia day ahead returns 250 days rolling Hurst exponents

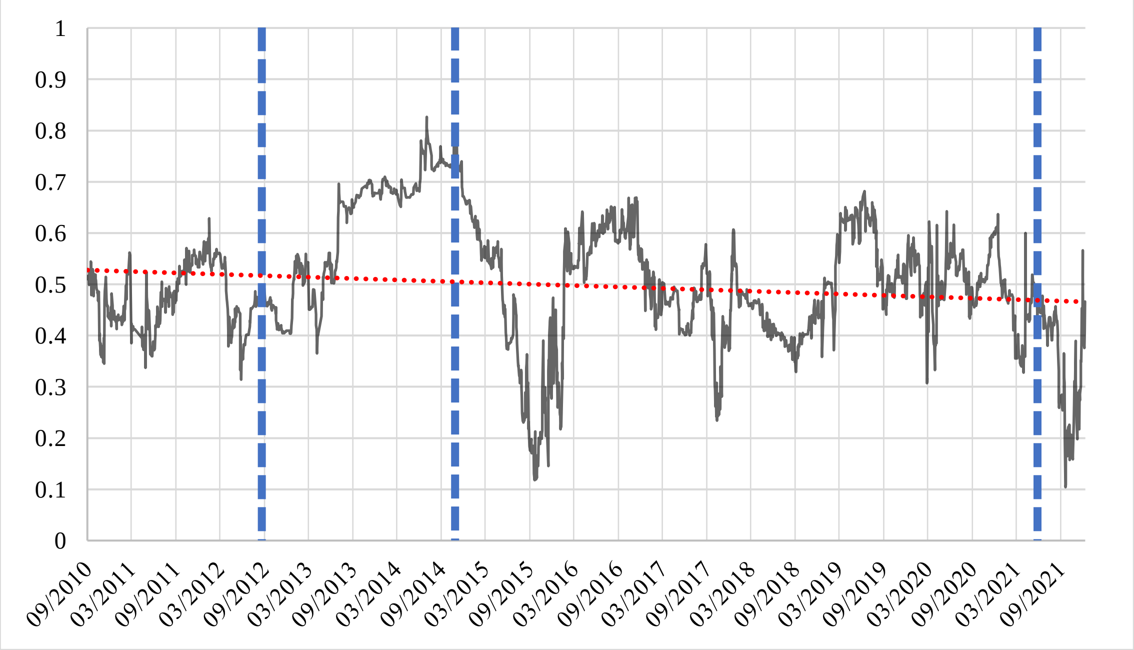

Figure D6. Czechia month ahead continuous returns 250 days rolling Hurst exponents

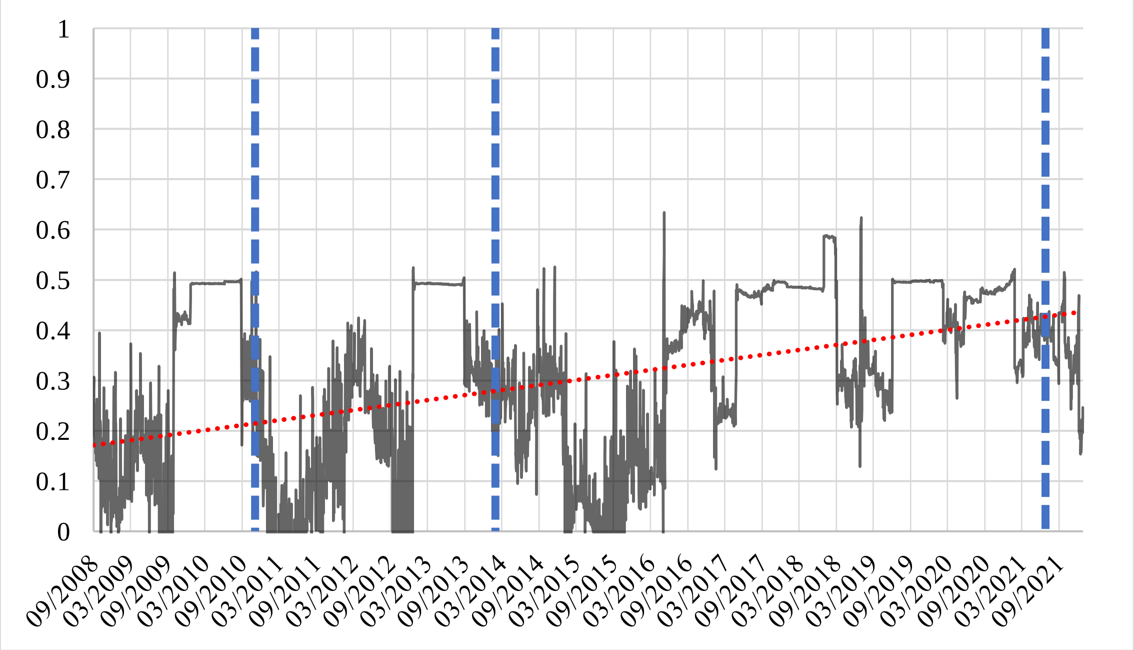

Figure D7. Germany day ahead returns 250 days rolling Hurst exponents

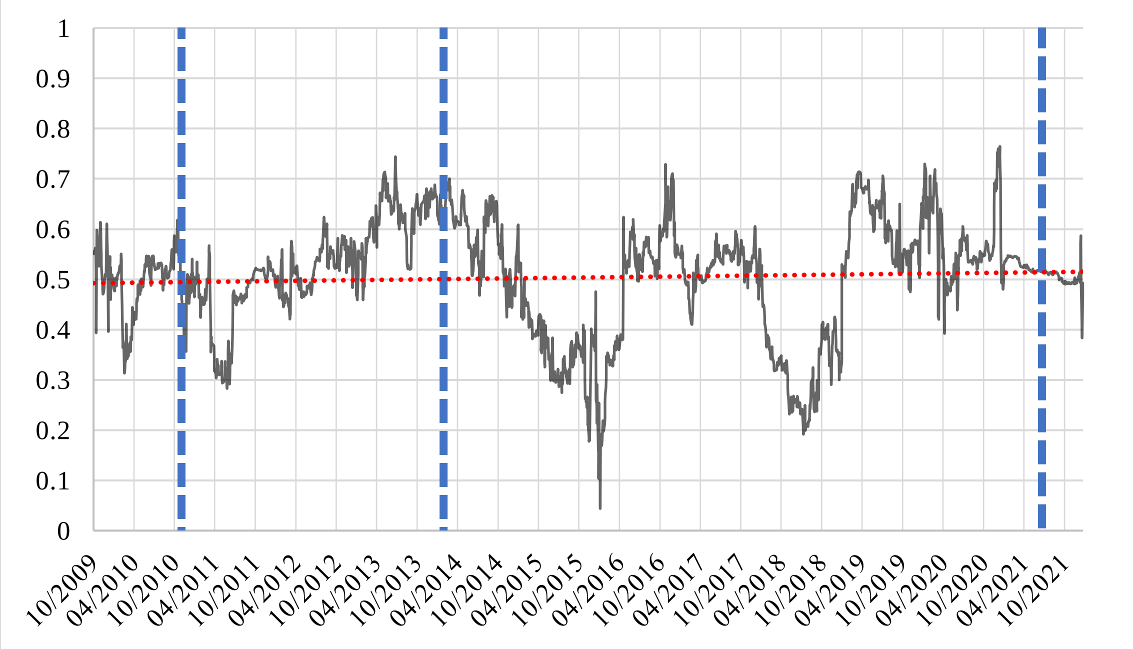

Figure D8. Germany month ahead continuous returns 250 days rolling Hurst exponents

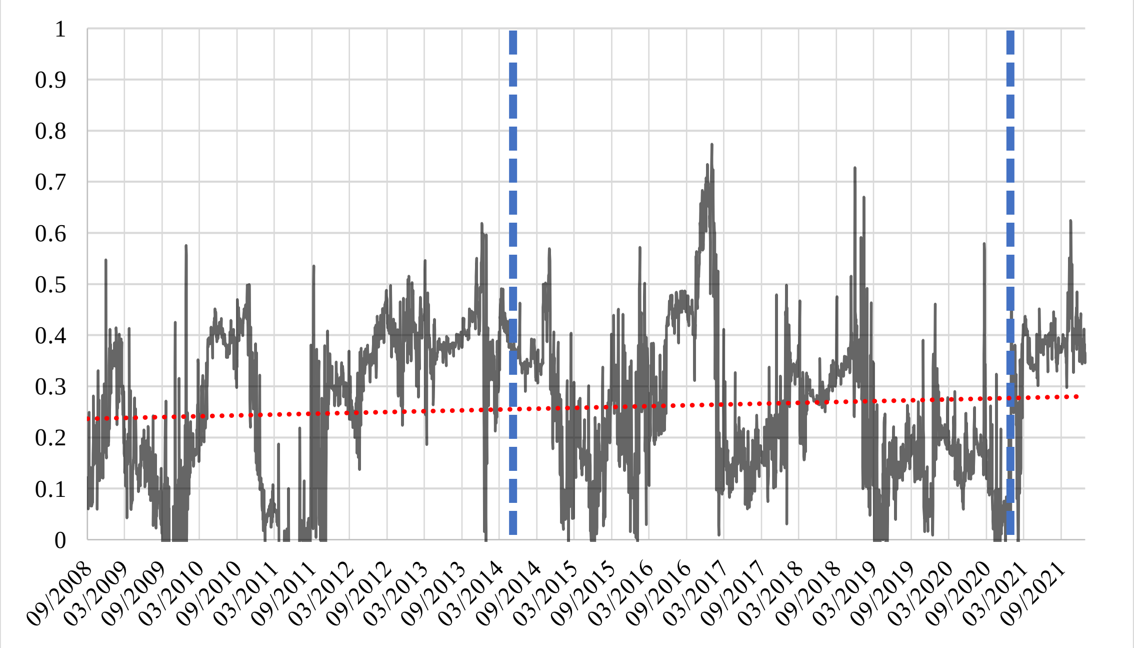

Figure D9. Spain day ahead returns 250 days rolling Hurst exponents

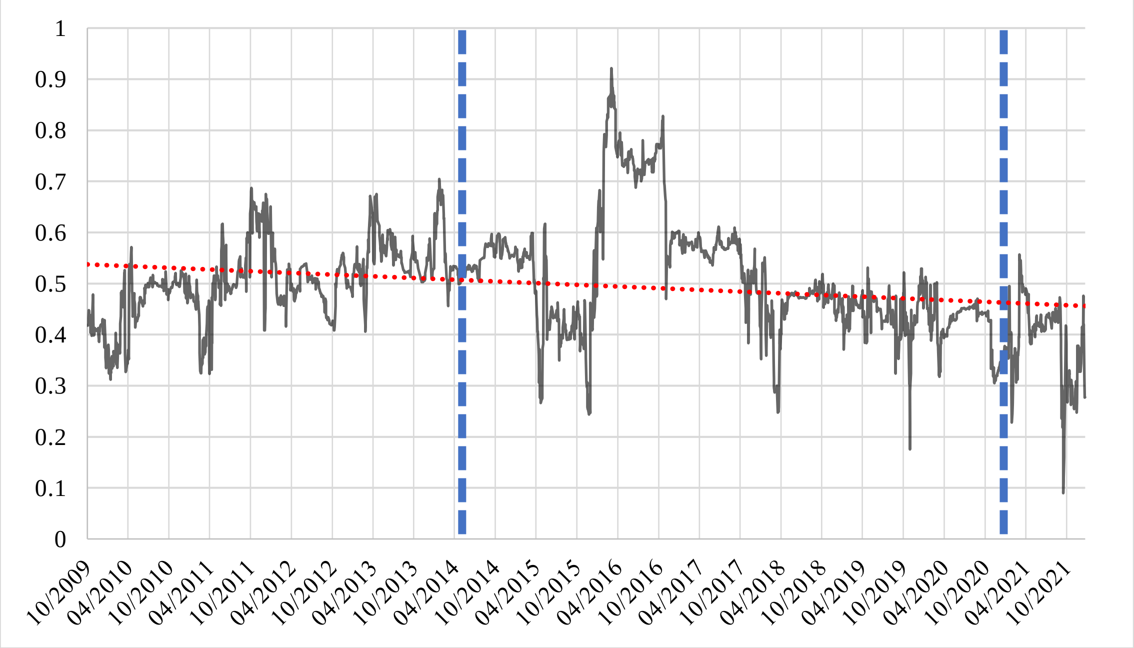

Figure D10. Spain month ahead continuous returns 250 days rolling Hurst exponents

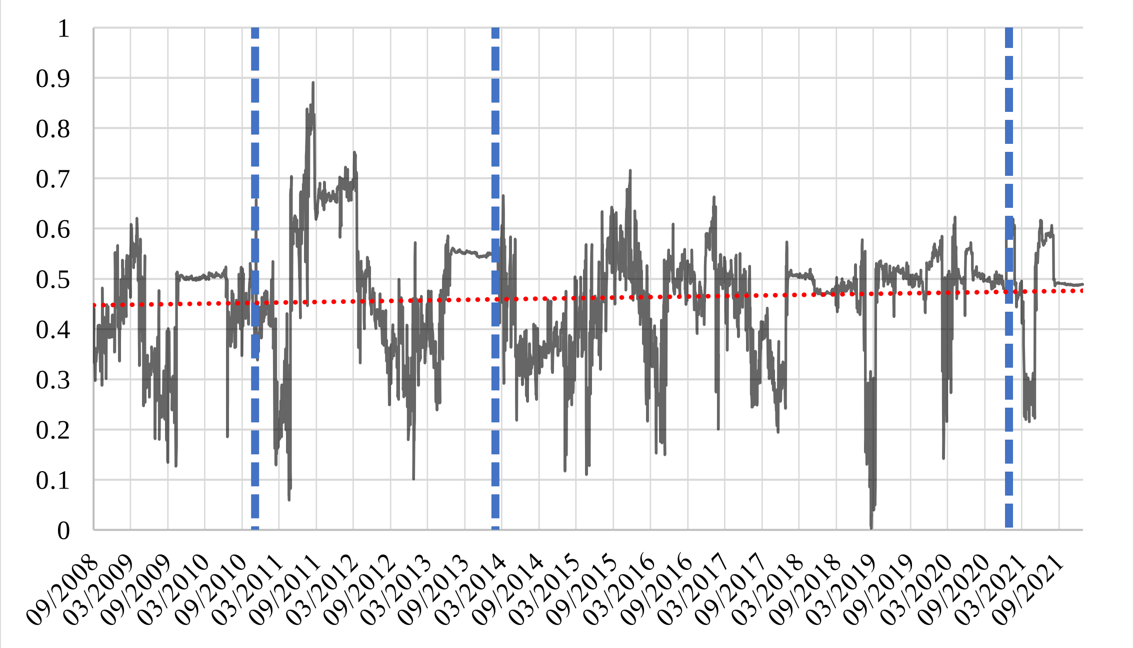

Figure D11. France day ahead returns 250 days rolling Hurst exponents

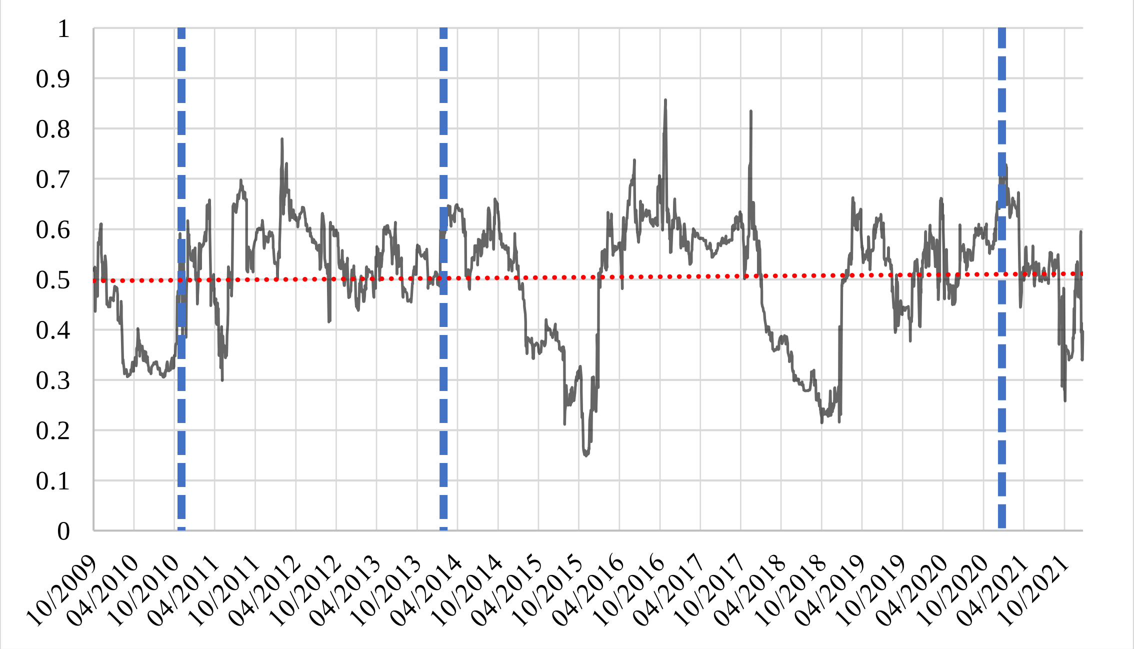

Figure D12. France month ahead continuous returns 250 days rolling Hurst exponents

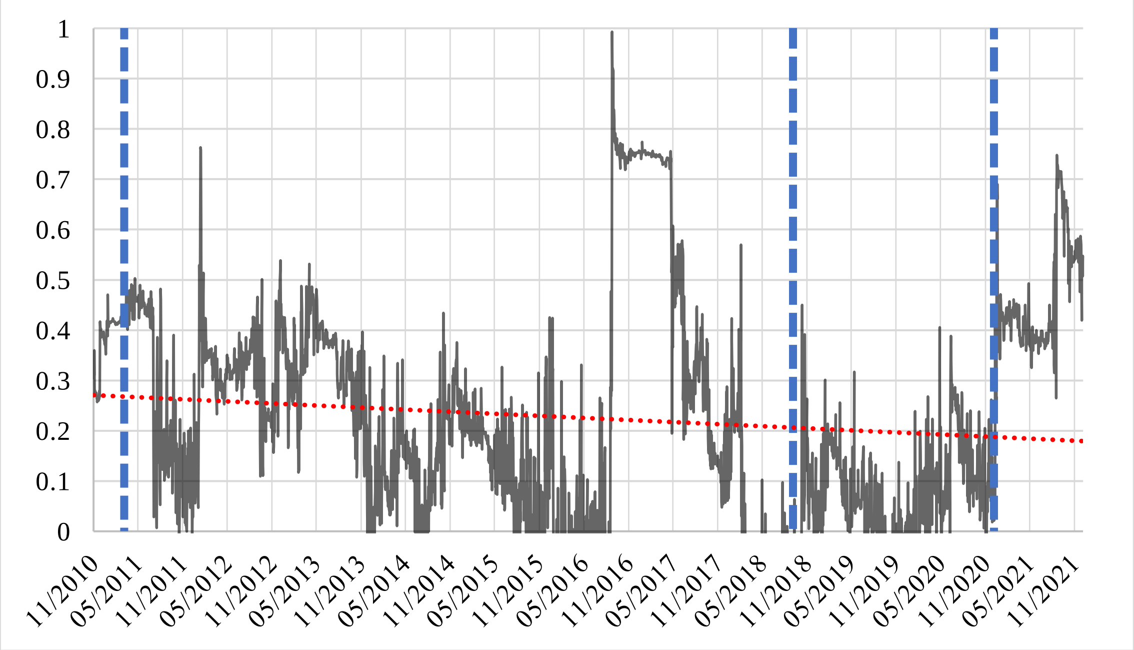

Figure D13. United Kingdom day ahead returns 250 days rolling Hurst exponents

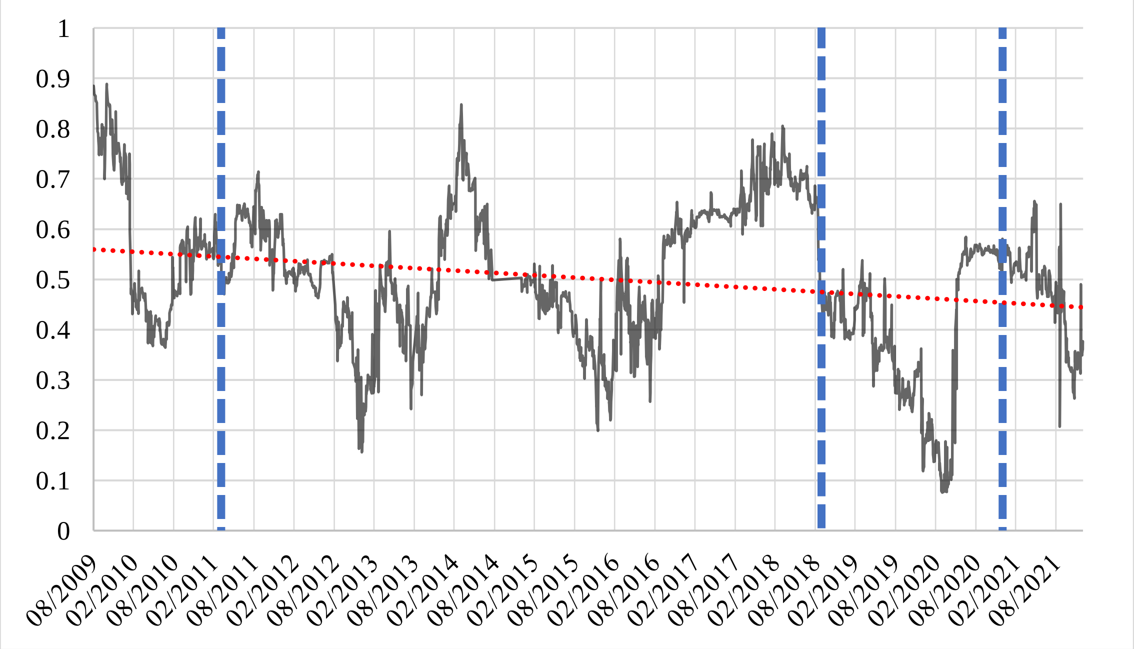

Figure D14. United Kingdom month ahead continuous returns 250 days rolling Hurst exponents

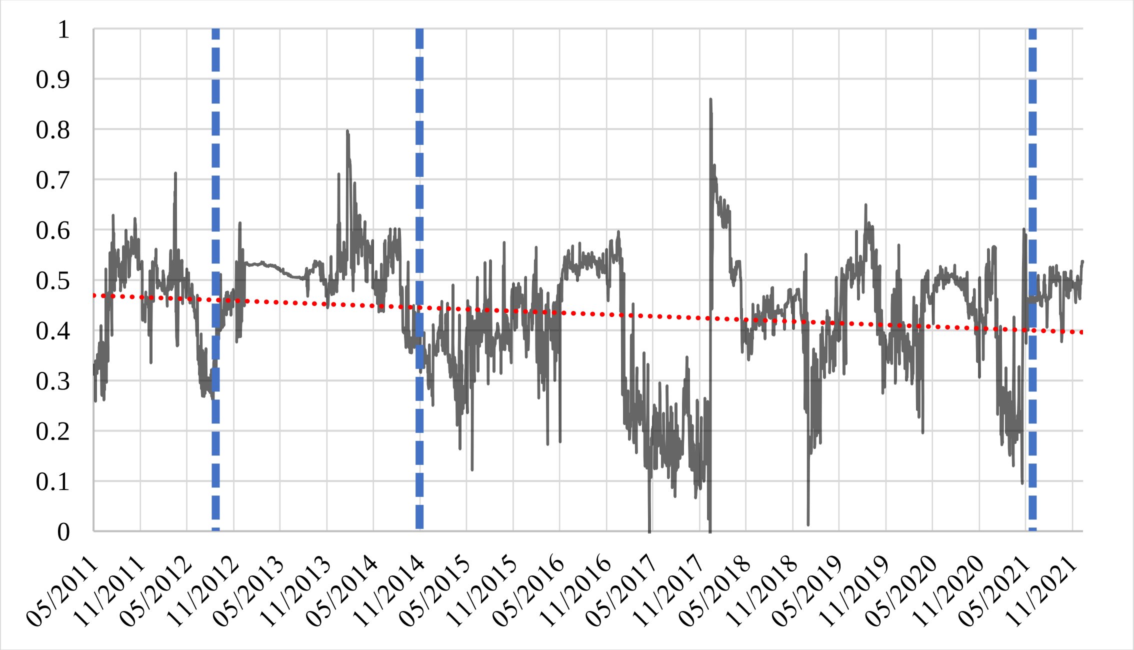

Figure D15. Hungary day ahead returns 250 days rolling Hurst exponents

Figure D16. Hungary month ahead continuous returns 250 days rolling Hurst exponents

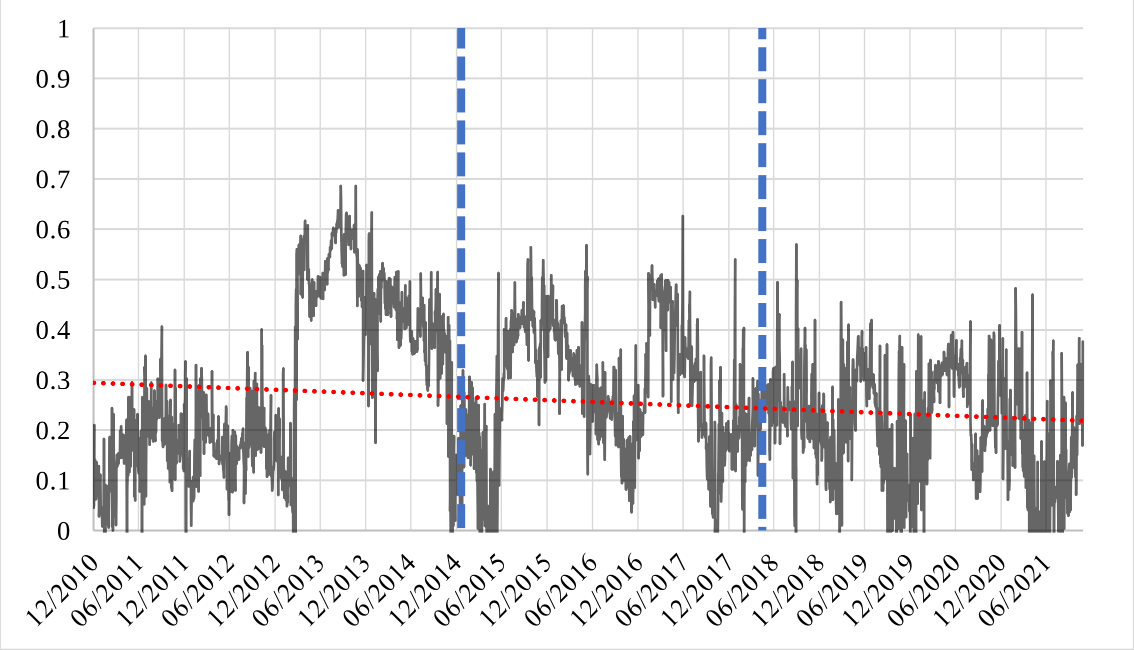

Figure D17. Italy day ahead returns 250 days rolling Hurst exponents

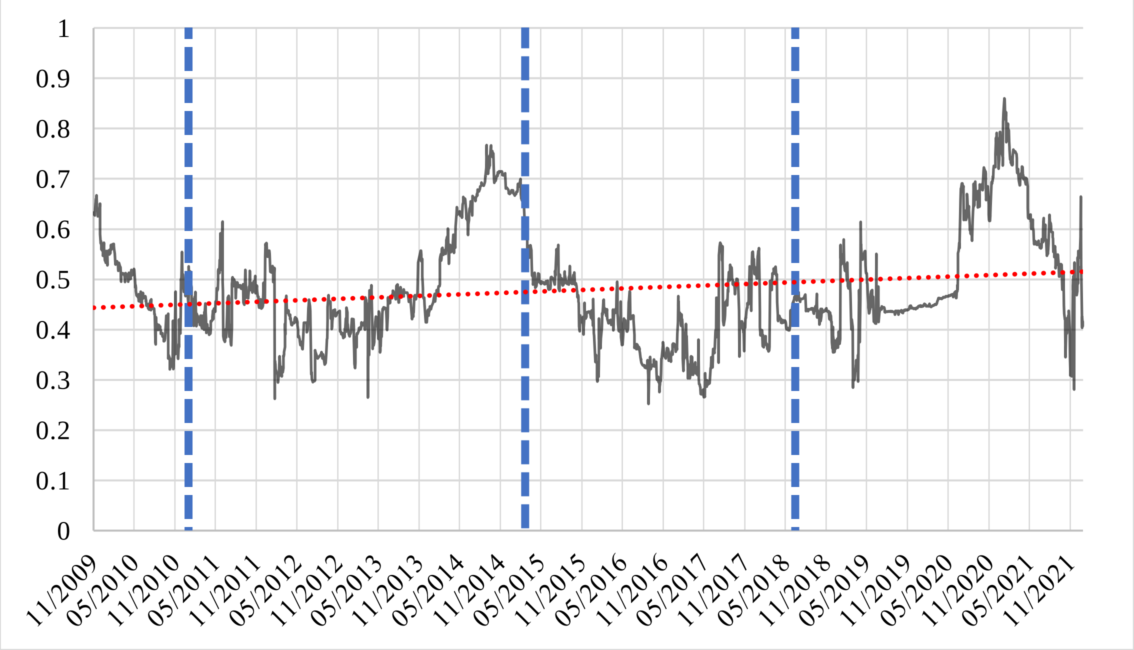

Figure D18. Italy month ahead continuous returns 250 days rolling Hurst exponents

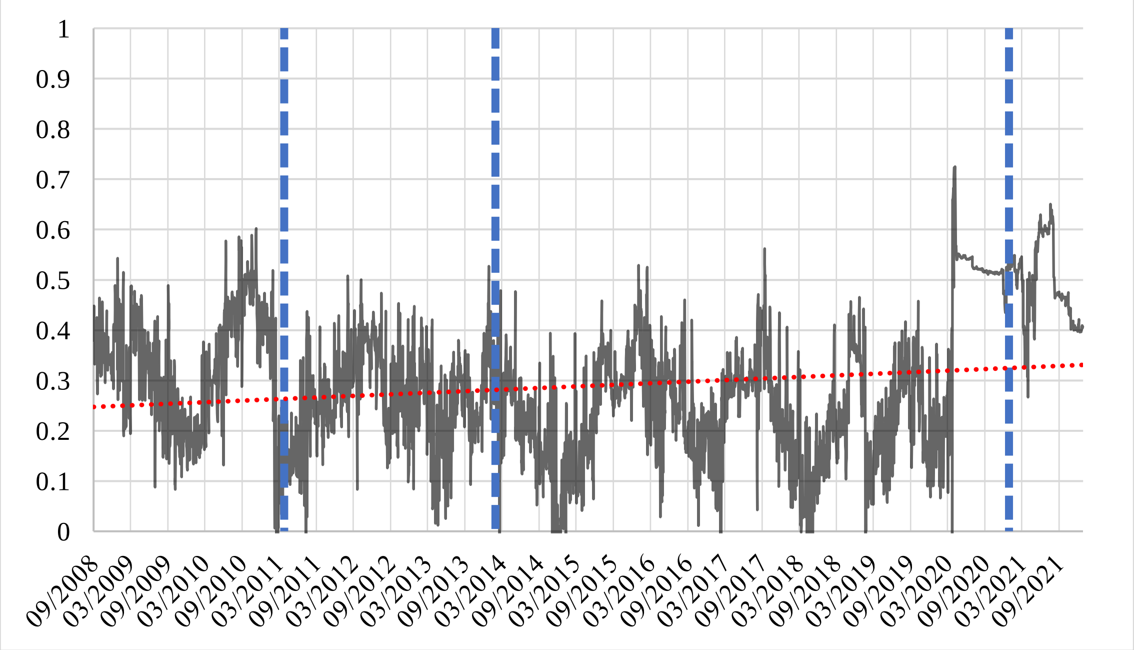

Figure D19. Netherlands day ahead returns 250 days rolling Hurst exponents

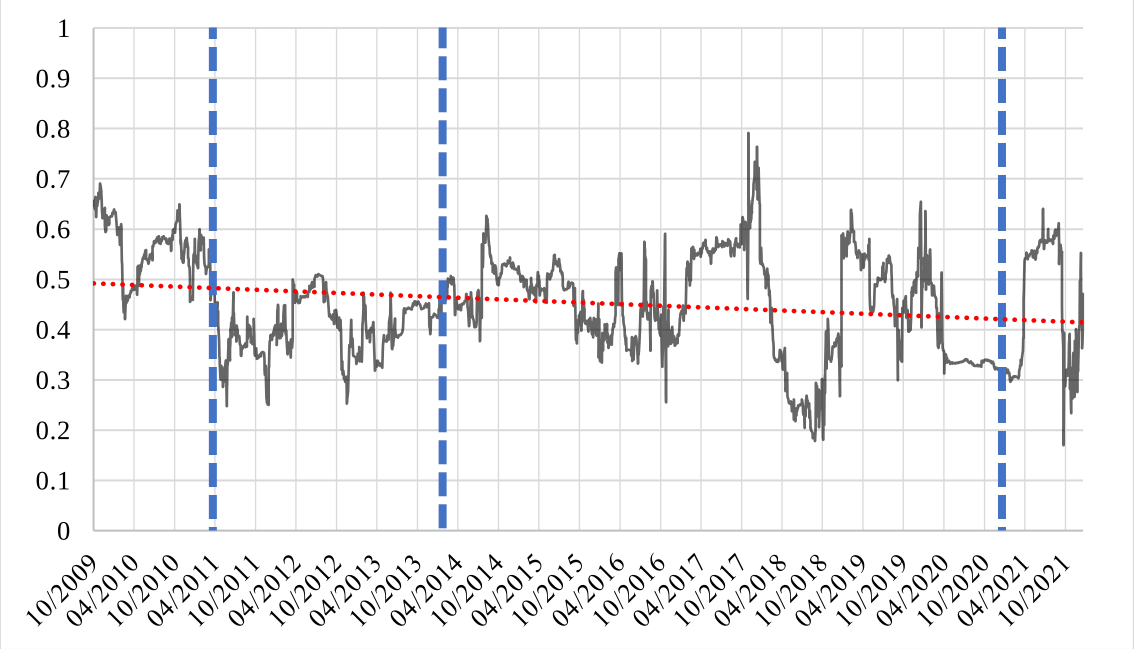

Figure D20. Netherlands month ahead continuous returns 250 days rolling Hurst exponents

# APPENDIX E

## FRACTAL DIMENSION

For each graph, vertical blue lines indicate the market coupling dates stated in Table 1, and red dashed lines indicate trend lines over the analyzed period. Y-Axis indicates average fractal dimension measure and X-Axis is the dates.

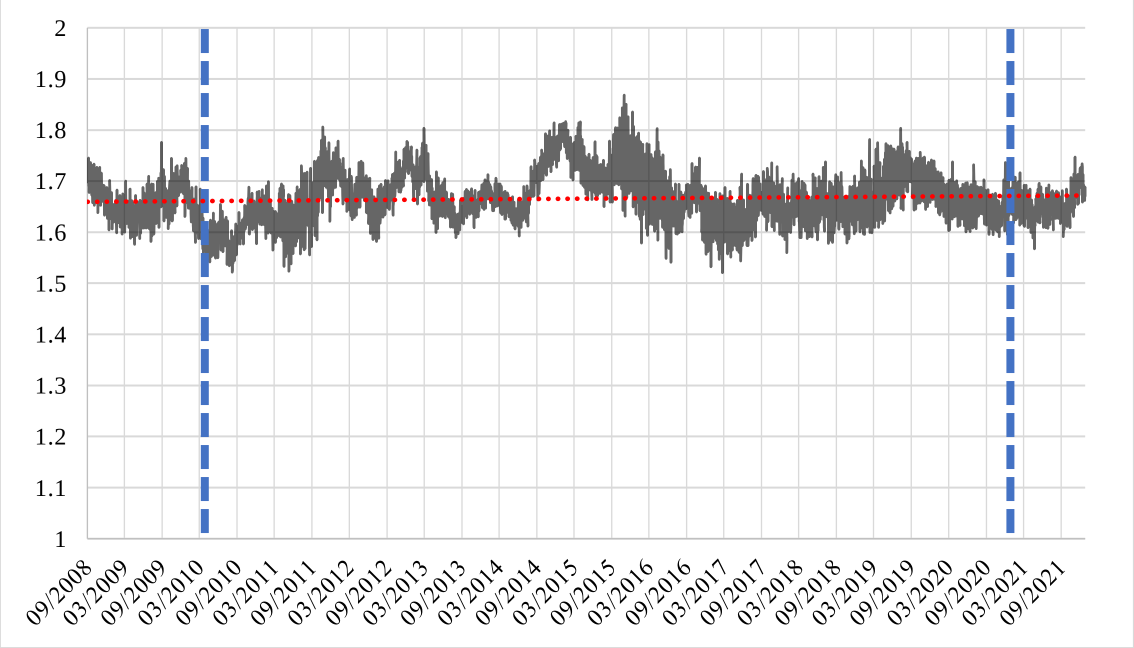

Figure E1. Belgium day ahead returns 250 days rolling fractal dimensions

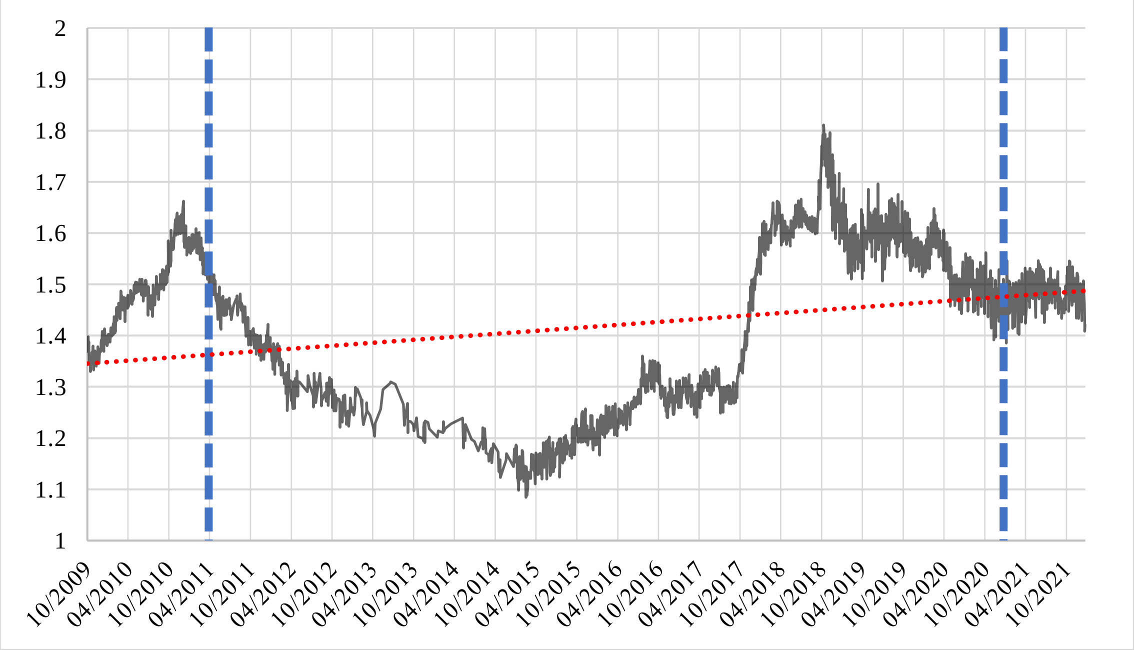

Figure E2. Belgium month ahead continuous returns 250 days rolling fractal dimensions

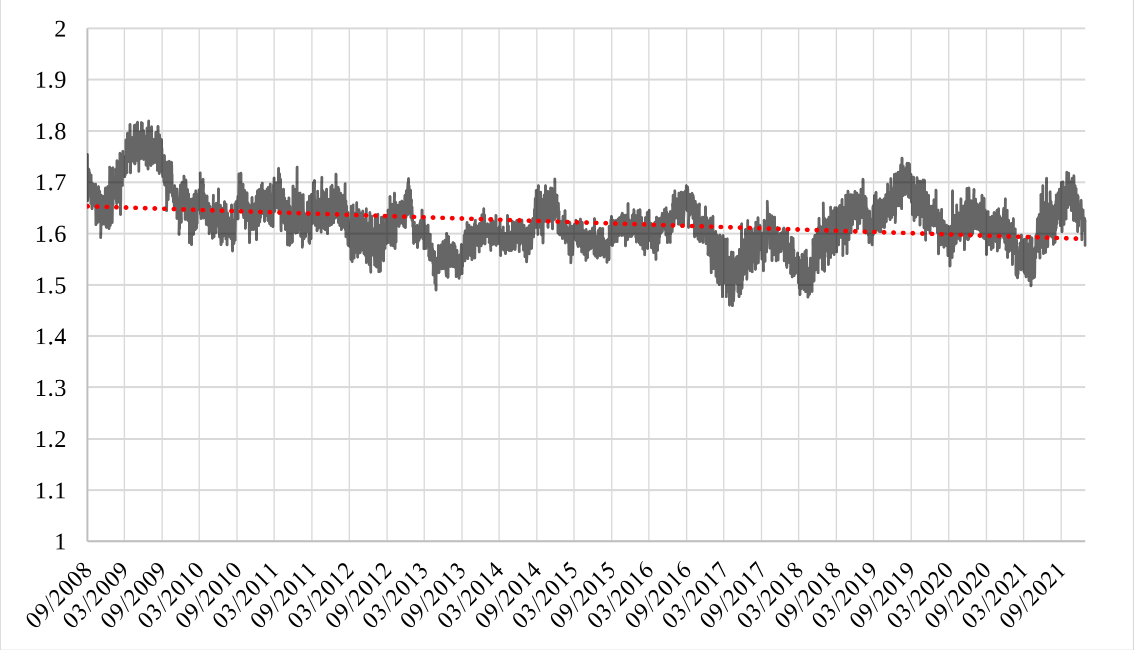

Figure E3. Switzerland day ahead returns 250 days rolling fractal dimensions

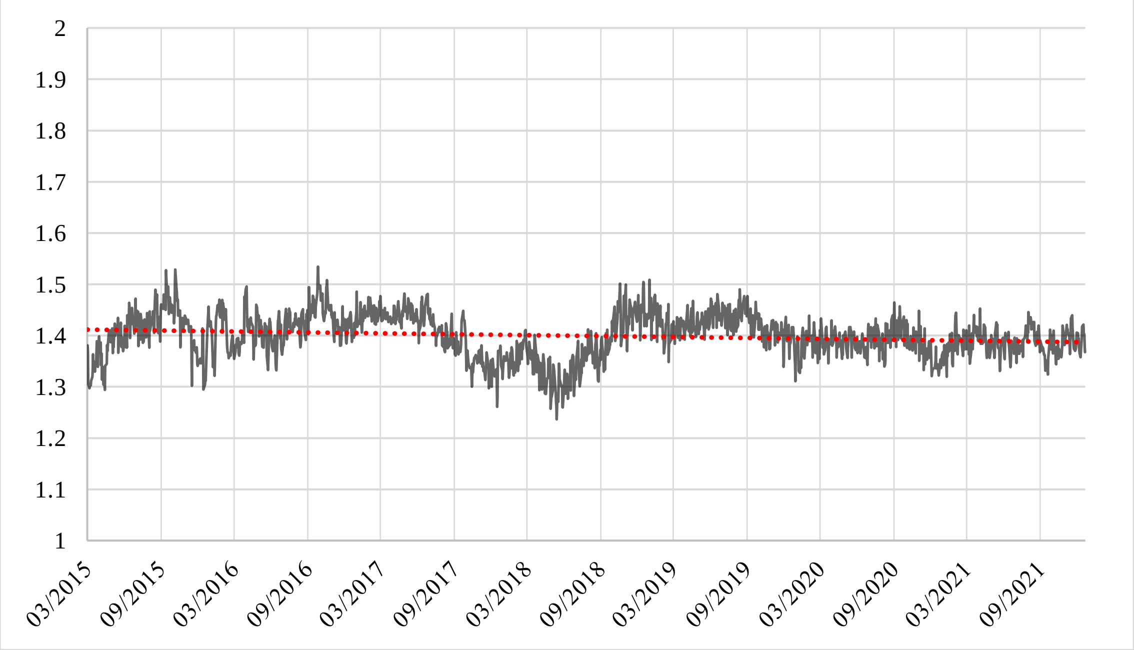

Figure E4. Switzerland month ahead continuous returns 250 days rolling fractal dimensions

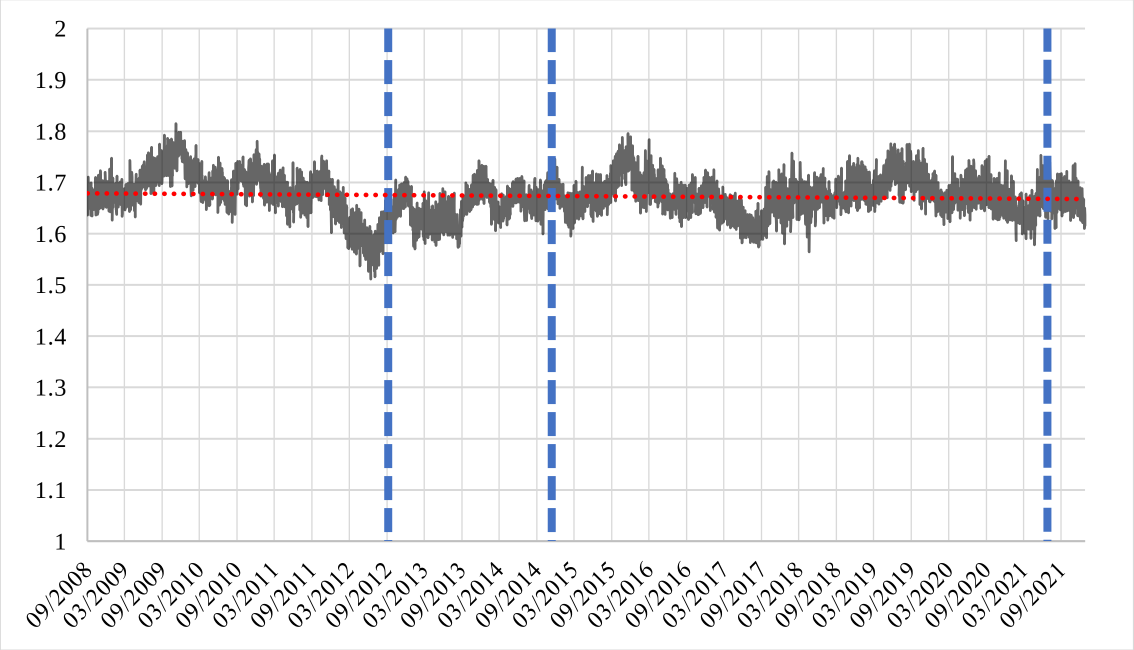

Figure E5. Czechia day ahead returns 250 days rolling fractal dimensions

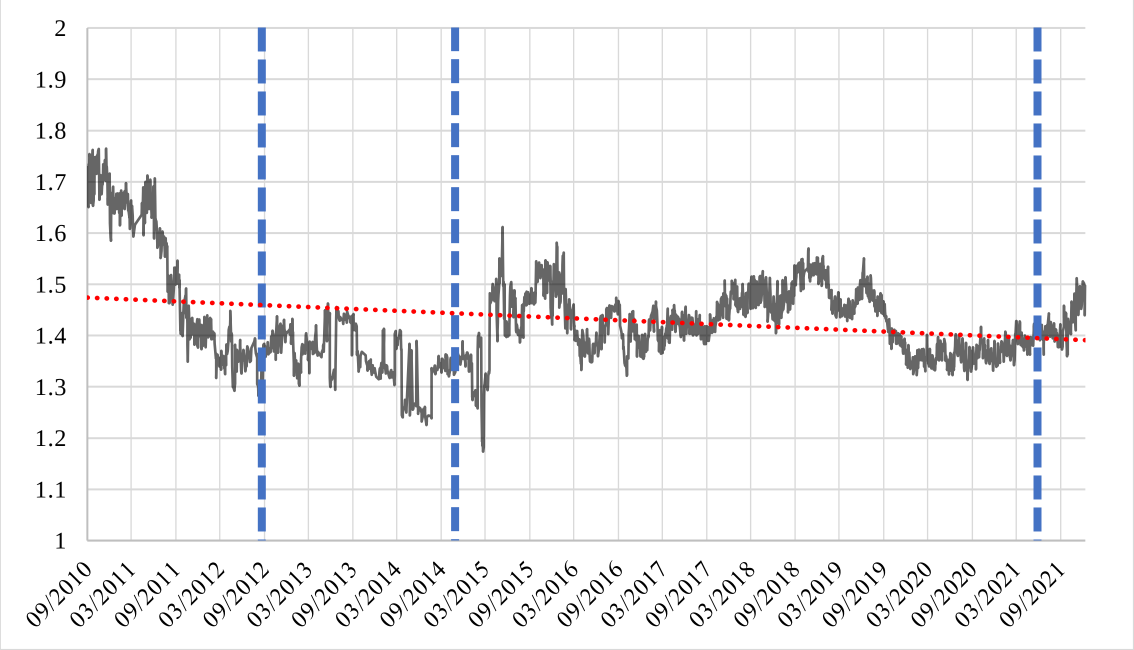

Figure E6. Czechia month ahead continuous returns 250 days rolling fractal dimensions

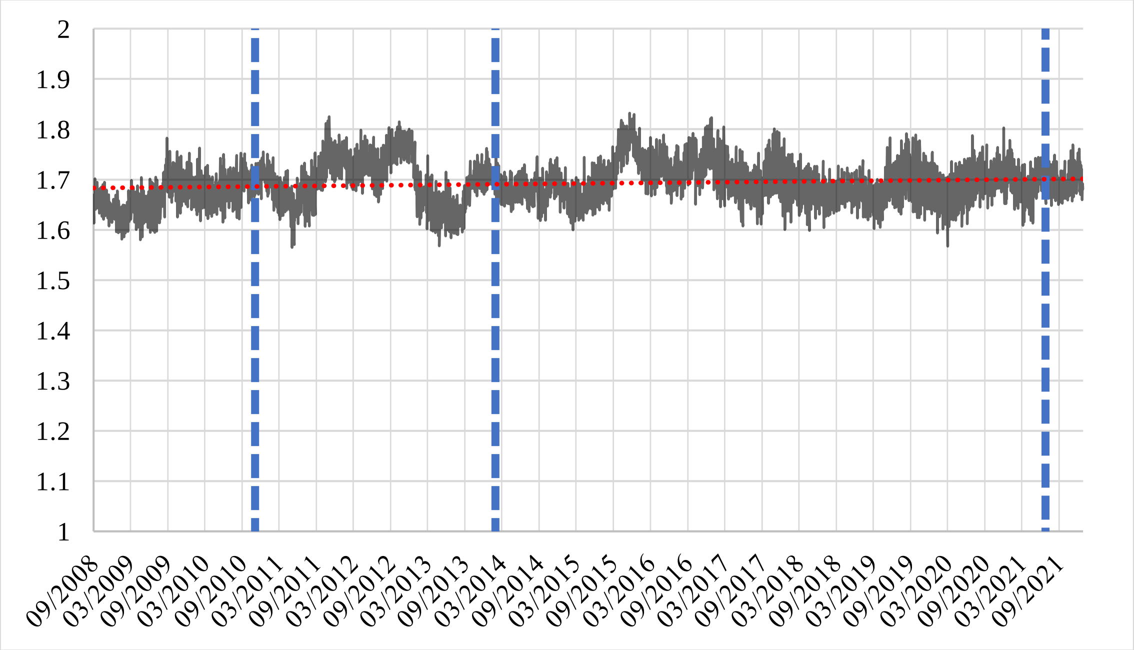

Figure E7. Germany day ahead returns 250 days rolling fractal dimensions

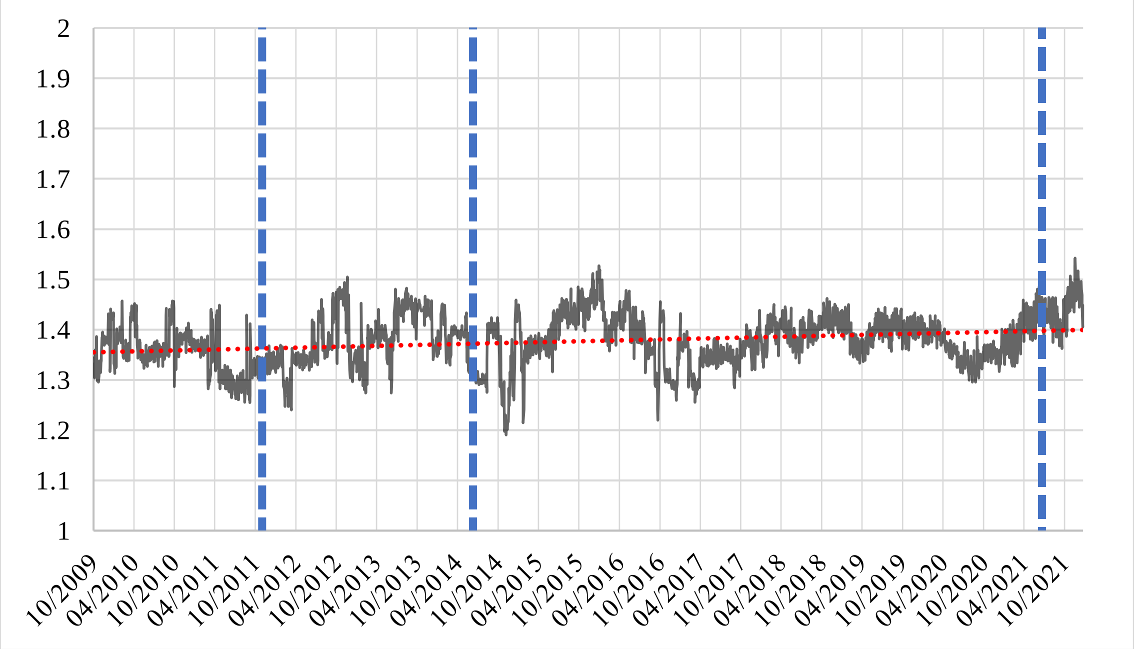

Figure E8. Germany month ahead continuous returns 250 days rolling fractal dimensions

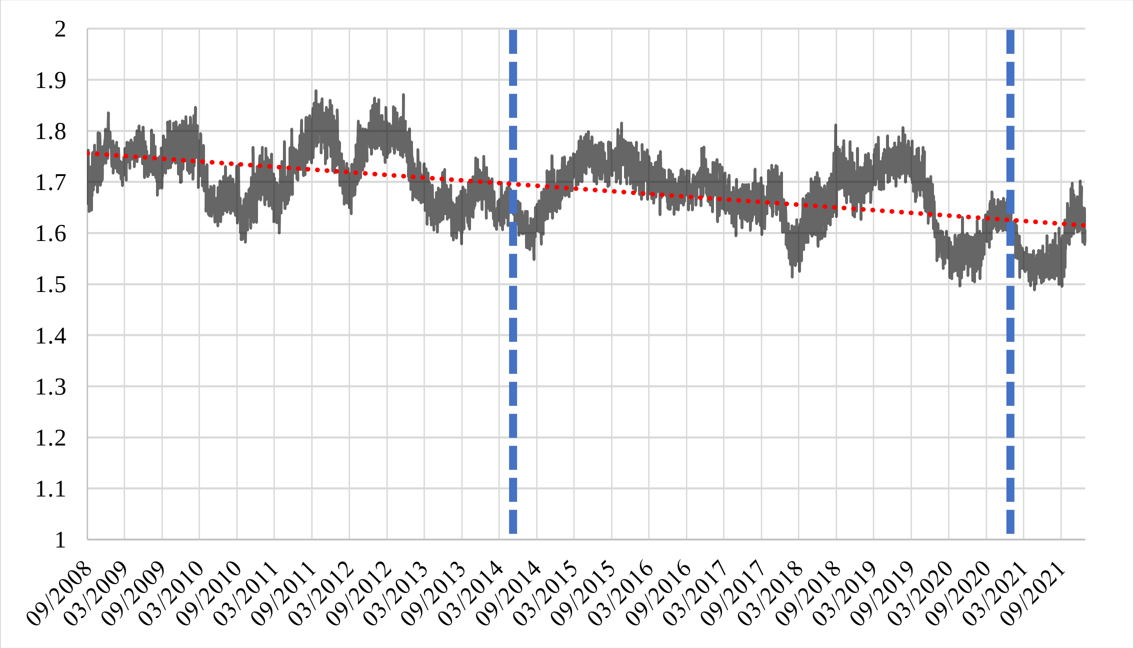

Figure E9. Spain day ahead returns 250 days rolling fractal dimensions

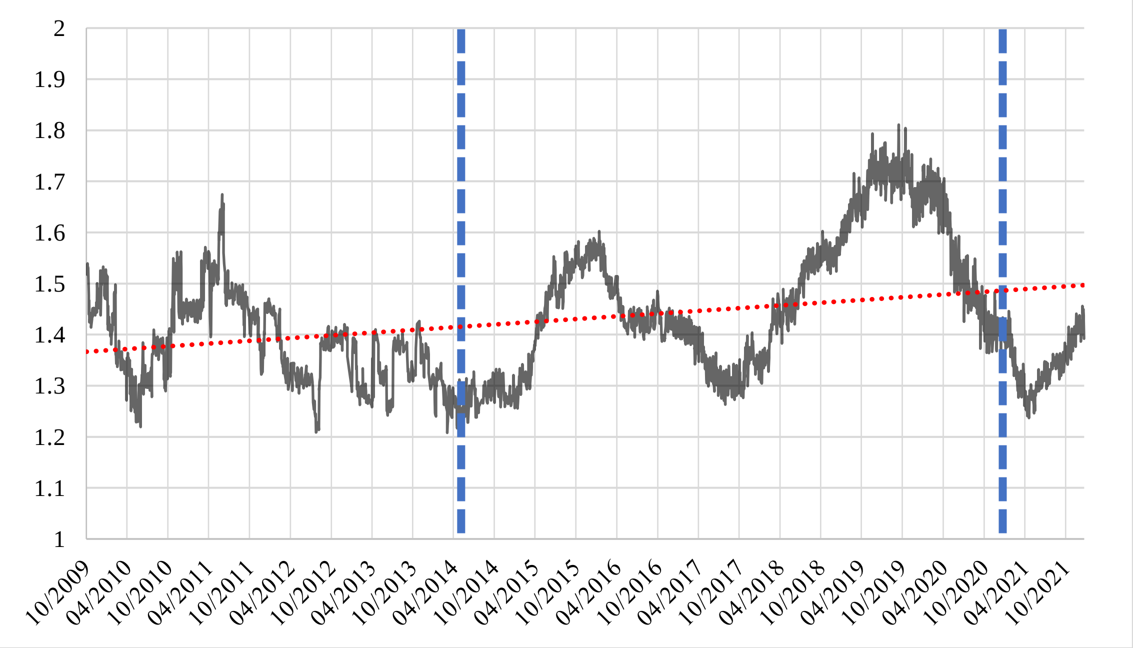

Figure E10. Spain month ahead continuous returns 250 days rolling fractal dimensions

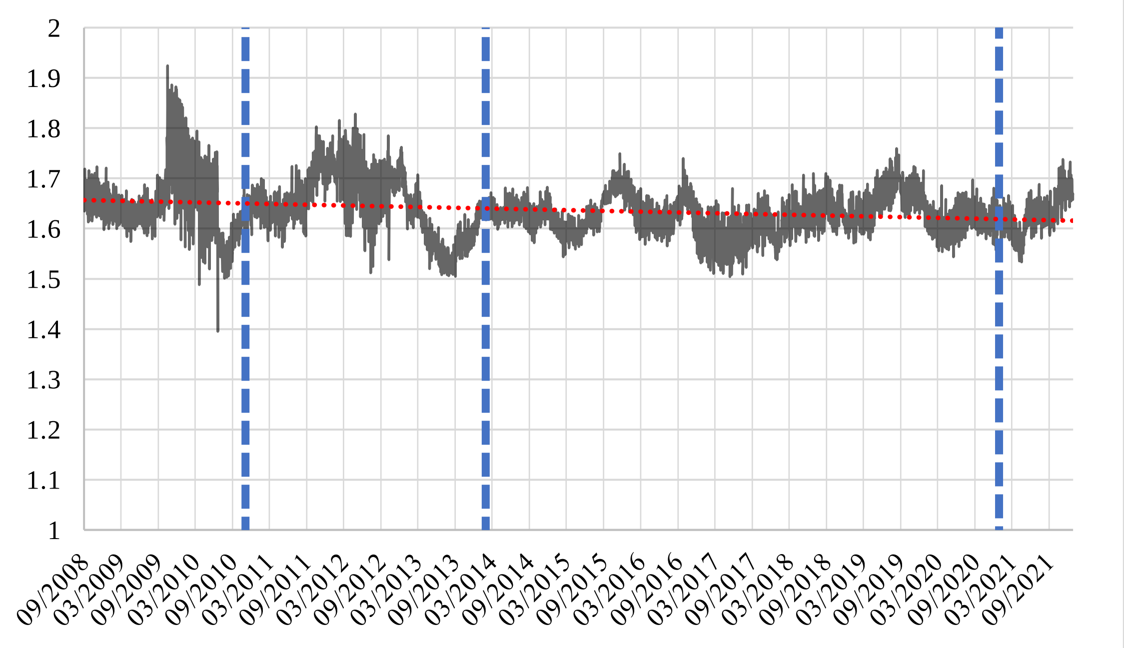

Figure E11. France day ahead returns 250 days rolling fractal dimensions

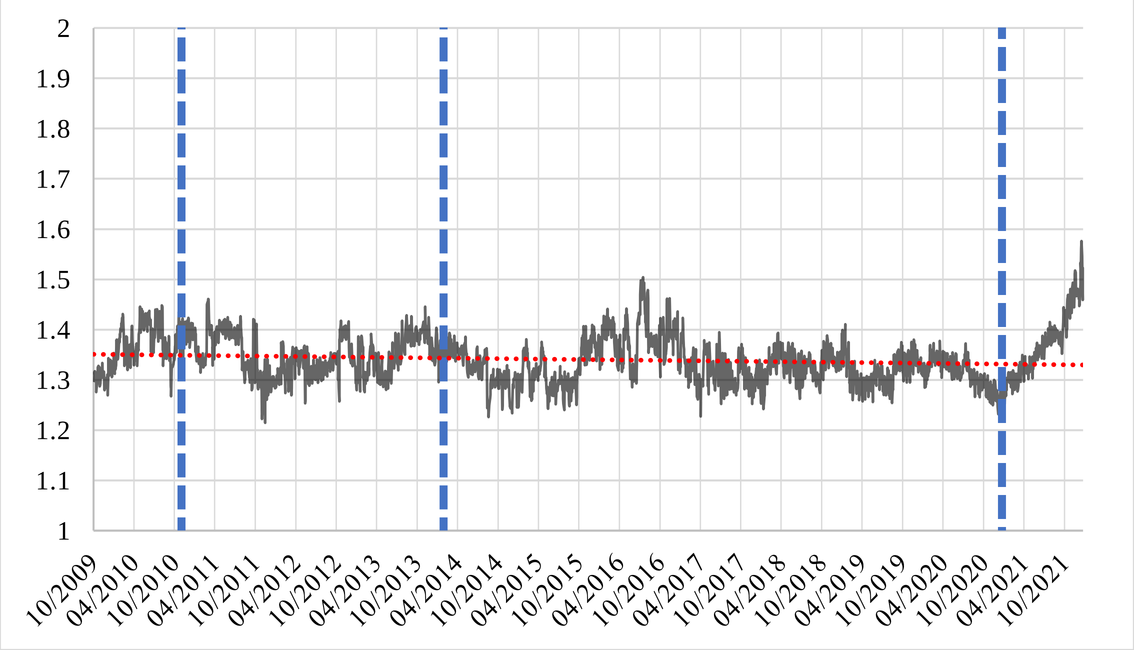

Figure E12. France month ahead continuous returns 250 days rolling fractal dimensions

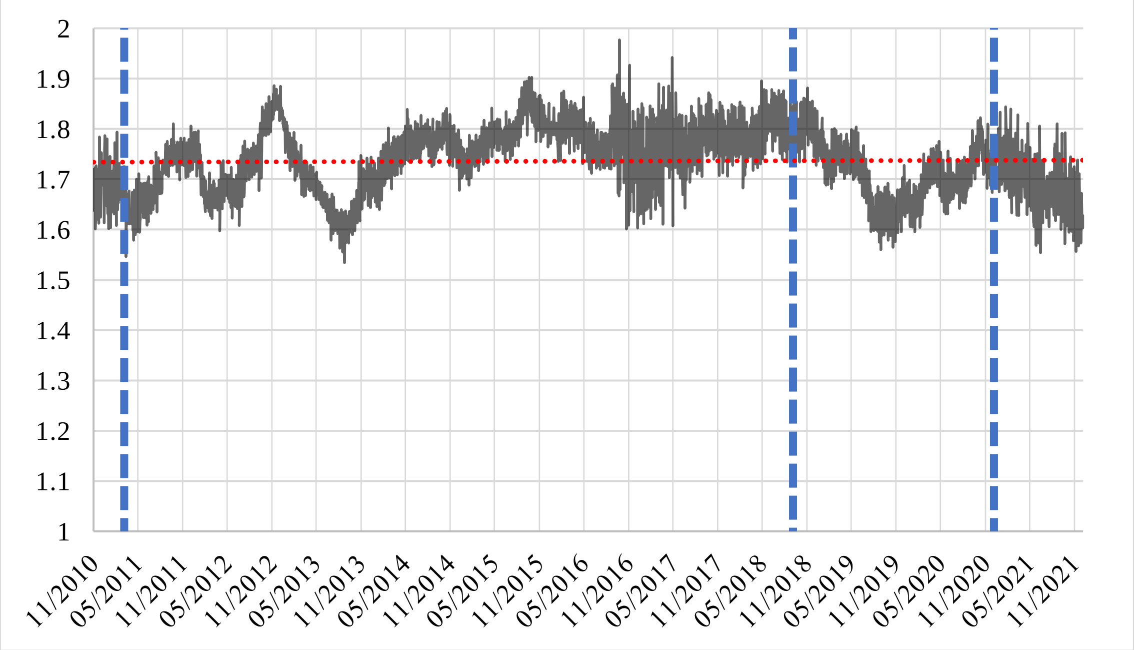

Figure E13. United Kingdom day ahead returns 250 days rolling fractal dimensions

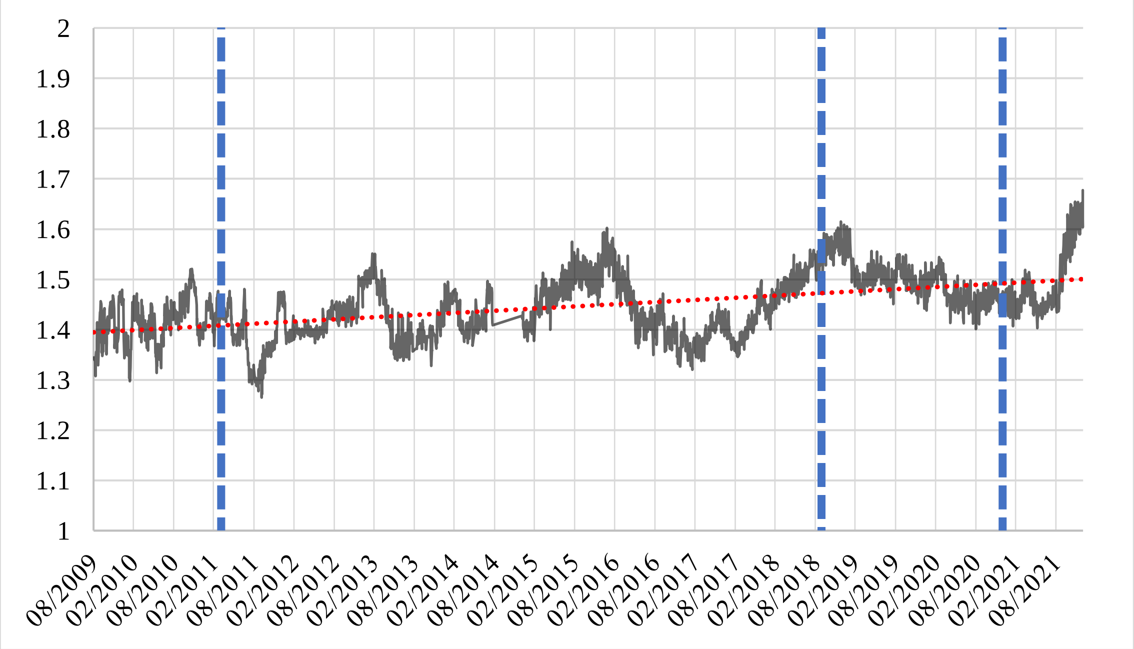

Figure E14. United Kingdom month ahead continuous returns 250 days rolling fractal dimensions

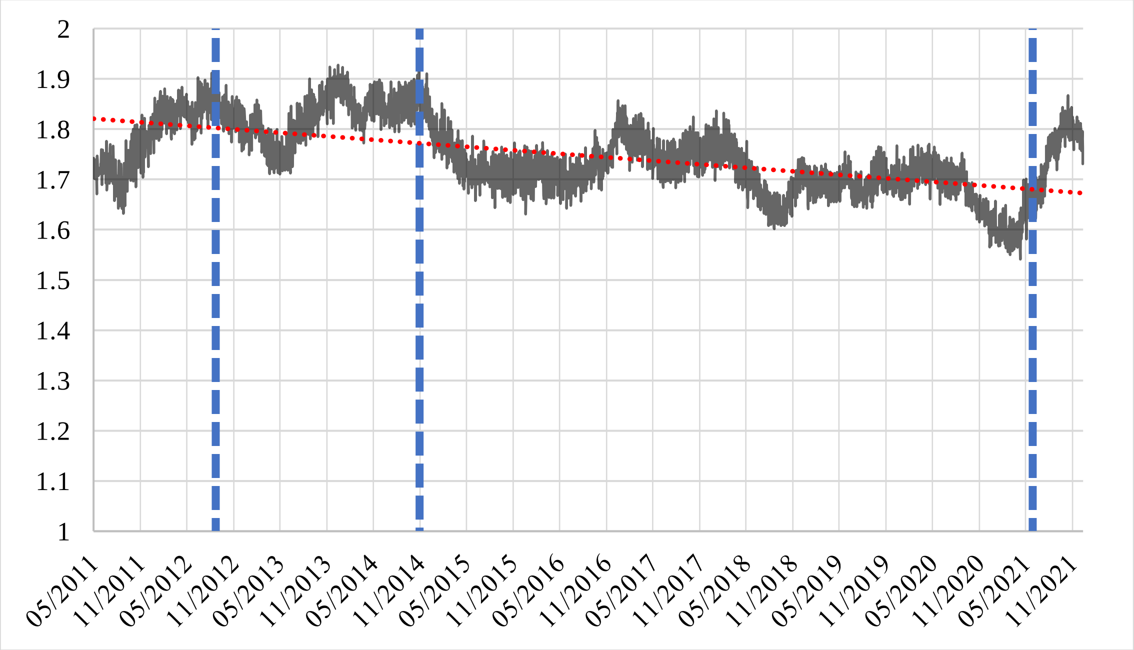

Figure E15. Hungary day ahead returns 250 days rolling fractal dimensions

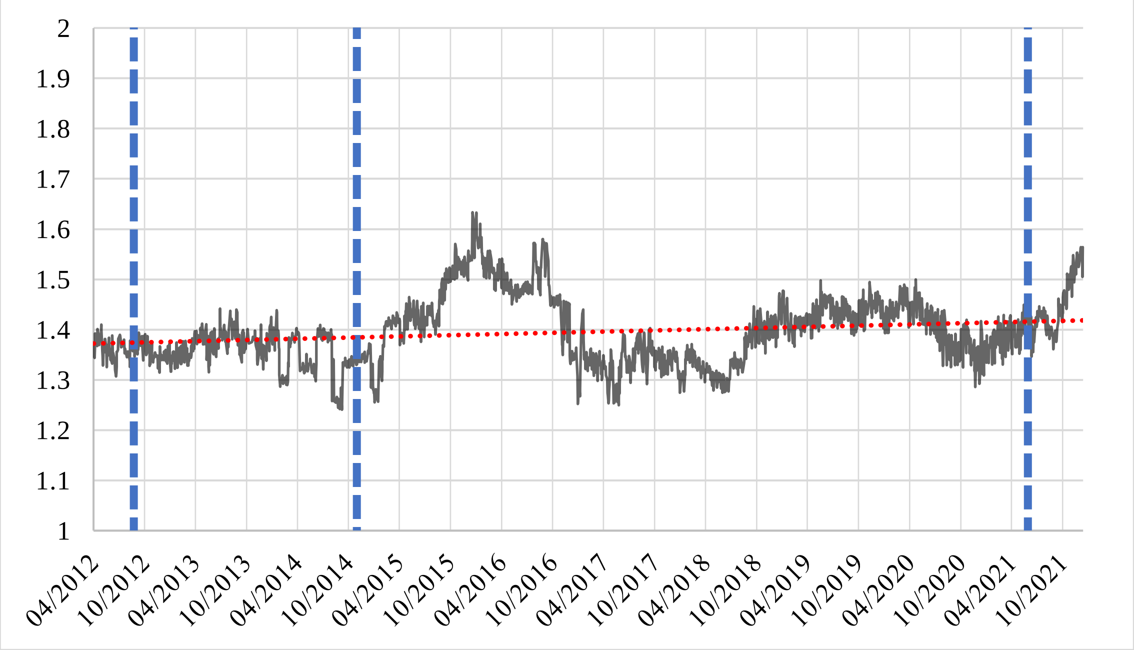

Figure E16. Hungary month ahead continuous returns 250 days rolling fractal dimensions

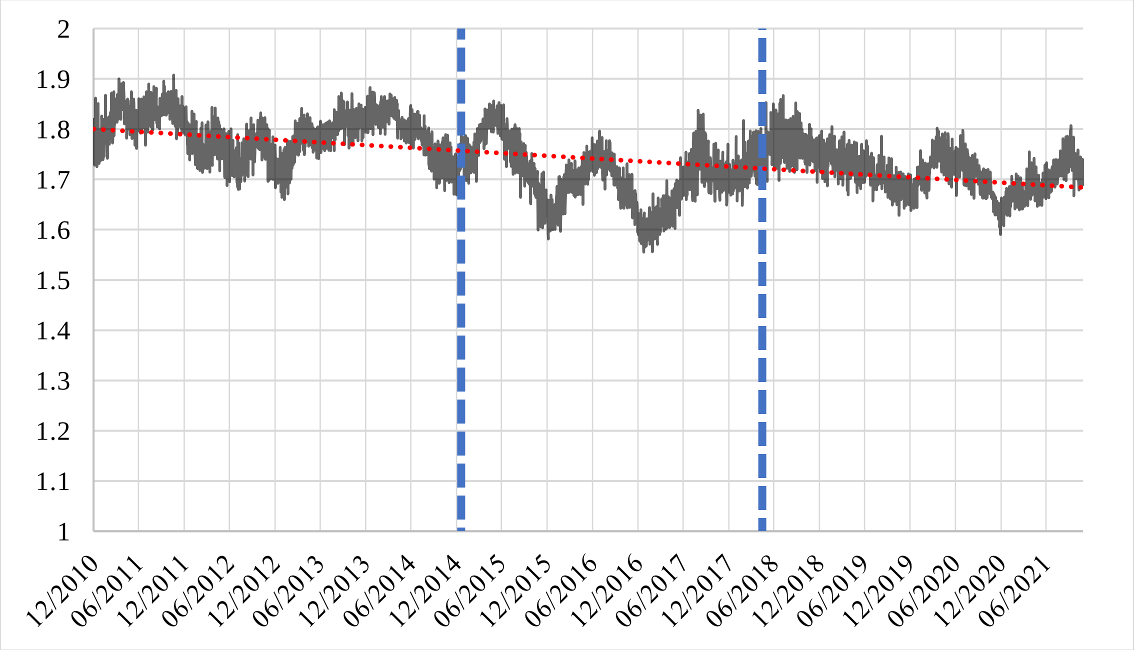

Figure E17. Italy day ahead returns 250 days rolling fractal dimensions

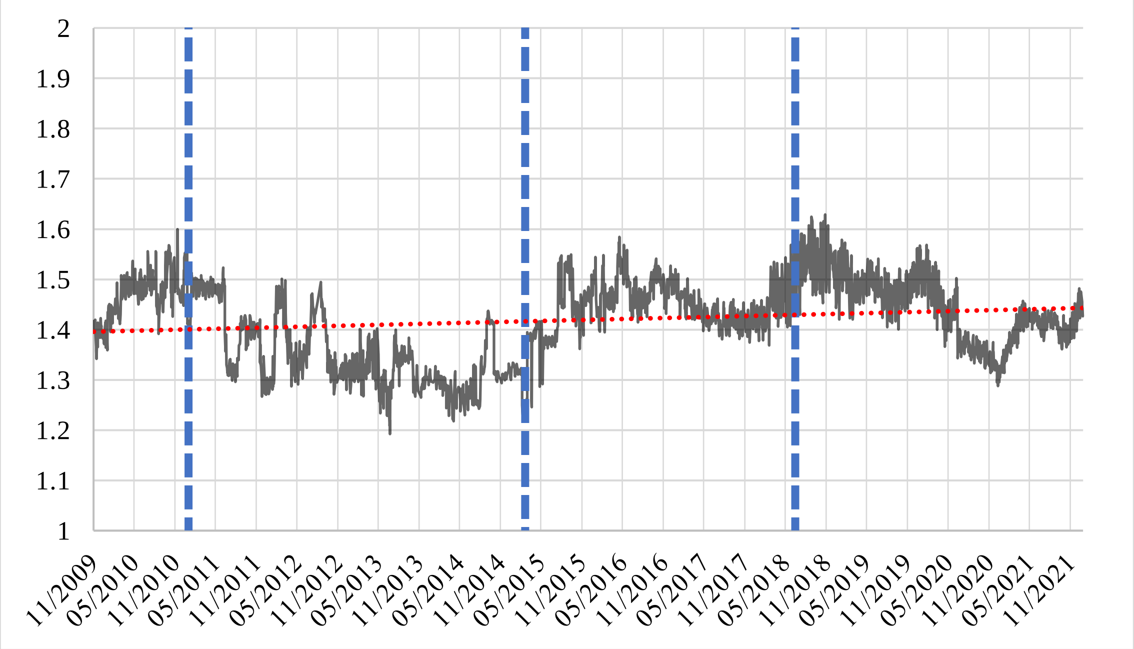

Figure E18. Italy month ahead continuous returns 250 days rolling fractal dimensions

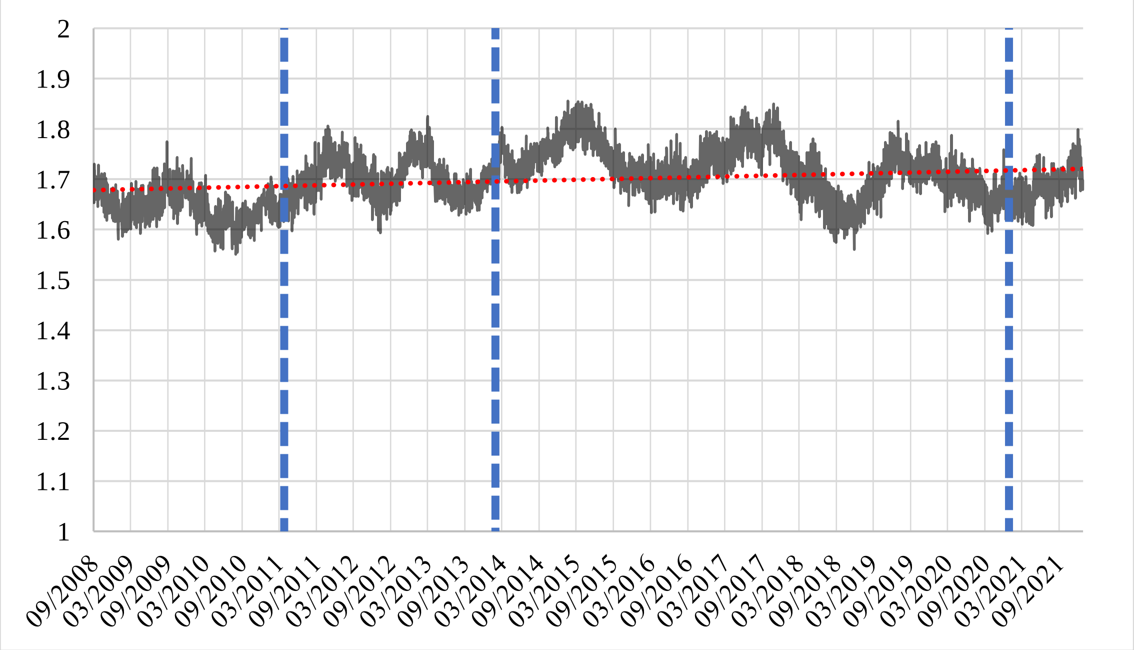

Figure E19.  Netherlands day ahead returns 250 days rolling fractal dimensions

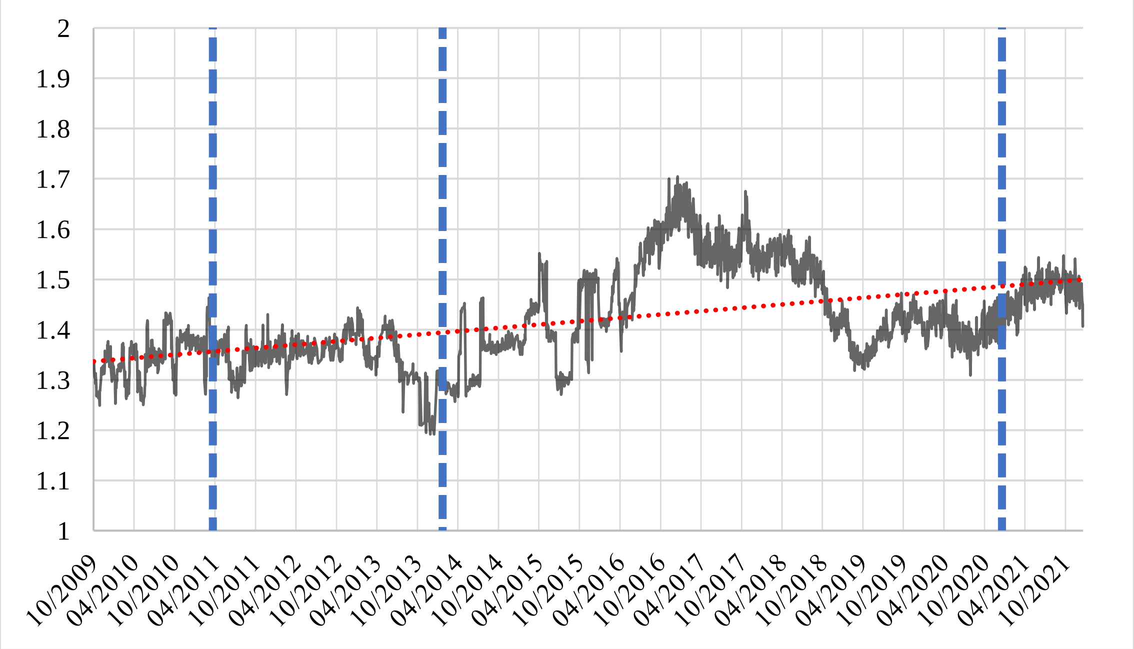

Figure E20. Netherlands month ahead continuous returns 250 days rolling fractal dimensions

# APPENDIX F

## EX-POST RISK PREMIUMS

For each percentage graph, vertical blue lines indicate the market coupling dates stated in Table 1, and red dashed lines indicate trend lines over the analyzed period. Y-Axis indicates calculated ex-post risk premium for the month. X-Axis shows the observation months.

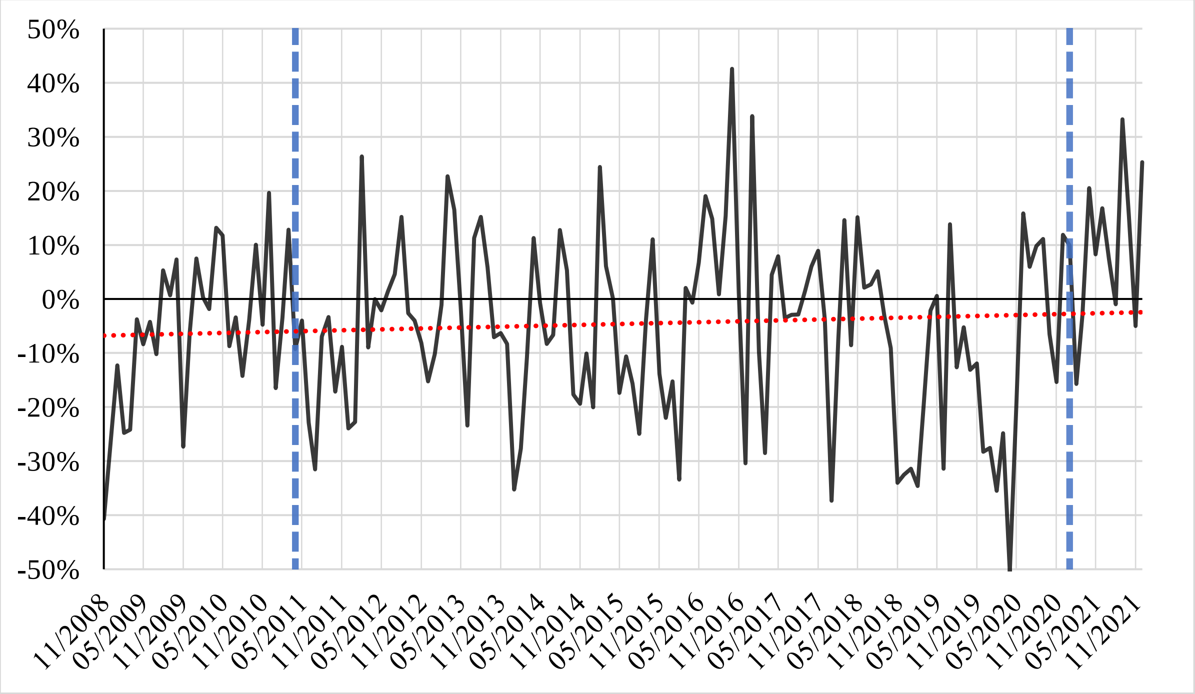

Figure F1. Belgium month ahead ex-post risk premium

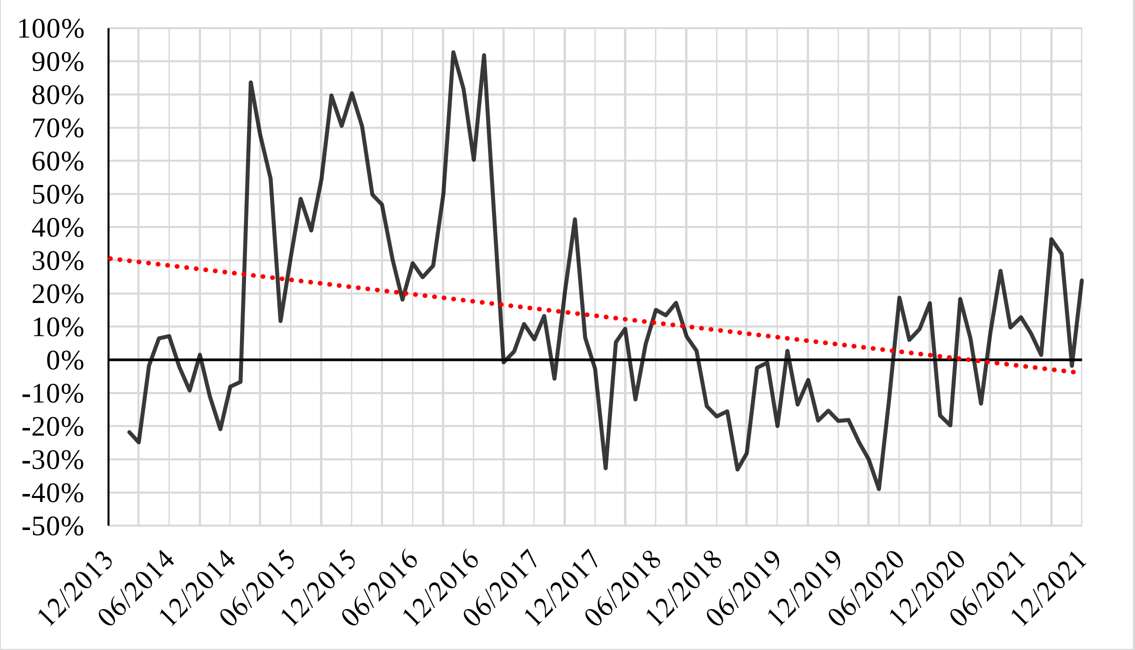

Figure F2. Switzerland month ahead ex-post risk premium

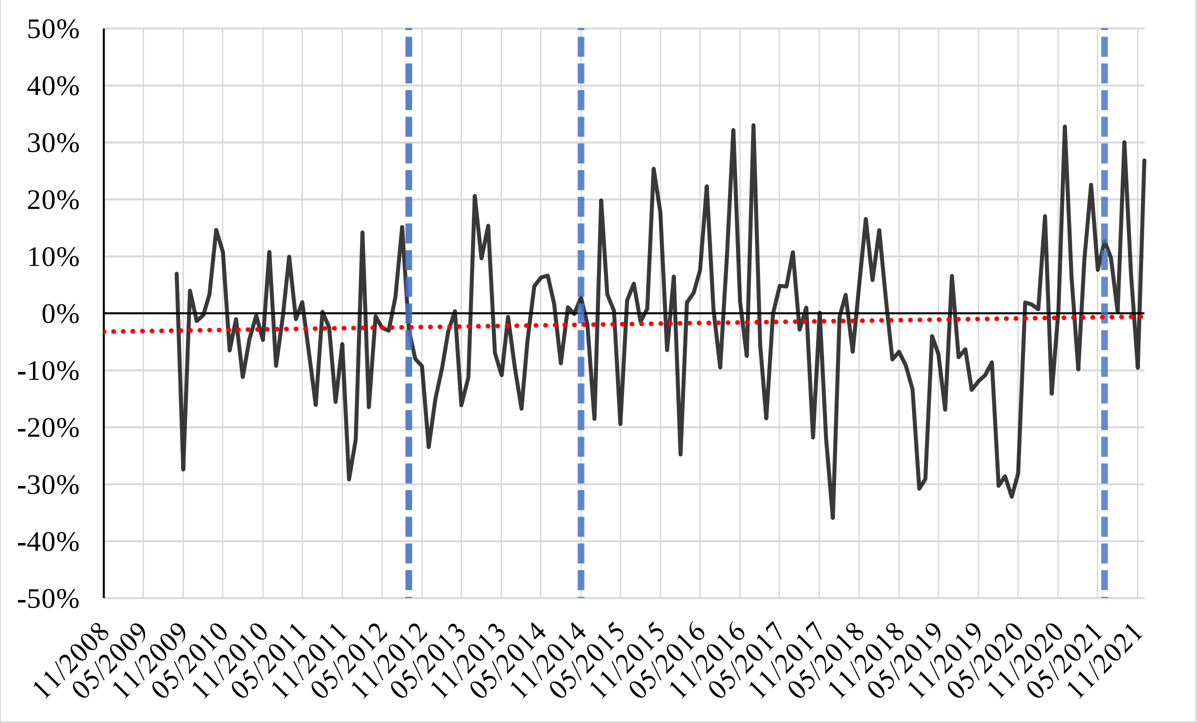

Figure F3. Czechia month ahead ex-post risk premium

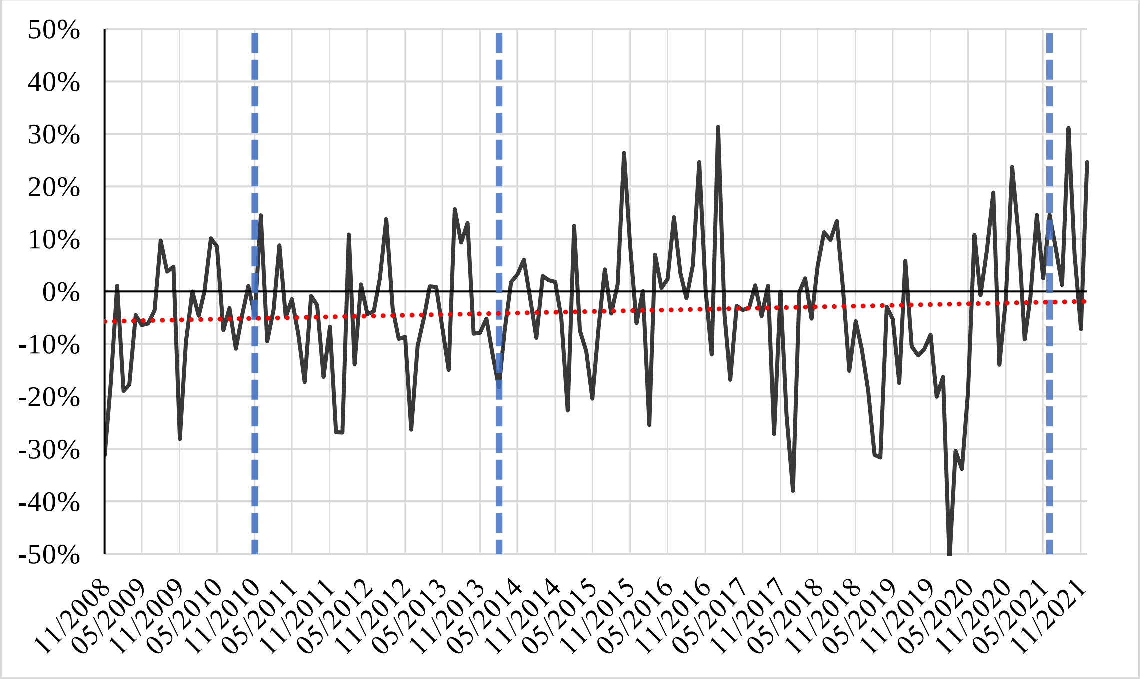

Figure F4. Germany month ahead ex-post risk premium

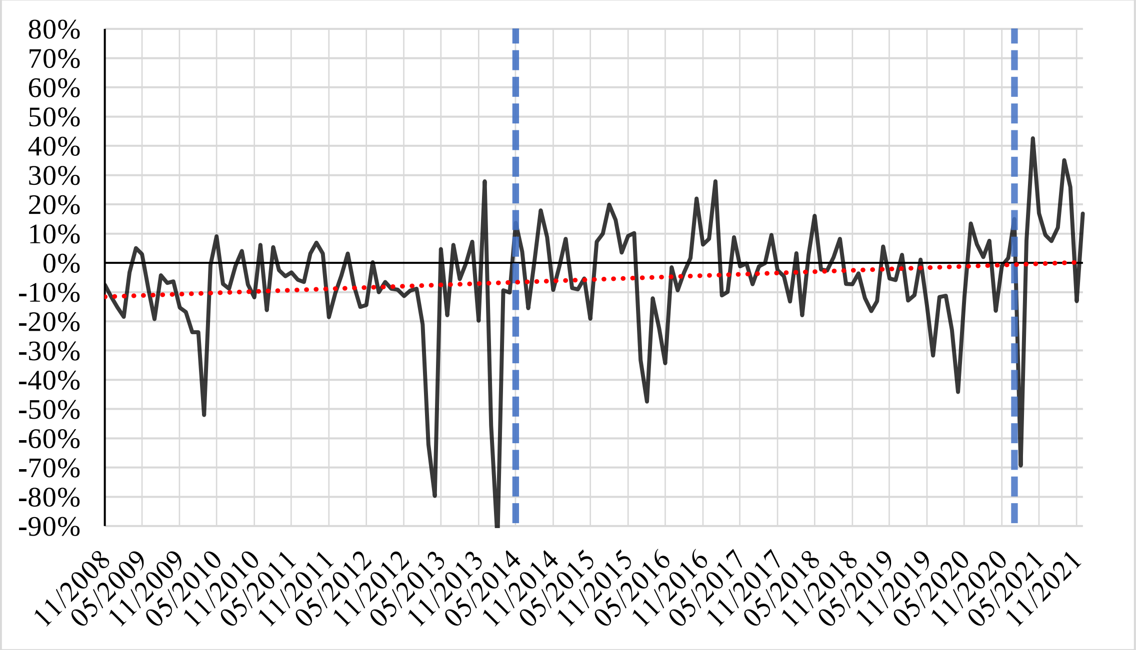

Figure F5. Spain month ahead ex-post risk premium

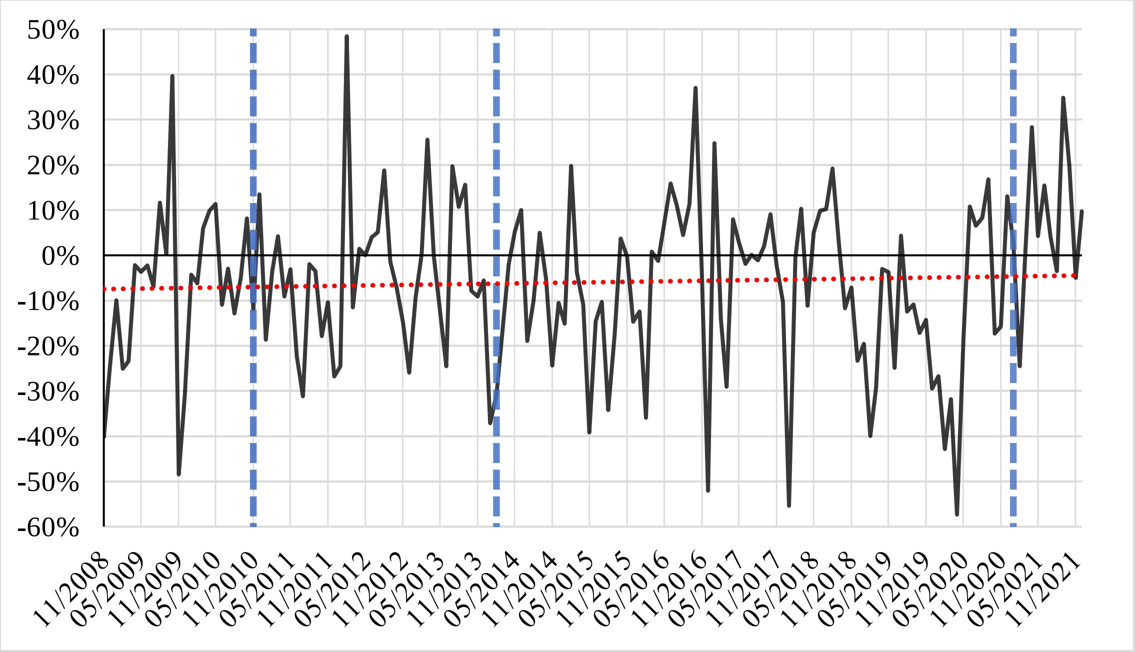

Figure F6. France month ahead ex-post risk premium

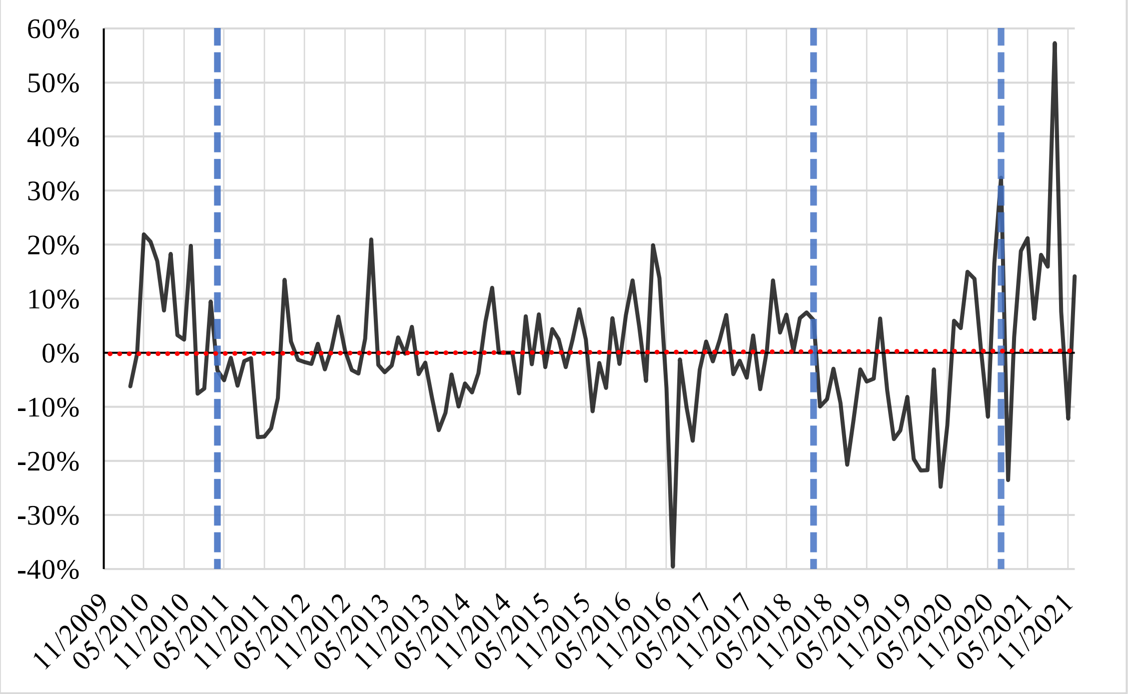

Figure F7. United Kingdom month ahead ex-post risk premium

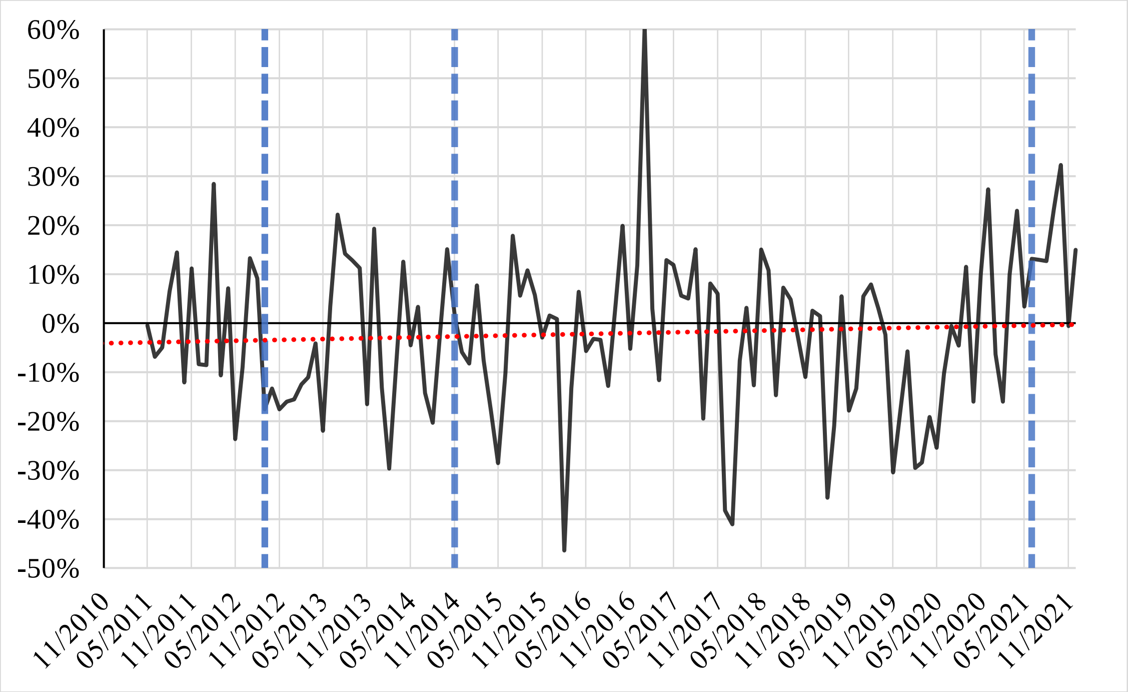

Figure F8. Hungary month ahead ex-post risk premium

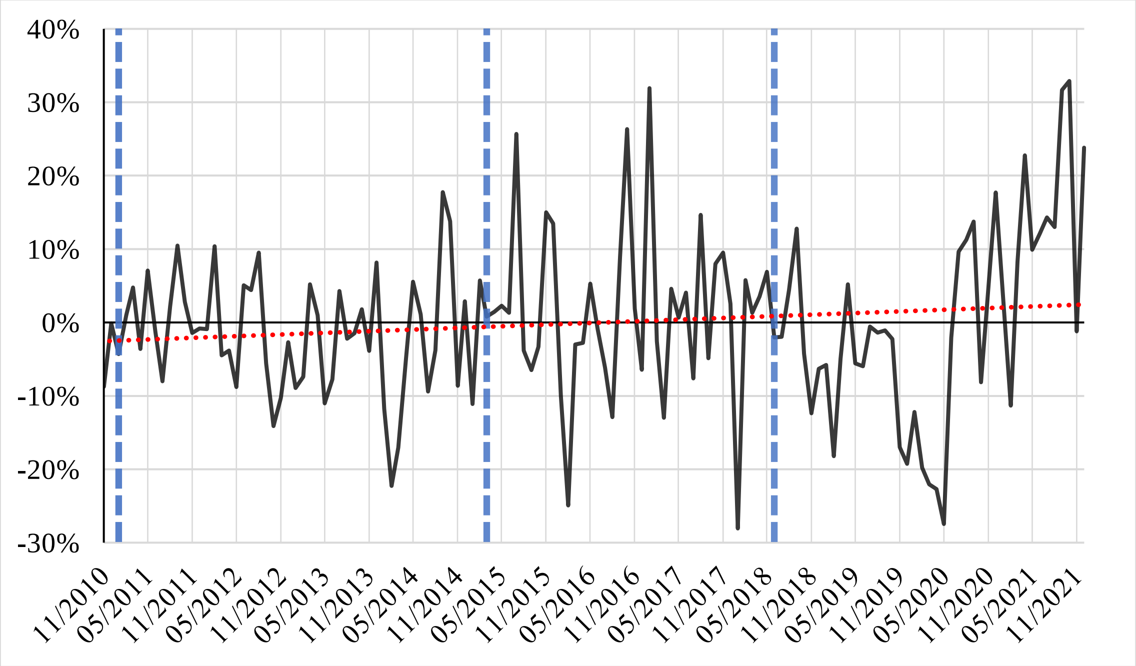

Figure F9. Italy month ahead ex-post risk premium

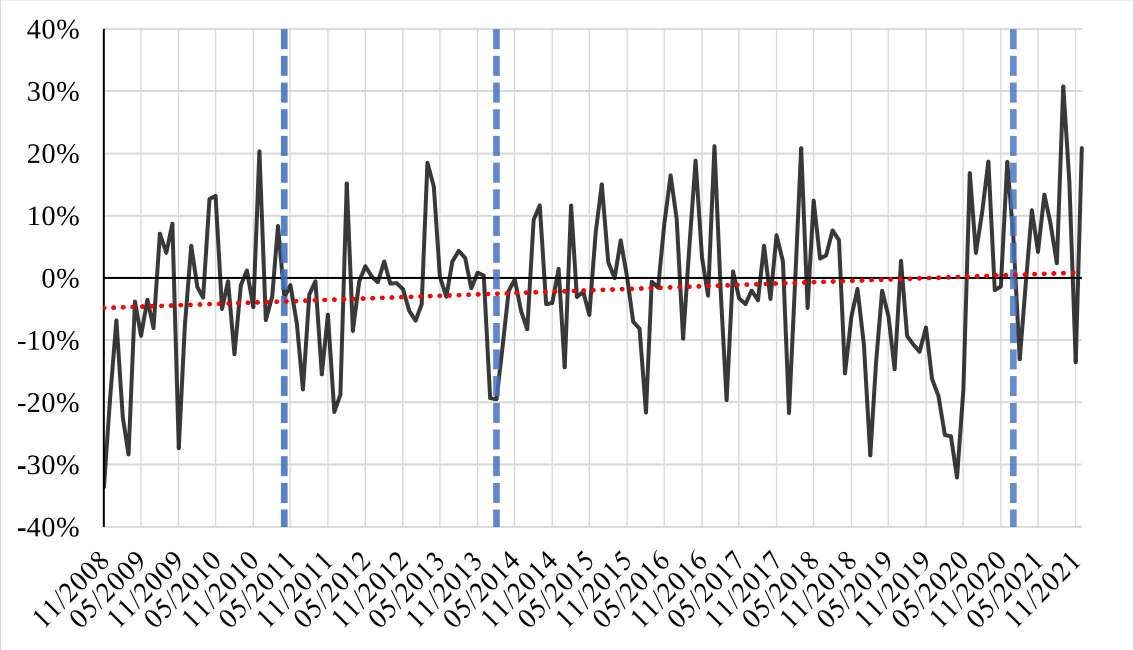

Figure F10. Netherlands month ahead ex-post risk premium

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