# Efficiency in the Central and Western European Wholesale Energy Future Market

Andre Marcatto

488782

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Erasmus School of Economics

ERASMUS UNIVERSITEIT ROTTERDAM

# Contents

## Abstract

Energy is essential for economic development. Society needs to understand the behaviour of electricity to maximise its potential deeply. Previous research unveils its unique characteristics and fundamental problems. I examine the main traits of energy, focusing on the wholesale electric market in the west and central Europe. I also assess if new trends in the sector already started to play a role, possibly changing the fundamental constraints. Energy primary constraint is that it cannot be stored easily, and supply must meet demand at all times. Furthermore, energy prices are assumed to be efficient, and it is impossible to generate reliable forecasts. Additionally, there is a significant seasonality in energy consumption and production, with peaks at different times during the day. According to previous research, the month in which the underlying is being traded also influences the current price. This paper found similar results, with a significant seasonality for all the regions under investigation (Italy, France, Germany and Spain). Moreover, as this study will further explain, previous energy prices play a role in current prices, especially for the yearly contracts. It results in lower risk for the contracts with a significant lag and vice-versa. This risk is estimated by implementing a signal base strategy considering the estimated forecast values. It is necessary to assess the energy market for its socio-economic relevance periodically and due to new trends gaining momentum, as the offering of dynamics rates for the final consumer. Lastly, future research can use other mathematical models as GARCH to assess the predictability power in the market, examine if other regions present a similar characteristic and if there is a significant correlation throw out time.


## Introduction

The world needs the energy to develop (Zohuri, 2020). Energy is also one of the critical factors for socio-economic development (Bergasse, 2013). Au contraire, electricity production and consumption are directly related to a series of serious environmental problems (EEA, 2017). Therefore, it is of great social, political, and economic interest to understand the electric behaviours, assisting society in preventing negative externalities while enhancing the positive ones. One manner of tackling some of the negative externalities is the implementation of renewable energy. With the proliferation of renewable power plants, a portion of the environmental hazards diminishes. However, this new scenario results in a behaviour change due to the clean energy supply, which may also present drawbacks.

Furthermore, renewable energy presents a strong seasonality, for weather conditions have a vital role in wind and solar energy production (Ansarin et al., 2016). This characteristic may increase the stress on the supply constraint under certain circumstances. In recent years, the share of energy production made by renewable sources has increased, and the prediction is that such changes will affect other market segments. Thus, it is mandatory to continue researching market developments. The electric marketplace can be perceived as a proxy for economic development. The energy price affects consumers in numerous ways, from their monthly bills to the unemployment rate (Karaki, 2018). Thus, efficiently regulating it is critical. At a pivotal level, the marketplace can be divided into wholesale and retail areas. Energy producers (supply) and energy providers (demand) represent the wholesale market participant. In contrast, energy distributors/providers and the final consumer divide the retail market.

In this research, I will focus on the European wholesale energy market for some reasons. Firstly, electricity is a relatively new type of market commodity, for until recently, it was heavily monopolised and presents unique characteristics. Moreover, future markets and derivatives are becoming commonplace in this area. Also, wholesale is potentially less regulated than retail, prone to price manipulation by the involved parties. Besides, market malfunctions in the wholesale band can have a higher impact on the country's socio-economic development. Lastly, changes in production or consumption are more likely to affect the wholesale market than its counterpart. Therefore, the research proposes the central research question:

*What are the wholesale future energy market characteristics in Italy, France, Germany, and Spain?*

It is pertinent to deeply understand the underlying settings of the market to investigate its characteristics. Initially, one can consider energy as a commodity, for it carries some of its aspects. For example, it does not change its properties if produced in different ways or locations; it can also be used in different quantities and traded in global markets (CME Group, 2021). However, as mentioned before, energy presents some fundamental differences. The main dissimilarity from other commodities is that, by nature, energy is complex to store and needs to be available on-demand (CME Group, 2021). This phenomenon potentially allows future energy prices to present a storage cost tending to infinity. However, that is not possible when pricing future commodity values because it leans to the infinite. Due to this fundamental difference, energy is the only commodity that does not directly consider its storage costs. The background literature will present a more detailed explanation of this phenomenon.

Commodity indexes have never directly considered energy throughout history but used oil and gas prices as proxies (Baffes, 2009). However, with the growth of the electric market and its importance, it is expected to see a new generation of commodity indexes with higher exposure to energy prices. It can have several consequences, such as the financialization of electricity. The market has emphasized such a trend since the beginning of 2000, with the surge of financial corporations searching for new ways to diversify their portfolio risk. The financialization of the electrical marketplace can increase the risk for energy providers, for the correlation with the market and price volatility is likely to increase (Tang & Xiong, 2012). In opposition, the financialization of the market should also come with an increase in liquidity for long-term contracts, which is currently a hurdle that companies need to assess when developing hedging strategies carefully.

A delicate situation emerged in the Californian market during the beginning of the current millennium (Borenstein, 2002). During this case, energy prices suddenly spiked, forcing companies to declare bankruptcy, decreasing economic development. The futures markets also present different unique characteristics that are relevant for this research. For instance, contracts with a short maturity are more liquid and volatile; they are highly regulated contracts with specific duration and usually present a transparent market (Neuberger, 1999). In the electric market, the standard unit used in the contracts is Megawatt-hour (MWh).

So, plenty of studies attempt to unveil the relevant factors affecting price changes by searching for trends, relevant variables, and similar investigations. These studies also check how the demand and supply change over time and space by reassessing variables and concepts from other researchers. This paper uses the same foundations when formulating the following three hypotheses:

(1) The lags of the future contracts present a significant coefficient when minimising the Bayesian Information Criteria (BIC).
(2) Autoregressive (AR) models with one lag present significantly lower Mean Square Error (MSE) for its forecasts than a dynamic Autoregressive Distributed Lag (ARDL) type model.
(3) The wholesale energy future market presents a significant seasonality in their price differences.

Those hypotheses are socially relevant, for further research on the fundamental characteristics of the market is extremely important when implementing new legislation. Not correctly considering its unique traits can enable dreadful consequences for the parties involved, as seen in the California energy market. The background literature section covers some dynamics related to the hypotheses. They also try to assist future legislation by providing data on the risks encountered in future contracts. The risk analysis can assist the regulatory entities to investigate potential market power abuse by energy suppliers. Knowing the market's seasonality also assists the legislation office by guiding their analysis of potential reactions from new regulations.

While energy cannot be easily stored and supply needs to be instantly met with demand, generating forecasts is extremely important. Because energy demand is inherently difficult to model, this paper uses prices as a proxy. This paper investigates and compares the forecasting power of an AR(1) and an ARDL(P, Q). Additionally, I comment on the financial consequences of the predicting power. As illustrated in the background literature, the scientific community asks for further research on how mathematical models perform different sections of the electrical market (Benini et al., 2002). During the following section, I will analyse Haas (2010) paper, which asks for more research regarding the potential seasonality present in energy prices focusing on different regions.

This research finds that some contracts present significant a significant coefficient on their lags. Signalling that not all the information from the previous day was incorporated in the current price. Thus, allowing a clearer expectation of future prices. However, that is not the case for most of the contracts. Also, as will be stressed in the results, the implementation of a signal base strategy present a considerable increase in risk for most of the contracts. However, if the lags do present a significant coefficient, the risk in the strategy decreases. Lastly, the contracts present a strong seasonality during winter and other months.

This paper maintains the following structure: in the background literature, I comment on relevant papers, providing a general overview of current research on the electric market and their current trends while further supporting the hypotheses' relevance. In addition, the manners of hypothesis testing are explained in the methodology section. Next, the data section will report on the dataset characteristics. Then, results from all the relevant tests and analysis are displayed and commented on separately. After that, the analysis will focus on answering the hypotheses and relevant topics raised in the background literature. Lastly, a conclusion drawns.

## Background Literature

This paper investigates fundamental characteristics of the future electrical market in wholesale. Therefore, I assessed core parts of the market by the hypotheses. There is indeed a seasonality for all the regions, and it appears to be increasing over time. However, it is impossible to affirm that the escalation of renewable energy in the grid is the leading cause. Therefore, more research on the topic is necessary. Another keystone to further develop our understanding of the market behaviour is reviewing the correlation of the price difference and its lags. Benini (2002) defines several factors that play a role in the Spanish energy market. Them being sources of energy production, management rules in the region and network congestions, among others. In his findings, he concluded that all those variables are relevant when explaining market volatility. It also affirms that being able to generate reliable forecasts for energy prices is essential for generating companies.

Furthermore, energy producers benefit from reliable forecasts, for it assists when developing hedging strategies. This paper adds to Benini's (2002), for it further investigates the Spanish market, focusing on the futures market instead of the Day-ahead market. It also assesses the prediction power of AR(P) type models in 4 different regions.

Another paper investigates the European power grid inputs and outputs (Ansarin et al., 2016). One of its findings is that, on average, market operators underestimate the power supply forecasts. Moreover, it also inspects the effect of renewable energy on the power supply. In these findings, I encountered different types of seasonality for the demand and supply of energy. This research can observe an inner day trend for both supply and demand. It is noticeable that the peak of the supply does not happen during the demand peak. Their paper also mentions that brokers could be more profitable to underestimate future energy demand, for there is room for profits in the balancing market. Given that brokers might be purposefully miscalculating future demands to generate arbitrage profits, I inferred that short-term and spot are inefficient. This paper expands on this hypothesis and tests the possibility of generating profits consistently in future markets and investigating its risks, keeping in mind that energy cannot be stored easily.

The paper made by Borenstein (2002) sheds light on the consequences of a deregulated wholesale energy market analysing a real-life event. During the investigated scenario, the average price per MWh was 200% higher than any previous month since the respective market opened in 1998. This unprecedented and unexpected price increase happened during June 2000 in the Californian wholesale electric marketplace. This spike in price forced several energy retailers to declare bankruptcy in the following years. One of the leading causes of such incidents is California's highly regulated retail and unregulated wholesale markets. This phenomenon also characterises France, Italy, Germany and Spain, to a certain degree. It is because these countries have a more developed market. However, the wholesale electric market is still considerably less regulated than retail, considering the four focus countries. If the factors present a relevant coefficient, it is possible to predict future prices, on average, and there is room for efficiency improvement. The market should become efficient by the different parties making a profit from this relationship.

Another point that investigates potential change in the market behaviour is the MSE comparison between different times, for it allows to examine potential repercussions of legislation and business practices. This paper focuses on future contracts, but other types of financial contracts affect the market too. Therefore, further research on other financial contracts as options is necessary to understand the fundamentals better, ergo assisting the legislative branch in preventing future market failures and efficiently stimulating positive externalities. Not modelling the price volatility is also a shortfall of this research, for it is plausible that it would increase the predicting power of the models. Additionally, due to the ongoing climate crises, the seasonality from the markets must be re-inspected to assess potential changes in the market characteristics. To sum up, it is possible to affirm that the fundamental hurdles from the market remain in force. Notwithstanding, specific market alterations are also in play, possibly triggering unforeseen changes.

Moreover, the author stated that policymakers were not emphasising a fundamental problem with the electric market when creating new policies, which showed to be a critical mistake. In other words, the regulation in place was not able to prevent market failures. Knowing that this dilemma is intrinsic to the wholesale energy market, I can see the same concept in different regions and times.

I can divide the fundamental problem into two subproblems that coexist, being supply problems and demand hurdles. The inherent supply problem is that energy producers are intermittently generating and distributing the underlying to the grid. It also must meet demand at peak times, and storage costs are incredibly high, which makes it an extremely unappealing option financially. Due to technological enhancement and legislation, the cost of making batteries decreases (Sanderson, 2020). Given the demand, it presents mainly two inherited problems. The first demand impediment is that energy prices and consumption are challenging to predict. Other papers analyse this phenomenon, including the one from Borenstein (2002), suggesting more regulation to reduce market inefficiencies. Their suggestions also consider the second innate demand problem, which consists of the highly inelastic demand from the energy retailer.

The paper supports further regulation suggesting creating a price cap and floor in the wholesale energy market. It understands as a solution in preventing potential exploitation of the inelasticity from the market demand. The case of the Californian wholesale market raised this concern when the government considered starting an investigation on market manipulation (Borenstein, 2002). This suggestion is sound when considering that big energy providers who acted in other markets with similar demand inelasticity, such as the healthcare sector, have been accused of collusion. One example being the cartel that GE, Siemens, and Philips created in the Brazilian healthcare sector, in conjunction with other parties. This investigation generated multibillion-dollar penalties for the parties involved (Brooks, 2019).

I may explain the high inelasticity because, independently of the price offered in the wholesale marketplace, contracts bind energy providers to provide energy to the final consumer with a predetermined fixed rate. This practice from retailers is changing, with some started offering dynamic rates for the final consumer (EURELECTRIC, 2017). Additionally, in the report from early 2017, the Union for the Electricity Industry in Europe used dynamic rates by energy providers as one of their main topics. The other points of emphasis were their carbon-neutral goals and their legislative suggestions for tackling climate change. If energy providers start escalating the implementation of dynamic rates with success, it potentially eases the burden of predicting the final consumer behaviour. I may expect rational consumers to minimise costs by decreasing their energy expenditure during peak hours and maximising their low consumption rates. This behavioural change can potentially withhold part of the fundamental supply problems as I ll. The previous statement is true because such changes in the final consumer behaviour will, in theory, reduce the frequency in which the demand pressures the energy supply and thus its constraints. However, this pressure results in price increases and the need to generate energy from less efficient and sustainable sources (EURELECTRIC, 2017).

The dynamic rates allow the retailer to share their price risk with the final consumer, permitting the retailer to offer lower rates. Contrarily, it allows consumers to incur highly high costs when acting irrationally potentially. It also potentially forces an unwanted change in behaviour on the part of the consumer. It is relevant to mention that the average person prefers the status quo (BehavioralEconomics.com, 2020). Therefore, they might face a utility decrease when imposed with a new risk, even if it comes with some benefits. This behaviour bias is known as loss aversion (BehavioralEconomics.com, 2020). Further studies in this subject are necessary to assist governmental institutions further to deepen their current knowledge concerning such new methods. Once the specific consequences of the dynamic pricing are clear, the legislative institutions should create policies that prevent misinformation, avoid severe market failures, increase market efficiency and social awareness regarding this new trend.

The factual analysis of the fundamental problem from the wholesale market described by Borenstein in 2002 and its implications are of high importance for the relevance of this research. One important implication is that the development of energy provides dynamic rates. Dynamic rates have been offered in Spain since 2018 and are showing an increase in consumer accession (Florence School of Regulation, 2020). Regarding France, Germany and Italy, I can observe a similar pattern and implementation date. This paper research whether the implementation of the dynamic contracts has already started to impose some effects on the fundamental hurdles from the wholesale electric market. One way of doing so is by checking if the predictability power of mathematical models increased after 2018 or later, for it may require some time until there is a fundamental change in the demand. The methodology section addresses a more detailed explanation of how to evaluate the predictability power of models. Another way is to investigate the change in the cumulative returns. There are several ways to perform it; for a more thorough evaluation, several analyses should be performed considering differences after 2018 or later, as generally done. Those analyses inspect the change in the average returns, VaR, convenience level, Sharpe ratio, Fama French, shortfall, and analogous variables.

The same Californian case study brought other relevant points regarding market risks and the main mitigation methods. The first one: short-term electricity prices are highly volatile. The causes are a) the high inelasticity presented in both supply and demand and b) the random walk behaviour that the demand for energy displays. Borenstein (2002) raised a possible solution: more prominent long-term contracts could have mitigated all crises. The recognition of the importance of long-term contracts comes from many different arguments. The main one is that long-term contracts are the main financial instrument for hedging strategies against price fluctuation (Borenstein, 2002). When comparing long-term contracts, futures contracts provide several benefits compared to other financial contracts, such as low transaction costs, small counterparty risk, and the possibility of high leverage (Neuberger, 1999). It is worth mentioning that hedging strategies using only long-term contracts usually are less efficient than strategies that mix both long and short-term contracts. The main downside of long-term contracts is the potential lack of liquidity in the secondary market. However, using short-term contracts also has its risks. The most prominent peril is a higher value at risk and a higher correlation with the spot market. According to our research, as I will comment on in the result section, an increase of volatility and ensuing risks are also found in futures contracts.

As mentioned before, energy has two unique characteristics. It must meet demand and is extremely hard to store. Haar’s (2010) research focuses on Germany’s future and spot market from 2002 until the end of 2010. When modelling the future curve, it is usually considered two specifications: seasonality and market volatility. In the findings, future prices, on average, present a higher price if their delivery date is during winter. I will add to Haar’s (2010) paper, for I will reevaluate the seasonality in the German market, considering a different period and point of reference. I expected it because the energy demand is higher during winter. Once the paper touches on the pricing strategy analysis for future contracts, considering the buy and hold hedging strategy, equation (1) derives from equation (2). This formula is valid for the way that energy behaves. Because this is a speculative strategy, the commodity’s convenience cost (y) is similarly not considered in the price calculation. Additionally, equation (1) does not consider storage cost (u). The paper (Haar, 2010) invites a more in-depth investigation of the potential seasonality present in energy prices, focusing on different regions.

(1) $F_t = S_t * e^{r(T-t)}$
(2) $F_t = S_t * e^{(r+u-y)(T-t)}$

## Methodology

Before starting with the methodology, I define mathematical models and concepts to investigate the hypotheses.

AR(P) model can be defined as equation 3:

$$(3)\quad Y_t = \beta_0 + \sum_{p=1}^{p} \beta_p Y_{t-p} + \epsilon_t$$

ARDL (P,Q) model can be defined as equation 4:

$$(4)\quad Y_t = \beta_0 + \sum_{p=1}^{p} \beta_p Y_{t-p} + \sum_{q=1}^{q} \phi_q X_{t-q} + \epsilon_t$$

Stationarity is present when it is impossible to reject the hypothesis that the coefficient from the lags is not different from one, which implies that past shocks are permanent. Also, the mean and variance of AR-type models do not exist in the presence of stationarity in the data (Iordanova, 2021). Additionally, a random walk exists in a time series when its lags are equal to zero, implying that future prices only depend on the error term, which is considered exogenous (Tuychiev, 2021).

I need the implementation of different statistical tests, and mathematical models are required to investigate this hypothesis. Hence, I will treat the data as follows: (i) first, I will apply the Dickey-Fuller test for the contract's prices and price differences; then, I will perform this treatment to verify non-stationarity; and (ii) second, I will implement a Value at Risk (VaR) when longing all the contracts.

In this analysis, I assume that the difference returns for the contracts follow a normal distribution. Furthermore, I assess the worst-case scenario with a 5% and 1% chance of a price drop of that value or more. This calculation considers the price difference of the contracts. I measure the mean and standard deviation for each contract type in order to permit such.

I pursue the minimization of the BIC with an ARDL type model when appraising the significance of the lags from the contracts price differences. I examine all the lags' combinations up to 4 lags and the one with the smaller BIC for the minimization. Additionally, the Newey-West standard error will be implemented to the regression, for it corrects for any autocorrelation with other lags higher than the ones used in the regression and heteroscedasticity of the variance (real- statistics, 2021). Finally, when verifying the significance from the lags, their respective p-value will be the deciding factor

To examine the existence of seasonality, I generated a categorical variable that represents the seasons of the year and the months in which the contracts are traded, using Python. I chose those categories because previous research showed a significant influence of the weather on energy consumption and production (Ansarin et al., 2016). Furthermore, such influence appears to have increased with the popularisation of renewable energy productions, such as solar energy. Consequently, I regressed the contracts' price difference against the seasonal variables aiming to evaluate the significance of seasonality.

I performed the Diebold-Mariano test to verify if an AR(1) model presents a significant difference in its forecast power compared with other types of time-series models. I adopted a pseudo out of sample forecast in this analysis, with a rolling window with a length of 100 traded days. Also, the coefficients are re-estimated for every new forecast made. In this comparison, I employed an ARDL model that minimizes the BIC in every new forecast and an AR(1) model for all the contracts. I calculated the MSE of all the contracts and models to quantify the forecast power. Lastly, I executed the Diebold-Mariano test for if the ARDL(P) MSEs are equal to the AR(1) model. A forecast is better if and only if it is statistically different and smaller than the other model.

I tackled a signal-based strategy to illustrate what the MSEs would represent from an economic perspective. This strategy entails longing the contract if the forecast presents a positive value and shorting if it is negative. The strategy also considers that the speculator is buying a new contract and selling the old one before the market closes, given the forecast for the next trading day. I calculated the compound growth for each contract and the average returns for each country, and all the contracts. Furthermore, the VaR for all the models and regions are analysed to inspect the potential changes in risk provided by the models.

# Data

I retrieved the data for this research, gathered by the European Energy Exchange (EEX), through personal contacts. The data consist of future contracts from Germany, Italy, France, and Spain from 2015 until 2020. Those countries were chosen for their similarities economically and culturally and their differences in energy production. Additionally, weekly, monthly, quarterly, and yearly are the durations of the futures contracts. Moreover, for each contract duration, up to 4 different timeframes are investigated. Meaning, when inspecting the characteristics of the contracts, the same is divided into 'current t', '1 t ahead', '2 t ahead' and '3 t ahead', where t stands for the contract duration. In total, there are 15 different contracts per country and 60 contracts. Additionally, the observations only consider trades made during weekdays. However, as stated in the introduction, futures contracts can be purchased and executed at any time inside the contract duration.

The data inspected in this paper is private and cannot be shared freely with the public. Therefore, despite the economic analysis on the futures contracts, financial actions performed by insights given by this dataset are prohibited. Furthermore, the dataset used in this research can only be shared with the explicit consent of EEX.

It is also important to mention that future contracts can only be purchased in bundles of 100 contracts, and each duration provides different quantities of MWH per contract. Additionally, to present the results in an organised manner, this section will be divided into 4 subsections. The sections are defined by Italy, France, Germany and Spain.

## Italy

Starting with Italy, I displayed its descriptive statistics under Table 1. I presented the Mean, Median, Standard Deviation, Variance, Skewness, Kurtosis, Observations (Obs) and their averages in the table. I maintained this same table structure for the other three countries. It leaps out of the page that only the three quarters ahead present an adverse arithmetic average, and the one week and one month ahead have a negative median. The average Kurtosis for all the Italian contracts is 33.43, which infer that the distribution presents fatter tails, prevalent from the price difference of future commodity contracts. The Italian dataset comprises 1101 observations, those observations being all the contract trading days using the EEX. Lastly, Italy is the only country that presents a negative skewness in its distribution.

**Table 1**

*Descriptive Statistics Italy*

| Variables | Mean | Median | Standard Deviation | Variance | Skewness | Kurtosis | Obs |
|---|---|---|---|---|---|---|---|
| Current week | 0.0001 | 0.0000 | 0.025 | 0.0006 | 0.48 | 22.87 | 1101 |
| **One week ahead** | 0.0002 | **-0.0002** | 0.021 | 0.0005 | 1.18 | 19.42 | 1101 |
| Two weeks ahead | 0.0004 | 0.0000 | 0.021 | 0.0005 | -0.33 | 22.25 | 1101 |
| Three weeks ahead | 0.0010 | 0.0000 | 0.037 | 0.0014 | 0.67 | 12.45 | 1101 |
| Current month | 0.0001 | 0.0000 | 0.025 | 0.0006 | 0.48 | 22.87 | 1101 |
| **One month ahead** | 0.0002 | **-0.0002** | 0.021 | 0.0005 | 1.18 | 19.42 | 1101 |
| Two months ahead | 0.0004 | 0.0000 | 0.021 | 0.0005 | -0.33 | 22.25 | 1101 |
| Three months ahead | 0.0003 | 0.0000 | 0.021 | 0.0004 | 0.04 | 23.22 | 1101 |
| Current quarter | 0.0003 | 0.0000 | 0.019 | 0.0003 | -1.54 | 58.36 | 1101 |
| One quarter ahead | 0.0002 | 0.0002 | 0.016 | 0.0003 | -6.24 | 108.37 | 1101 |
| Two quarters ahead | 0.0002 | 0.0002 | 0.015 | 0.0002 | -2.98 | 65.56 | 1101 |
| Three quarters ahead | 0.0000 | 0.0000 | 0.018 | 0.0003 | -3.65 | 67.31 | 1101 |
| Current year | 0.0000 | 0.0002 | 0.009 | 0.0001 | -1.60 | 17.50 | 1101 |
| One year ahead | 0.0001 | 0.0000 | 0.009 | 0.0001 | -0.22 | 7.32 | 1101 |
| Two years ahead | 0.0002 | 0.0000 | 0.009 | 0.0001 | -0.86 | 12.29 | 1101 |
| **Average** | **0.0002** | **0.0000** | 0.019 | 0.0004 | -0.92 | 33.43 | 1101 |

*Note.* Table 1 contains the mean, median, standard deviation, variance, skewness, kurtosis and number of observations in the dataset for each contract displayed in its cells.

## France

France presents the highest average returns. All future contracts present a positive average price difference, and its kurtosis is 11 points higher than Italy. France also has the second-highest kurtosis between the groups. They present a negative median for the current quarter, and the majority have a median of 0, as is displayed in Table 2. All the contracts traded in France comprises 1523 days, from 2015 until the end of 2020. France presents the highest standard deviation, it being 0.0356.

**Table 2**

*Descriptive Statistics France*

| Variables | Mean | Median | Standard Deviation | Variance | Skewness | Kurtosis | Obs |
|---|---|---|---|---|---|---|---|
| Current week | 0.0014 | 0.0000 | 0.0511 | 0.0026 | 3.81 | 55.10 | 1523 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| One week ahead | 0.0012 | 0.0004 | 0.0449 | 0.0020 | 1.61 | 22.37 | 1523 |
| Two weeks ahead | 0.0011 | 0.0000 | 0.0391 | 0.0015 | 0.71 | 21.78 | 1523 |
| Three weeks ahead | 0.0029 | 0.0000 | 0.0736 | 0.0054 | 1.08 | 10.50 | 1523 |
| Current month | 0.0014 | 0.0000 | 0.0511 | 0.0026 | 3.81 | 55.10 | 1523 |
| One month ahead | 0.0012 | 0.0004 | 0.0449 | 0.0020 | 1.61 | 22.37 | 1523 |
| Two months ahead | 0.0011 | 0.0000 | 0.0391 | 0.0015 | 0.71 | 21.78 | 1523 |
| Three months ahead | 0.0010 | 0.0003 | 0.0392 | 0.0015 | 1.26 | 32.96 | 1523 |
| **Current quarter** | 0.0010 | **-0.0006** | 0.0415 | 0.0017 | 5.96 | 107.26 | 1523 |
| One quarter ahead | 0.0010 | 0.0000 | 0.0387 | 0.0015 | 2.70 | 110.38 | 1523 |
| Two quarters ahead | 0.0008 | 0.0327 | 0.0004 | 0.0011 | -0.88 | 92.04 | 1523 |
| Three quarters ahead | 0.0008 | 0.0000 | 0.0343 | 0.0012 | 2.36 | 91.79 | 1523 |
| Current year | 0.0003 | 0.0000 | 0.0141 | 0.0002 | -0.30 | 10.98 | 1523 |
| One year ahead | 0.0003 | 0.0000 | 0.0116 | 0.0001 | 0.08 | 8.44 | 1523 |
| Two years ahead | 0.0002 | 0.0000 | 0.0111 | 0.0001 | 0.21 | 8.01 | 1523 |
| **Average** | 0.0010 | **0.0022** | 0.0356 | 0.0017 | 1.65 | 44.72 | 1523 |

*Note.* Table 2 contains the mean, median, standard deviation, variance, skewness, kurtosis and number of observations in the dataset for each contract displayed in its cells.

## Germany

The main difference between German data and the other countries is that Germany has a negative median. Also, most of the futures contract median is negative or 0. Moreover, Germany has 1401 observations, an average skewness of 0.695425 and a kurtosis of 29.70513. I illustrated the descriptive statistics for each contract and its averages in Table 3.

**Table 3**

*Descriptive Statistics Germany*

| Variables | Mean | Median | Standard Deviation | Variance | Skewness | Kurtosis | Obs |
|---|---|---|---|---|---|---|---|
| **Current week** | 0.00081 | **-0.0003** | 0.0377 | 0.00142 | 3.85 | 48.22 | 1401 |
| One week ahead | 0.00047 | 0.0000 | 0.0294 | 0.00086 | 0.10 | 22.97 | 1401 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Two weeks ahead** | 0.0004 | **-0.0002** | 0.0264 | 0.0007 | 0.68 | 24.52 | 1401 |
| **Three weeks ahead** | **0.00267** | 0.0000 | 0.0691 | 0.00477 | 2.04 | 31.21 | 1401 |
| Current month | 0.00081 | -0.0003 | 0.0377 | 0.00142 | 3.85 | 48.22 | 1401 |
| One month ahead | 0.00047 | 0.0000 | 0.0294 | 0.00086 | 0.10 | 22.97 | 1401 |
| Two months ahead | 0.0004 | -0.0002 | 0.0264 | 0.0007 | 0.68 | 24.52 | 1401 |
| Three months ahead | 0.00044 | -0.0003 | 0.0249 | 0.00062 | 0.69 | 19.96 | 1401 |
| Current quarter | 0.00041 | -0.0004 | 0.0229 | 0.00052 | 3.49 | 53.17 | 1401 |
| One quarter ahead | 0.0003 | -0.0003 | 0.0205 | 0.00042 | 0.07 | 44.72 | 1401 |
| Two quarters ahead | 0.00027 | 0.0003 | 0.0195 | 0.00038 | -2.74 | 42.44 | 1401 |
| Three quarters ahead | 0.00036 | 0.0003 | 0.0204 | 0.00042 | -1.86 | 40.86 | 1401 |
| Current year | 0.00024 | 0.0003 | 0.0144 | 0.00021 | -0.03 | 6.22 | 1401 |
| One year ahead | 0.00029 | 0.0000 | 0.0131 | 0.00017 | -0.15 | 6.27 | 1401 |
| Two years ahead | 0.00032 | 0.0000 | 0.0122 | 0.00015 | -0.36 | 9.30 | 1401 |
| **Average** | 0.00058 | **-0.0001** | 0.0269 | 0.00091 | 0.70 | 29.71 | 1401 |

*Note.* Table 3 contains the mean, median, standard deviation, variance, skewness, kurtosis and number of observations in the dataset for each contract displayed in its cells.

## Spain

The Spanish dataset has positive averages for all the categories inspected in the descriptive analysis. I demonstrated a detailed overview of all the categories in Table 4. It stands out that Spain has a higher kurtosis, skewness, and median than the other countries.

**Table 4**

*Descriptive Statistics Spain*

| Variables | Mean | Median | Standard Deviation | Variance | Skewness | Kurtosis | Obs |
|---|---|---|---|---|---|---|---|

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Current week | 0.0010 | 0.0004 | 0.0011 | 0.0011 | 7.02 | 130.01 | 1310 |
| One week ahead | 0.0007 | 0.0000 | 0.0273 | 0.0007 | 6.99 | 110.15 | 1310 |
| Two weeks ahead | 0.0003 | 0.0000 | 0.0225 | 0.0005 | 1.86 | 42.34 | 1310 |
| Three weeks ahead | 0.0014 | 0.0000 | 0.0423 | 0.0018 | 0.52 | 17.66 | 1310 |
| Current month | 0.0010 | 0.0004 | 0.0326 | 0.0011 | 7.02 | 130.01 | 1310 |
| One month ahead | 0.0007 | 0.0000 | 0.0273 | 0.0007 | 6.99 | 110.15 | 1310 |
| Two months ahead | 0.0003 | 0.0225 | 0.0005 | 0.0005 | 1.86 | 42.34 | 1310 |
| Three months ahead | 0.0002 | 0.0000 | 0.0235 | 0.0006 | -0.52 | 28.10 | 1310 |
| Current quarter | 0.0002 | 0.0160 | 0.0003 | 0.0003 | 0.86 | 59.59 | 1310 |
| One quarter ahead | 0.0000 | 0.0000 | 0.0155 | 0.0002 | 0.71 | 74.69 | 1310 |
| Two quarters ahead | 0.0000 | 0.0000 | 0.0149 | 0.0002 | 1.96 | 70.25 | 1310 |
| Three quarters ahead | 0.0000 | 0.0000 | 0.0158 | 0.0003 | -0.55 | 51.24 | 1310 |
| Current year | 0.0002 | 0.0000 | 0.0069 | 0.0000 | -3.81 | 47.81 | 1310 |
| One year ahead | 0.0000 | 0.0000 | 0.0064 | 0.0000 | -1.98 | 29.91 | 1310 |
| **Two years ahead** | **-0.0001** | 0.0000 | 0.0061 | 0.0000 | -0.73 | 11.72 | 1310 |
| Average | 0.0004 | 0.0026 | 0.0162 | 0.0005 | 1.88 | 63.73 | 1310 |

*Note.* Table 4 contains the mean, median, standard deviation, variance, skewness, kurtosis and number of observations in the dataset for each contract displayed in its cells.

## Results

I divided this section into eight subsections to present the results in an organised manner, each of them representing each test performed. I highlighted the results for Italy under each section, followed by France, Germany, and Spain, respectively. This section briefly lists and comments on the results, whereas the next section dives deeper into the dynamics and consequences of the results, aiming to test the hypotheses.

## Dickey-Fuller Test

Initially, the Dickey-Fuller test was performed for the contracts to investigate their stationarity. One can find the summarised information regarding the test for Italy in Appendix Table 1. I somewhat expected the results displayed, given that I are working with futures contracts, for there is plenty of literature showing that financial contracts present stationary (Maples & Brorsen, 2017). Interestingly, a few contracts are not stationary when considering only contract prices. Given that many of the contracts presented stationary, I calculated the price difference. After treating the data, I performed the Dickey-Fuller test once again. For the price differences, their respective p-values are rounded to 0.00, meaning there is not enough information to reject the null of non-stationary in the dataset. When considering the data for France, most of the futures contracts passed the Dickey-Fuller test. In other words, the futures contracts present a p-value smaller than 0.05, which is counterintuitive given how financial contracts usually behave. When analysing the price difference of the contract, all the contracts present a p-value of 0 — moving on to Germany's Dickey-fuller test. Thus, the futures contract prices, in their majority, are stationary.

In contrast, all the price differences present a p-value equal to 0. The same can be seen in Appendix Table 1. Spanish contracts present similar characteristics to Germany and Italy.

## VaR

Moving on, to assess the risk from longing the contracts, I performed a VaR valuation. The summary of the results is shown in Table 2 in the Appendix for all the countries. The table displays all the 5% and 1% VaR for each contract, the regional averages and the total average. Also, the point of reference for this table is 1, which means that a cell displaying .9000 has a 10.00% VaR.

For all the contracts in Italy, their expected VaR for the worst 5% and 1% decreases as the length and periods ahead increases, meaning that short-term longing contracts present a higher risk when considering their VaR. Additionally, when only considering long positions in the future contracts, Italy faces the lowest risk, followed by Spain, Germany and France.

When considering the VaR for the other countries' future contracts, I observed a similar pattern of risk as for the Italian contracts.

## PAC and AC

Also, I calculated the PAC and the AC for all the contracts using the contract price differences in STATA. Appendix Table 3 states the relevant lags for all the contracts. Knowing their PAC and AC is relevant when determining how many lags should be used when estimating ARIMA type models and calculating the Newey-West standard errors. It is essential to highlight that a few contracts with a quarterly duration do not present autocorrelation nor partial autocorrelation. It implies that the price difference from those contracts follows a random walk. They indicate that current prices have incorporated all the information from the past and its lags are of no use when explaining future prices.

Nevertheless, those contracts will be further analysed to test the hypotheses stated at the beginning of this paper. Moreover, it is noticeable that all the Germanic contracts present a PAC and AC. Additionally, many future contracts present the lag ten or twenty as highly relevant, potentially indicating that the half a month and one-month lags have relevant information regarding the current price.

## General AR model

Once I calculated their PAC and AC, the AR(p) type models were estimated to minimize the BIC with Newey-West standard errors. Under Table 4 in the Appendix, I displayed the coefficients, Newey-West standard errors and p-values for Italy, France, Germany and Spain, respectively. The Newey-West standard errors estimation uses the first relevant lags from the contracts displayed in Appendix Table 3. It is relevant to stress that when minimizing the BIC, all the contracts estimated an AR(1) model as optimal.

Only five contracts present significant lags for Italy. Those future contracts are the current week, one week ahead, current month, current quarter and one year ahead. That fact indicates that most of the contracts follow a random walk, for it is not possible to reject the null hypothesis of the lag difference being different from 0.

When observing results from France, eight contracts present significant coefficients once minimizing the information criteria. As shown in Appendix Table 4, all the significant coefficients, despite the three weeks ahead, are positive, indicating that the current day will follow the direction from the previous day.

Moving on to Germany's general regressions, it is noticeable that all the yearly contracts present a positive, relevant lag. Therefore, it is possible to infer the same behaviour for the Germanic yearly contracts as for the French. However, Germany also presents eight contracts with significant lags with a threshold of 95% significance. Those contracts are the current week, three weeks ahead, current month, three months ahead, current quarter, current year, one year ahead, and two years ahead.

Spain is the country with the least relevant coefficients. There are only four relevant coefficients: the three weeks ahead, current quarter, current year and one year ahead. This observation signals that the Spanish market might be the most efficient and, therefore, the hardest to take advantage of its structure, which I will elaborate on in the analysis section.

## Forecasts

Other points relevant to be assessed are the predictability power from the dynamic and the static model and discovering if there is a significant difference between them.

I created Tables 5, 6, 7 and 8 for the previously stated countries following the methodology described under the methodology. Those tables summarised the Diebold-Mariano Test by the p-values for more minor, different and more considerable differences between the MSEs. For hypothesis 2, the AR(1) models need to present a different and more negligible difference to have a more substantial forecasting power.

For Italy, only the three weeks ahead present a more critical forecasting power. Now French does marginally better, with two AR(1) forecasts being statistically more robust. Those contracts being the current week and current month. Additionally, Germany has two statistically more robust forecasts: the one year and two years ahead contracts. The current year contracts almost pass the criteria with a p-value of 0.0572 for a different MSE and 0.0286 for a more negligible difference. Lastly, Spain has four AR(1) models that are significantly stronger than the dynamic model. The contracts that present such characteristics are one week ahead, two weeks ahead, one month ahead and two months ahead.

**Table 5**

*Diebold-Mariano Test Italy*

| Test ARDL = AR | x<y | x≠y | x>y |
|---|---|---|---|
| Current week | 0.82 | 0.37 | 0.18 |
| 1 week ahead | 0.85 | 0.29 | 0.15 |
| 2 weeks ahead | 0.86 | 0.28 | 0.14 |
| **3 weeks ahead** | **1.00** | **0.00** | **0.00** |
| Current month | 0.82 | 0.37 | 0.18 |
| 1 month ahead | 0.85 | 0.29 | 0.15 |
| 2 months ahead | 0.86 | 0.28 | 0.14 |
| 3 months ahead | 0.89 | 0.21 | 0.11 |
| Current quarter | 0.92 | 0.16 | 0.08 |
| 1 quarter ahead | 0.93 | 0.15 | 0.07 |
| 2 quarters ahead | 0.68 | 0.64 | 0.32 |
| 3 quarters ahead | 0.87 | 0.26 | 0.13 |
| Current year | 0.38 | 0.76 | 0.62 |
| 1 year ahead | 0.87 | 0.25 | 0.13 |
| **2 years ahead** | **0.94** | **0.11** | **0.06** |

*Note.* Table 5 presents the p-values for the Diebold-Mariano Test considering the MSE of the pseudo out of sample forecasts. The p-values are for smaller, different and larger differences between the ARDL models against the AR(1) models

**Table 6**

*Diebold-Mariano Test France*

| Test ARDL = AR | x<y | x≠y | x>y |
|---|---|---|---|
| **Current week** | **0.99** | **0.01** | **0.01** |
| One week ahead | 0.70 | 0.60 | 0.30 |
| Two weeks ahead | 0.90 | 0.20 | 0.10 |
| Three weeks ahead | 0.89 | 0.22 | 0.11 |
| **Current month** | **0.99** | **0.01** | **0.01** |
| One month ahead | 0.70 | 0.60 | 0.30 |
| Two months ahead | 0.90 | 0.20 | 0.10 |
| Three months ahead | 0.84 | 0.32 | 0.16 |
| Current quarter | 0.24 | 0.49 | 0.76 |
| One quarter ahead | 0.80 | 0.41 | 0.20 |
| Two quarters ahead | 0.83 | 0.33 | 0.17 |
| Three quarters ahead | 0.15 | 0.30 | 0.85 |

| | | | |
|---|---|---|---|
| Current year | 0.73 | 0.55 | 0.27 |
| **One year ahead** | **0.94** | **0.12** | **0.06** |
| Two years ahead | 0.77 | 0.45 | 0.23 |

*Note.* Table 6 presents the p-values for the Diebold-Mariano Test considering the MSE of the pseudo out of sample forecasts. The p-values are for smaller, different and larger differences between the ARDL models against the AR(1) models

**Table 7**

*Diebold-Mariano Test Germany*

| Test ARDL = AR | x<y | x≠y | x>y |
|---|---|---|---|
| Current week | 0.72 | 0.55 | 0.28 |
| One week ahead | 0.76 | 0.48 | 0.24 |
| **Two weeks ahead** | **0.92** | **0.15** | **0.08** |
| Three weeks ahead | 0.15 | 0.30 | 0.85 |
| Current month | 0.72 | 0.55 | 0.28 |
| One month ahead | 0.76 | 0.48 | 0.24 |
| **Two months ahead** | **0.92** | **0.15** | **0.08** |
| Three months ahead | 0.84 | 0.31 | 0.16 |
| Current quarter | 0.77 | 0.45 | 0.23 |
| One quarter ahead | 0.85 | 0.31 | 0.15 |
| Two quarters ahead | 0.89 | 0.22 | 0.11 |
| **Three quarters ahead** | **0.92** | **0.16** | **0.08** |
| **Current year** | **0.97** | **0.06** | **0.03** |
| **One year ahead** | **0.98** | **0.04** | **0.02** |
| **Two years ahead** | **1.00** | **0.00** | **0.00** |

*Notes*. Table 7 presents the p-values for the Diebold-Mariano Test considering the MSE of the pseudo out of sample forecasts. The p-values are for smaller, different and larger differences between the ARDL models against the AR(1) models

**Table 8**

*Diebold-Mariano Test Spain*

| Test ARDL = AR | x<y | x≠y | x>y |
|---|---|---|---|
| Current week | 0.56 | 0.88 | 0.44 |
| **One week ahead** | **0.99** | **0.02** | **0.01** |
| **Two weeks ahead** | **0.98** | **0.05** | **0.02** |
| Three weeks ahead | 0.93 | 0.14 | 0.07 |
| Current month | 0.56 | 0.88 | 0.44 |
| **One month ahead** | **0.99** | **0.02** | **0.01** |
| **Two months ahead** | **0.98** | **0.05** | **0.02** |
| Three months ahead | 0.94 | 0.12 | 0.06 |
| **Current quarter** | **0.96** | **0.08** | **0.04** |
| One quarter ahead | 0.77 | 0.47 | 0.23 |

| | | | |
|---|---|---|---|
| Two quarters ahead | 0.82 | 0.35 | 0.18 |
| **Three quarters ahead** | **0.97** | **0.06** | **0.03** |
| Current year | 0.77 | 0.46 | 0.23 |
| One year ahead | 0.87 | 0.26 | 0.13 |
| Two years ahead | 0.79 | 0.42 | 0.21 |

*Note.* Table 8 presents the p-values for the Diebold-Mariano Test considering the MSE of the pseudo out of sample forecasts. The p-values are for smaller, different and larger differences between the ARDL models against the AR(1) models.

## Profitability of investment strategies

I based the strategies on the signal base strategy explained under the methodology section.

I presented a table with the compound growth starting from 0 in Table 9 for all the strategies. I subdivided the table between the static (AR) and dynamic (ARDL) strategies. I also displayed the average for each region in the tables under the row "Averages". Also, I demonstrated the overall sum for all the ARDL and AR strategies under "All countries". There is a row with the sum of all the strategies.

It becomes evident that both strategies present a positive return after five years. Also, the AR(1) models are more profitable, on average. When observing the countries individually, Spain sustained most of the losses as well as the largest. On the other hand, France presented more than 200% profit when trading all contracts. Furthermore, Germany and Italy have lower positive returns, of around 30% and 20% respectively. Additionally, the yearly contracts had the most stable returns in comparison to the other contracts. Finally, it also leapt the page that contracts with a statistically insignificant coefficient presented positive returns.

**Table 9**

*Compound Returns*

| variables | Italy | | France | | Germany | | Spain | | All countries | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ARDL | AR | ARDL | AR | ARDL | AR | ARDL | AR | ARDL | AR |
| Current week | 0.367 | 0.367 | 2.593 | 2.929 | 0.563 | 0.563 | -0.841 | -1.109 | 2.682 | 2.750 |
| **One week ahead** | **1.617** | **1.539** | **5.054** | **4.124** | **0.409** | **0.409** | **-1.202** | **-0.358** | **5.878** | **5.714** |
| **Two weeks ahead** | **-0.359** | **-0.356** | **2.460** | **3.021** | **0.315** | **0.395** | **-0.823** | **-0.781** | **1.593** | **2.280** |
| **Three weeks ahead** | **0.763** | **0.950** | **3.427** | **4.609** | **0.877** | **0.841** | **-1.013** | **-0.512** | **4.053** | **5.888** |
| Current month | 0.367 | 0.367 | 2.593 | 2.929 | 0.563 | 0.563 | -0.841 | -1.109 | 2.682 | 2.750 |
| **One month ahead** | **1.617** | **1.539** | **5.054** | **4.124** | **0.409** | **0.409** | **-0.449** | **-0.358** | **6.631** | **5.714** |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Two months ahead | -0.359 | -0.356 | 2.460 | 3.021 | 0.315 | 0.395 | -0.823 | -0.781 | 1.593 | 2.280 |
| Three months ahead | -0.526 | -0.526 | 0.583 | 0.562 | -0.234 | -0.234 | -1.301 | -1.193 | -1.478 | -1.392 |
| **Current quarter** | **0.454** | **0.491** | **3.517** | **3.557** | **0.777** | **0.665** | **0.800** | **0.848** | **5.548** | **5.562** |
| One quarter ahead | -0.408 | -0.438 | 0.806 | 1.469 | 0.656 | 0.650 | 0.422 | 0.441 | 1.476 | 2.121 |
| Two quarters ahead | -0.151 | -0.151 | 0.146 | 0.177 | -0.843 | -0.874 | -0.959 | -0.858 | -1.807 | -1.705 |
| Three quarters ahead | -1.007 | -0.728 | 0.903 | 0.897 | -0.071 | -0.043 | -1.202 | -1.122 | -1.377 | -0.997 |
| **Current year** | **0.201** | **0.131** | **1.194** | **1.110** | **0.380** | **0.473** | **-0.008** | **-0.047** | **1.766** | **1.666** |
| **One year ahead** | **0.198** | **0.347** | **0.332** | **0.329** | **0.545** | **0.500** | **0.408** | **0.264** | **1.483** | **1.440** |
| **Two years ahead** | **0.191** | **0.218** | **0.651** | **0.536** | **0.388** | **0.706** | **0.086** | **0.051** | **1.316** | **1.510** |
| **Average** | **0.198** | **0.226** | **2.118** | **2.226** | **0.337** | **0.361** | **-0.516** | **-0.442** | **0.534** | **0.593** |
| **Sums** | **2.967** | **3.394** | **31.774** | **33.392** | **5.048** | **5.418** | **-7.747** | **-6.625** | **32.042** | **35.579** |

*Note.* Table 9 is subdivided between the static (AR) and dynamic (ARDL) strategies. The average for each region is also displayed in the tables under the row "Average". Also, the overall sum for all the ARDL and AR strategy is displayed under "All countries". There is also a row with the sum of all the strategies in the bottom.

## Risk of investment strategies

It is clear from the VaR analysis of the forecasts that the risk increases considerably in most cases, with more than 200% at risk in specific strategies in Spain. On the other hand, with the implementation of the strategies, all the countries present at least one contract with a positive value at risk. Those contracts are in their majority the yearly contracts. The phenomena of contracts with smaller duration entail, on average, a higher risk continuing to exist with some exceptions. Given the VaR, it is clear that AR(1) strategies are less risky than dynamic strategies. I present the Tables with the VaR analysis for all the strategies in Appendix Table 5, 6, 7 and 8. Despite France having the higher returns, they do not present the lowest risk for the 1% worst-case scenario, whereas they present the lowest risk for the worst 5% case scenario. Spain presents the worst risk and returns for the signal base strategy.

## Seasonality

When checking for seasonality in future contracts, I created a categorical variable. I defined this categorical variable as winter, summer, spring and autumn. I specified the other seasonal variable as the months of the year. Additionally, I showed the regressions considering the average price difference for all contracts by country in Table 10. The table shows the coefficient for the constant and their seasonal variable, with their respective standard deviation and p-value.

For the year's season, all the countries have the winter variable with a significant coefficient — however, the price signal of the coefficient changes depending on the country. Additionally, Germany is the country with the least relevant coefficient for the seasons of the year, with only one season passing the 5% benchmark, whereas France presents the highest number of relevant seasons, with three. Another phenomenon is January being the only month with a p-value smaller than 0.05 for all regions. Lastly, all the countries have at least four pertinent months, despite Germany having only three.

**Table 10**

*Seasonality Summary*

| Seasons of the year | | | | |
|---|---|---|---|---|
| Variables | Italy | French | German | Spain |
| Constant | 0.0003 | 0.0008 | 0.0004 | 0.0003* |
| | (0) | (-0.001) | (0) | (0) |
| Summer | 0.0002 | 0.0029*** | 0.0012 | 0.0001 |
| | (0) | (-0.001) | (-0.001) | (0) |
| Spring | 0.0014*** | 0.0008 | 0.0009 | 0.0012*** |
| | (0) | (-0.001) | (-0.001) | (0) |
| Autumn | 0.0008* | 0.003*** | 0.0009 | 0.0005 |
| | (0) | (-0.001) | (-0.001) | (0) |
| **Winter** | **-0.0021*** ** | **-0.0059*** ** | **-0.0026*** ** | **-0.0015*** ** |
| | **(0)** | **(-0.001)** | **(-0.001)** | **(0)** |
| Months of the year | | | | |
| Constant | 0.0004* | 0.0009 | 0.0004 | 0.0004** |
| | (0) | (-0.001) | (0) | (0) |
| **January** | **-0.0036*** ** | **-0.007*** ** | **-0.0041** ** | **-0.0015** ** |
| | **(-0.001)** | **(-0.002)** | **(-0.002)** | **(-0.001)** |
| **February** | **-0.0016* ** | **-0.0077*** ** | **-0.0044** ** | **-0.0029*** ** |
| | **(-0.001)** | **(-0.002)** | **(-0.002)** | **(-0.001)** |
| March | -0.0009 | -0.0016 | -0.0002 | -0.0004 |
| | (-0.001) | (-0.002) | (-0.002) | (-0.001) |
| April | 0.0018** | 0.0006 | 0.0003 | 0.0021** |
| | (-0.001) | (-0.002) | (-0.002) | (-0.001) |
| May | 0.0033*** | 0.0033 | 0.0023 | 0.0017** |
| | (-0.001) | (-0.002) | (-0.002) | (-0.001) |
| June | 0.0008 | 0.0022 | 0.0008 | -0.0004 |
| | (-0.001) | (-0.002) | (-0.001) | (-0.001) |
| July | 0.0001 | 0.0012 | 0.0018 | -0.0002 |
| | (-0.001) | (-0.002) | (-0.001) | (-0.001) |
| August | -0.0004 | 0.0047*** | 0.0011 | 0.0008 |

| | | | | |
|---|---|---|---|---|
| | (-0.001) | (-0.002) | (-0.001) | (-0.001) |
| September | 0.0016* | 0.0034* | 0.0011 | 0.0005 |
| | (-0.001) | (-0.002) | (-0.002) | (-0.001) |
| **October** | **0.0018**** | **0.006***** | **0.0038***** | **0.0007** |
| | **(-0.001)** | **(-0.002)** | **(-0.002)** | **(-0.001)** |
| November | -0.0013 | -0.0009 | -0.0021 | 0.0002 |
| | (-0.001) | (-0.002) | (-0.002) | (-0.001) |
| December | -0.0012 | -0.0033 | -0.00001 | -0.0002 |
| | (-0.001) | (-0.002) | (-0.002) | (-0.001) |

*Note.* In Table 10 the coefficients, standard errors and p-values are displayed for all the variables. The coefficients are the first numbers, the standard errors are below between brackets and the p-values are represented by * (<= 0.01 ***; <= 0.05 **; <=0.01 *)

# Analysis

This section will focus on analysing the hypotheses, and I highlighted some of the points in the background literature. I will then divide this section into four subsections: the three hypotheses and general insights from the background literature.

## Hypothesis 1

If I cannot reject the first hypothesis, all the future contrasts analysed have at least one relevant lag. As displayed in the results section, this is not the case. Thus, the first hypothesis can be rejected. However, there are some patterns between the relevant ones. One of them is that for all countries, the one year ahead contracts present a relevant lag. That predictability power resulted in a positive VaR for both strategies. All current quarter future contracts also present significant lags. Contrarily to 1 year ahead, not all current quarters contracts present positive VaR. The region that presents a negative VaR also has a higher risk than not following any strategy. This region is Italy, and it is also the only country that does not have lags considering their PAC and AC for the current quarter contracts. Another pattern is that their respected strategies presented more than 100% profits or a positive risk for all significant French contracts. For all other contracts, at least one contract presents a significant lag. When there is a significant coefficient, there are also economic consequences.

## Hypothesis 2

Being able to predict future prices is of extreme importance for all parties involved in the electric marketplace. Many mathematical models can perform such tasks. However, there is no consensus on which one is more efficient because there are so many ways. This hypothesis aims to test if the AR(p) models present statistically lower MSE than the dynamic model. Being able to rank different models is also relevant for the legislative branch to evaluate potential misconduct of other parties involved in the market. Given the results present in Tables 5-8, it is possible to reject the null hypothesis. One crucial point is that the majority of the AR(1) models present a p-value smaller than 15% when testing if their difference is only smaller than the dynamic model. Another peculiar point is that AR models also present higher profitability and lower risk. It suggests that, despite AR(1) models displaying statistically insignificant differences, they still present some relevant advantages on their behaviour.

### Hypothesis 3

The scientific literature makes it well known that future prices and the electric marketplace present seasonality to a certain degree. I encountered the same result in this research. As mentioned in the seasonality sub-section from the results, all the countries present winter and January are statistically significant. Furthermore, all the countries also present at least one relevant month outside the winter season. However, the months vary according to the country. I can explain it by regional differences in the weather or their energy production, which means that during this period, contracts traded do present a relevant seasonal factor in the price difference. Therefore, it is not possible to reject hypothesis 3.

### General insights

There are two main questions raised during the background literature: firstly, if the implementation of dynamic rates in the retail market increased the predictability of energy demand and, consequently, prices; secondly, if Germany still presents a relevant seasonality for the price differences. I implemented the Diebold-Mariano test to investigate the first topic, comparing the MSE of the same models in different years. Unfortunately, there is not a significant increase in the predictability power throughout the investigated time. Thus, there is no relaxation from the fundamental constraints imposed by the market. On the other hand, Germany still presents a winter seasonality, even when taking the traded day as the point of reference rather than the execution date, as is done in Haar's (2010) paper. This papers' finding differs, for it encounters three relevant months for Germany; January, February and October. The proliferation of renewable power plants may cause this increase in seasonality. In contrast to previous research, December has the highest p-value for Germany's future contracts.

## Conclusion

This paper investigates fundamental characteristics of the future electrical market in wholesale. Therefore, I assessed core parts of the market by this hypotheses. There is indeed a seasonality for all the regions, and it appears to be increasing over time. However, it is impossible to affirm that the escalation of renewable energy in the grid is the leading cause. Therefore, more research on the topic is necessary. Another keystone to further develop our understanding of the market behaviour is reviewing the correlation of the price difference and its lags. If the factors present a relevant coefficient, it is possible to predict future prices, on average, and there is room for efficiency improvement. The market should become efficient by the different parties making a profit from this relationship.

Another point that investigates potential change in the market behaviour is the MSE comparison between different times, for it allows to examine potential repercussions of legislation and business practices. This paper focuses on future contracts, but other types of financial contracts affect the market too. Therefore, further research on other financial contracts as options is necessary to understand the fundamentals better, ergo assisting the legislative branch in preventing future market failures and efficiently stimulating positive externalities. Not modelling the price volatility is also a shortfall of this research, for it is plausible that it would increase the predicting power of the models. Additionally, due to the ongoing climate crises, the seasonality from the markets must be re-inspected to assess potential changes in the market characteristics. To sum up, it is possible to affirm that the fundamental hurdles from the market remain in force. Notwithstanding, specific market alterations are also in play, possibly triggering unforeseen changes.

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# Appendix

**Table 1**

*Dickey-Fuller Test*

| | Italy | | France | | Germany | | Spain | |
|---|---|---|---|---|---|---|---|---|
| Contracts | P-Value Price Difference | P-Value Price | P-Value Price Difference | P-Value Price | P-Value Price Difference | P-Value Price | P-Value Price Difference | P-Value Price |
| Current week | 0 | 0.000 | 0 | 0.000 | 0 | 0.008 | 0 | 0.001 |
| One week ahead | 0 | 0.003 | 0 | 0.000 | 0 | 0.000 | 0 | 0.001 |
| Two weeks ahead | 0 | 0.003 | 0 | 0.015 | 0 | 0.002 | 0 | 0.010 |
| Three weeks ahead | 0 | 0.045 | 0 | 0.011 | 0 | 0.005 | 0 | 0.016 |
| Current month | 0 | 0.034 | 0 | 0.002 | 0 | 0.079 | 0 | 0.063 |
| One month ahead | 0 | 0.055 | 0 | 0.084 | 0 | 0.299 | 0 | 0.050 |
| Two months ahead | 0 | 0.147 | 0 | 0.054 | 0 | 0.411 | 0 | 0.125 |
| Three months ahead | 0 | 0.108 | 0 | 0.087 | 0 | 0.261 | 0 | 0.162 |
| Current quarter | 0 | 0.072 | 0 | 0.033 | 0 | 0.233 | 0 | 0.178 |
| One quarter ahead | 0 | 0.097 | 0 | 0.028 | 0 | 0.397 | 0 | 0.232 |
| Two quarters ahead | 0 | 0.172 | 0 | 0.066 | 0 | 0.588 | 0 | 0.327 |
| Three quarters ahead | 0 | 0.184 | 0 | 0.160 | 0 | 0.674 | 0 | 0.229 |
| Current year | 0 | 0.360 | 0 | 0.454 | 0 | 0.765 | 0 | 0.478 |
| One year ahead | 0 | 0.558 | 0 | 0.664 | 0 | 0.821 | 0 | 0.522 |
| Two years ahead | 0 | 0.495 | 0 | 0.760 | 0 | 0.837 | 0 | 0.567 |

*Note.* Table 1 presents the variables in the first axis. Furthermore, the columns are divided between countries. Also, there is a differentiation between the p-values of price differences and absolute prices, where the first p-values are related to the price's differences and the second one to the absolute prices.

**Table 2**

*VaR for long positions*

| Variables | France | | Italy | | Germany | | Spain | | All countries | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 5% | 1% | 5% | 1% | 5% | 1% | 5% | 1% | 5% | 1% |
| Current week | 0.880 | 0.830 | 0.928 | 0.897 | 0.843 | 0.776 | 0.903 | 0.862 | 0.889 | 0.841 |
| One week ahead | 0.842 | 0.775 | 0.925 | 0.894 | 0.844 | 0.778 | 0.905 | 0.865 | 0.879 | 0.828 |
| Two weeks ahead | 0.882 | 0.832 | 0.939 | 0.913 | 0.889 | 0.842 | 0.928 | 0.897 | 0.909 | 0.871 |
| Three weeks ahead | 0.882 | 0.832 | 0.939 | 0.913 | 0.889 | 0.842 | 0.928 | 0.897 | 0.909 | 0.871 |
| Current month | 0.917 | 0.882 | 0.958 | 0.940 | 0.939 | 0.913 | 0.946 | 0.923 | 0.940 | 0.915 |
| One month ahead | 0.927 | 0.897 | 0.961 | 0.945 | 0.951 | 0.931 | 0.952 | 0.932 | 0.948 | 0.926 |
| Two months ahead | 0.937 | 0.910 | 0.963 | 0.947 | 0.957 | 0.939 | 0.961 | 0.945 | 0.954 | 0.935 |
| Three months ahead | 0.937 | 0.910 | 0.963 | 0.948 | 0.959 | 0.942 | 0.961 | 0.945 | 0.955 | 0.936 |
| Current quarter | 0.933 | 0.904 | 0.964 | 0.950 | 0.962 | 0.946 | 0.970 | 0.958 | 0.957 | 0.939 |
| One quarter ahead | 0.937 | 0.911 | 0.971 | 0.959 | 0.967 | 0.953 | 0.973 | 0.962 | 0.962 | 0.946 |
| Two quarters ahead | 0.947 | 0.925 | 0.974 | 0.963 | 0.968 | 0.955 | 0.976 | 0.965 | 0.966 | 0.952 |
| Three quarters ahead | 0.944 | 0.921 | 0.971 | 0.959 | 0.966 | 0.951 | 0.973 | 0.962 | 0.964 | 0.948 |
| Current year | 0.977 | 0.968 | 0.983 | 0.975 | 0.976 | 0.966 | 0.987 | 0.982 | 0.981 | 0.973 |
| One year ahead | 0.981 | 0.973 | 0.984 | 0.978 | 0.979 | 0.970 | 0.989 | 0.984 | 0.983 | 0.976 |
| Two years ahead | 0.982 | 0.974 | 0.985 | 0.979 | 0.980 | 0.972 | 0.990 | 0.986 | 0.984 | 0.978 |
| Average | 0.927 | 0.896 | 0.960 | 0.944 | 0.938 | 0.912 | 0.956 | 0.938 | 0.945 | 0.922 |

*Note.* Table 2 displays VaR for all the countries separately and together divided by contracts. Also, there is a sub section in the columns named 5% and 1%. Those columns represent the worst 5% and 1% scenario. The point of reference is 1. Meaning that 0.90 implies a 10% value at risk for that strategy, 1 signal 0 value at risk and 1.1 represents represent a profit of 10%.

**Table 3**

*PAC and AC relevant lags*

| Variables | Italy | | France | | Germany | | Spain | |
|---|---|---|---|---|---|---|---|---|
| | PAC | AC | PAC | AC | PAC | AC | PAC | AC |
| Current week | 1, 9, 20 | 1, 9, 20 | 1, 2, 3, 9, 15, 20 | 1, 2, 3, 9, 15, 20 | 1, 10, 20 | 1, 10, 20 | 21, 22 | 21, 22 |
| One week ahead | 1, 20 | 1, 19, 20 | 20 | 10, 20 | 1, 8 | 1 | 18, 20, 22 | 19 ,21 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Two weeks ahead | 19, 20 | 19, 20 | 1, 10, 20 | 1, 10, 20 | 20, 21 | 20, 21 | 22, 23 | 22, 23 |
| Three weeks ahead | 5, 6, 9, 10, 11 | 6, 9, 10 | 1, 40 | 1, 40 | 1, 10, 16, 30, 40 | 1, 10, 16 | 1, 2, 3, 5, 15, 20 | 1, 2, 5, 6, 15, 20, 21 |
| Current month | 1, 9, 20 | 1, 9, 20 | 1, 2, 3, 10, 15, 19, 20, 21 | 1, 2, 3, 5, 10, 15, 19, 20, 21 | 1, 10, 20 | 1, 10, 20 | 22, 23 | 22, 23 |
| One month ahead | 1, 20, 22 | 1, 20, 21 | 20 | 20 | 1, 8 | 1 | 17, 28, 21 | 19, 21 |
| Two months ahead | 19, 20 | 19, 20 | 1, 10, 20 | 1, 10, 20 | 20, 21 | 20, 21 | 1, 10, 20 | 22, 23 |
| Three months ahead | 23 | 23 | 17, 20, 21 | 17, 20, 21 | 20, 22 | 1, 21 | 2, 17, 20, 21, 22 | 2, 17, 20, 22 |
| Current quarter | 0 | 0 | 1 | 1, 18 | 1 | 1 | 1, 22 | 1, 22 |
| One quarter ahead | 27 | 27 | 0 | 0 | 1, 13, 22 | 1, 13 | 0 | 0 |
| Two quarters ahead | 0 | 0 | 0 | 0 | 2, 20 | 2, 19 | 0 | 0 |
| Three quarters ahead | 0 | 0 | 0 | 0 | 6 | 5 | 5, 23 | 5, 23 |
| Current year | 3, 24 | 3, 24 | 1, 4, 20 | 1, 20 | 13, 16, 20 | 20 | 1, 12, 15, 19 | 1, 12, 15, 19 |
| One year ahead | 1, 3, 5, 17, 25 | 1, 3, 5, 17, 25 | 1, 13, 20 | 1, 12, 15, 20 | 1, 15, 20 | 1, 16 | 1 | 1 |
| Two years ahead | 13, 19 | 13, 19 | 1, 16 | 1, 16, 20 | 1, 16 | 1, 16 | 1, 7 | 1, 7 |

*Notes.* Table 3 displays all relevant lags divided by countries and contracts separately consideration their PAC and AC

**Table 4**

*AR(1) Regression with Newey-West standard error*

| | Italy | France | Germany | Spain |
|---|---|---|---|---|
| Current week | | | | |
| Constant | 0.0001 | 0.0012 | 0.0008 | 0.0010 |
| | (0.0008) | (0.0013) | (0.0010) | (0.0010) |
| First lag | 0.0921 | 0.0790 | 0.0575** | -0.0102 |
| | (0.0368) | (0.0326) | (0.0282) | (0.0301) |
| One week ahead | | | | |
| Constant | 0.0001 | 0.0012 | 0.0004 | 0.0008 |
| | (0.0006) | (0.0011) | (0.0008) | (0.0008) |
| First lag | 0.1559*** | 0.0404 | 0.0557* | 0.0351 |
| | (0.0444) | (0.0563) | (0.0326) | (0.0284) |
| Two weeks ahead | | | | |
| Constant | 0.0004 | 0.0010 | 0.0004 | 0.0003 |
| | (0.0007) | (0.0010) | (0.0007) | (0.0007) |
| First lag | 0.0472 | 0.0724** | 0.0476 | 0.0206 |
| | (0.0349) | (0.0351) | (0.0295) | (0.0206) |
| Three weeks ahead | | | | |
| Constant | 0.0011 | 0.0031 | 0.0029 | 0.0015 |
| | (0.0011) | (0.0019) | (0.3030) | (0.0012) |
| First lag | -0.0587 | -0.0898* | -0.1103** | -0.1092** |
| | (0.0409) | (0.0319) | (0.0432) | (0.0458) |
| Current month | | | | |
| Constant | 0.0001 | 0.0012 | 0.0008 | 0.0010 |
| | (0.0008) | (0.0013) | (0.0010) | (0.0010) |
| First lag | 0.0921 | 0.0789** | 0.0575** | -0.0102 |
| | (0.0368) | (0.0326) | (0.0282) | (0.0300) |
| One month ahead | | | | |
| Constant | 0.0001 | 0.0011 | 0.0004 | 0.0351 |
| | (0.0006) | (0.0012) | (0.0008) | (0.0285) |
| First lag | 0.1559*** | 0.0404 | 0.0557 | 0.0008 |
| | (0.0444) | (0.0571) | (0.0326) | (0.0008) |
| Two months ahead | | | | |
| Constant | 0.0004 | 0.0010 | 0.0004 | 0.0003 |
| | (0.0007) | (0.0010) | (0.0007) | (0.0006) |
| First lag | 0.0472 | 0.0724** | 0.0476 | 0.0206 |
| | (0.0349) | (0.0351) | (0.0295) | (0.0231) |
| Three months ahead | | | | |
| Constant | 0.0003 | 0.0010 | 0.0004 | 0.0004 |
| | (0.0006) | (0.0011) | (0.0007) | (0.0006) |
| First lag | 0.0159 | 0.0090 | 0.0532** | -0.0075 |
| | (0.0248) | (0.0266) | (0.0255) | (0.0192) |
| Current quarter | | | | |

| | | | | |
|---|---|---|---|---|
| Constant | 0.0003 | 0.0009 | 0.0004 | 0.0002 |
| | (0.0006) | (0.0011) | (0.0006) | (0.0004) |
| First lag | 0.0579*** | 0.0654** | 0.0814** | 0.0755*** |
| | (0.0296) | (0.0291) | (0.0344) | (0.0237) |
| One quarter ahead | | | | |
| Constant | 0.0002 | 0.0010 | 0.0003 | 0.0000 |
| | (0.0005) | (0.0010) | (0.0005) | (0.0004) |
| First lag | -0.0420 | -0.0098 | 0.0548 | 0.0025 |
| | (0.0622) | (0.0362) | (0.0349) | (0.0332) |
| Two quarter ahead | | | | |
| Constant | 0.0002 | 0.0008 | 0.0002 | 0.0000 |
| | (0.0004) | (0.0008) | (0.0004) | (0.0004) |
| First lag | 0.0011 | -0.0099 | -0.0155 | -0.0042 |
| | (0.0217) | (0.0150) | (0.0192) | (0.0220) |
| Three quarter ahead | | | | |
| Constant | 0.0000 | 0.0008 | 0.0004 | 0.0000 |
| | (0.0006) | (0.0009) | (0.0005) | (0.0004) |
| First lag | -0.0369 | -0.0071 | 0.0012 | 0.0000 |
| | (0.0241) | (0.0167) | (0.0239) | (0.0004) |
| Current year | | | | |
| Constant | 0.0000 | 0.0003 | 0.0002 | 0.0002 |
| | (0.0003) | (0.0004) | (0.0004) | (0.0002) |
| First lag | 0.0364 | 0.1139** | 0.0507** | 0.0754** |
| | (0.0377) | (0.0527) | (0.0248) | (0.0332) |
| One year ahead | | | | |
| Constant | 0.000 | 0.0002 | 0.0003 | 0.0000 |
| | (0.000) | (0.0003) | (0.0003) | (0.0002) |
| First lag | -0.0856* | 0.0953*** | 0.0863** | 0.0911** |
| | (0.0448) | (0.0352) | (0.0348) | (0.0369) |
| Two years ahead | | | | |
| Constant | 0.0001 | 0.0002 | 0.0003 | -0.0001 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0002) |
| First lag | 0.0457 | 0.0616 | 0.1176*** | -0.0071 |
| | (0.0310) | (0.0379) | (0.0318) | (0.0198) |

*Note.* In Table 6 the coefficients, standard errors and p-values are displayed for all the variables. Regressions are made for each country and contract separately. The coefficients are the first numbers, the standard errors are below between brackets and the p-values are represented by * (<= 0.01 ***; <= 0.05 **; <=0.01 *)

**Table 5**

*VaR Italy*

| Variables | ARDL | | AR | |
|---|---|---|---|---|
| | 5% | 1% | 5% | 1% |
| Current week | -0.156 | -0.272 | -0.156 | -0.272 |
| One week ahead | -0.494 | -1.052 | -0.425 | -0.934 |
| Two weeks ahead | -0.375 | -0.503 | -0.377 | -0.504 |
| Three weeks ahead | -1.302 | -1.650 | -1.080 | -1.440 |
| Current month | -0.156 | -0.272 | -0.156 | -0.272 |
| One month ahead | -0.494 | -1.052 | -0.425 | -0.934 |
| Two months ahead | -0.375 | -0.503 | -0.377 | -0.504 |
| Three months ahead | -0.417 | -0.542 | -0.417 | -0.542 |
| Current quarter | -0.165 | -0.313 | -0.184 | -0.345 |
| One quarter ahead | -0.606 | -0.725 | -0.638 | -0.760 |
| Two quarters ahead | -0.576 | -0.698 | -0.576 | -0.698 |
| Three quarters ahead | -0.928 | -1.105 | -0.710 | -0.833 |
| Current year | -0.037 | -0.095 | -0.031 | -0.078 |
| One year ahead | 0.039 | -0.015 | 0.048 | -0.045 |
| Two years ahead | -0.040 | -0.109 | -0.026 | -0.099 |
| Average | -0.405 | -0.594 | -0.369 | -0.551 |

*Notes.* Table 5 displays VaR for Italy when following the AR and ARDL models. Also, there is a sub section in the columns named 5% and 1%. Those columns represent the worst 5% and 1% scenario. The point of reference is 0. Meaning that -0.10 implies a 10% value at risk for that strategy, 0.00 has no value at risk and 0.1 represents represent a profit of 10%.

**Table 6**

*VaR France*

| Variables | ARDL | | AR | |
|---|---|---|---|---|
| | 5% | 1% | 5% | 1% |
| Current week | -0.279 | -0.849 | -0.273 | -0.939 |
| One week ahead | -0.561 | -1.759 | -0.417 | -1.510 |
| Two weeks ahead | 0.191 | -0.386 | 0.169 | -0.431 |
| Three weeks ahead | -0.342 | -1.240 | -0.465 | -1.545 |
| Current month | -0.279 | -0.849 | -0.273 | -0.939 |
| One month ahead | -0.561 | -1.759 | -0.417 | -1.510 |
| Two months ahead | 0.191 | -0.386 | 0.169 | -0.431 |
| Three months ahead | -0.133 | -0.372 | -0.150 | -0.388 |
| Current quarter | 0.223 | -0.600 | 0.188 | -0.650 |
| One quarter ahead | -0.574 | -0.913 | -0.641 | -1.016 |
| Two quarters ahead | -0.904 | -1.125 | -0.882 | -1.103 |
| Three quarters ahead | 0.053 | -0.196 | 0.050 | -0.198 |
| Current year | -0.007 | -0.295 | 0.013 | -0.247 |
| One year ahead | 0.023 | -0.059 | 0.002 | -0.079 |
| Two years ahead | 0.098 | -0.028 | 0.075 | -0.027 |
| Average | -0.191 | -0.721 | -0.190 | -0.734 |

*Note.* Table 6 displays VaR for France when following the AR and ARDL models. Also, there is a sub section in the columns named 5% and 1%. Those columns represent the worst 5% and 1% scenario. The point of reference is 0. Meaning that -0.10 implies a 10% value at risk for that strategy, 0.00 has no value at risk and 0.1 represents represent a profit of 10%.

**Table 7**

*VaR Germany*

| Variables | ARDL | | AR | |
|---|---|---|---|---|
| | 5% | 1% | 5% | 1% |
| Current week | -0.14 | -0.34 | -0.14 | -0.34 |
| One week ahead | -0.06 | -0.21 | -0.06 | -0.21 |
| Two weeks ahead | -0.22 | -0.40 | -0.24 | -0.42 |
| Three weeks ahead | -1.48 | -2.04 | -1.47 | -2.02 |
| Current month | -0.14 | -0.34 | -0.14 | -0.34 |
| One month ahead | -0.06 | -0.21 | -0.06 | -0.21 |
| Two months ahead | -0.22 | -0.40 | -0.24 | -0.42 |
| Three months ahead | -0.09 | -0.18 | -0.09 | -0.18 |
| Current quarter | 0.14 | -0.10 | 0.15 | -0.07 |
| One quarter ahead | -0.17 | -0.31 | -0.17 | -0.32 |
| Two quarters ahead | -0.88 | -1.05 | -0.91 | -1.09 |
| Three quarters ahead | -0.19 | -0.27 | -0.18 | -0.26 |
| Current year | 0.07 | -0.05 | 0.08 | -0.06 |
| One year ahead | 0.09 | -0.05 | 0.10 | -0.03 |
| Two years ahead | 0.06 | -0.08 | 0.01 | -0.19 |
| Average | -0.22 | -0.40 | -0.22 | -0.41 |

*Note.* Table 5 displays VaR for Germany when following the AR and ARDL models. Also, there is a sub section in the columns named 5% and 1%. Those columns represent the worst 5% and 1% scenario. The point of reference is 0. Meaning that -0.10 implies a 10% value at risk for that strategy, 0.00 has no value at risk and 0.1 represents represent a profit of 10%.

**Table 8**

VaR Spain

| Variables | ARDL | | AR | |
|---|---|---|---|---|
| | 5% | 1% | 5% | 1% |
| Current week | -1.00 | -1.16 | -1.26 | -1.43 |
| One week ahead | -1.31 | -1.63 | -0.89 | -1.01 |
| Two weeks ahead | -1.12 | -1.32 | -1.07 | -1.27 |
| Three weeks ahead | -1.75 | -2.07 | -1.61 | -1.99 |
| Current month | -1.00 | -1.16 | -1.26 | -1.43 |
| One month ahead | -0.89 | -1.00 | -0.89 | -1.01 |
| Two months ahead | -1.12 | -1.32 | -1.07 | -1.27 |
| Three months ahead | -1.78 | -2.13 | -1.66 | 2.00 |
| Current quarter | 0.03 | -0.11 | 0.04 | -0.10 |

| | | | | |
|---|---|---|---|---|
| One quarter ahead | -0.46 | -0.58 | -0.45 | -0.57 |
| Two quarters ahead | -1.08 | -1.32 | -0.96 | -1.18 |
| Three quarters ahead | -1.31 | -1.63 | -1.21 | -1.50 |
| Current year | -0.14 | -0.19 | -0.18 | -0.23 |
| One year ahead | 0.04 | -0.03 | -0.09 | -0.15 |
| Two years ahead | -0.09 | -0.15 | -0.15 | -0.21 |
| Average | -0.87 | -1.05 | -0.85 | -0.76 |

*Note.* Table 5 displays VaR for Spain when following the AR and ARDL models. Also, there is a sub section in the columns named 5% and 1%. Those columns represent the worst 5% and 1% scenario. The point of reference is 0. Meaning that -0.10 implies a 10% value at risk for that strategy, 0.00 has no value at risk and 0.1 represents represent a profit of 10%.