Four essays on quantitative economics applications to volatility analysis in Emerging Markets and renewable energy projects

DOCTORAL THESIS

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To Socorro, Ana María, Enrique, Claudia y Sofía.
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ABSTRACT

Financial decisions can be divided in investment and financing decisions. Concerning investment decisions, the uncertainty about the future dynamics of financial and economic variables has a central role, considering that the returns expected by firms and investors can be affected by the adverse movements in financial markets and their high volatility. In consequence, the adequate volatility analysis and modeling is crucial for the firm’s financial decision-making process and the design of investing and hedging strategies by investors. In this regard, the study of volatility has become one of the most interesting topics in finance research. The foregoing has become more relevant in recent years considering the scenario of high volatility and uncertainty faced by markets globally. This document aims to address four central issues related to financial volatility as a research area. These are, volatility transmission and spillovers in Emerging Markets, the calibration of the volatility surface for renewable energy projects and the forecast of energy assets returns and volatility spillovers through machine learning techniques.

In the first chapter of the document, the volatility transmission effects between an energy index and a financial index for Emerging Markets are examined. Then, by using a DCC model, it is shown that the volatility transmission effects between the employed indices for the subprime crisis and the COVID-19 pandemic were different. This, considering that the former crisis originated in the financial sector and spread to the rest of the economy, while the second originated in the real sector and trasmitted to the rest of the economy posteriorly. Considering that the relationship between markets volatility is time-varying, in the second chapter, a dynamic analysis of volatility spillovers between commodities, Bitcoin and an
Emerging Markets index is developed. Employing the methodology proposed by Diebold and Yilmaz (2012), it is concluded that the volatility spillovers effects between the analyzed assets is not constant in direction and intensity over time. In particular, for periods of crisis such as the COVID-19 pandemics, there are reversals in the direction of volatility spillovers due to the sector in which the crises originate. In addition, in this chapter the dynamic nature of volatility spillovers is exploited. Hence, the volatility spillover index proposed by Diebold and Yilmaz is forecasted to be used as a measure to anticipate high turbulence periods. This, through both traditional econometric models and machine learning techniques.

In the third chapter, a model for the prediction of carbon and oil prices is proposed. In this sense, a hybrid model that ensembles the forecasts obtained from different machine learning techniques and traditional econometric models is developed, obtaining results that show the advantages of employing hybrid models which combine machine learning techniques, exclusively, to forecast financial variables.

In Chapter four, a methodology for the estimation of volatility in renewable energy projects valuation through real options is presented. In this methodology, which is an extension of the implied volatility approach employed for financial options, the volatility of the project is the implied volatility obtained from the volatility surface of comparable firms for a certain valuation date and given debt-to-equity relation of a renewable energy project. In this analysis, the stochastic ‘alpha-beta-rho’ model is utilized to calibrate the volatility surface for real option valuation purposes.

Finally, the conclusions derived from the mentioned chapters are presented at the end of the document as well as some recommendations for future research.
RESUMEN

Las decisiones financieras se pueden dividir en decisiones de inversión y decisiones de financiación. En lo que respecta a las decisiones de inversión, la incertidumbre acerca de la dinámica futura de las variables económicas y de las financieras tiene un rol fundamental. Eso, se explica porque los retornos esperados por las empresas y por los inversionistas se pueden ver afectados por los movimientos adversos en los mercados financieros y por los altos niveles de volatilidad. Como consecuencia, resulta crucial realizar un adecuado análisis y modelación de la volatilidad para el proceso de toma de decisiones financieras, por parte de las empresas y el diseño de estrategias de inversión y cobertura por parte de los inversionistas. En este sentido, el estudio de la volatilidad se ha convertido en uno de los temas más interesantes de la investigación en finanzas. Lo anterior ha cobrado mayor relevancia en los últimos años, teniendo en cuenta el escenario de alta volatilidad e incertidumbre que afrontan los mercados a nivel global. Este documento tiene como objetivo abordar cuatro cuestiones centrales, las cuales están relacionadas con la volatilidad financiera como campo de investigación. Esas cuestiones son, la transmisión y spillovers de volatilidad en mercados emergentes, la calibración de la superficie de volatilidad para proyectos de energía renovable y el pronóstico de los rendimientos de activos energéticos y spillovers de volatilidad a través de técnicas de machine learning.

En el primer capítulo del documento, se examinan los efectos de transmisión de volatilidad entre un índice de energía y un índice financiero para los Mercados Emergentes. En consecuencia, mediante el uso de un modelo DCC, se muestra que los efectos de transmisión de volatilidad entre los índices empleados para la crisis subprime y la crisis del COVID-19
fueron diferentes. Lo anteriormente dicho, considerando que la primera crisis se originó en el sector financiero y luego se extendió al resto de la economía, mientras que la segunda se originó en el sector real y posteriormente afectó al resto de la economía.

Teniendo en cuenta que la relación entre la volatilidad de los mercados es cambiante en el tiempo, en el segundo capítulo se llevó a cabo un análisis dinámico de los spillovers de volatilidad entre materias primas, Bitcoin y un índice de Mercados Emergentes. Así, empleando la metodología propuesta por Diebold y Yilmaz (2012), se concluyó que los efectos de los spillovers de volatilidad entre los activos analizados no son constantes en dirección e intensidad a través del tiempo. En particular, para períodos de crisis como el de la pandemia del COVID-19, hay reversiones en la dirección de los spillovers de volatilidad debido al sector en el que se originó la crisis. Además, en este capítulo se explota la naturaleza dinámica de los spillovers de volatilidad. Por lo tanto, se planteó que el índice de spillovers de volatilidad propuesto por Diebold y Yilmaz puede ser usado como una medida para pronosticar períodos de alta turbulencia. Lo anterior se desarrolló a través de modelos econométricos tradicionales y de técnicas de machine learning.

En el tercer capítulo del documento, se propone un modelo que predice los retornos de los precios del carbono y del petróleo. En este sentido, se desarrolló un modelo híbrido, el cual combina las proyecciones obtenidas a partir de diferentes técnicas de machine learning y modelos econométricos tradicionales, obteniéndose resultados los cuales muestran las ventajas de emplear modelos híbridos que incorporan técnicas de machine learning, exclusivamente, para pronosticar variables financieras.

Finalmente, en el capítulo cuatro, se presenta una metodología para la estimación de la volatilidad en la valoración de proyectos de energías renovables mediante opciones reales.
En esta metodología, la cual es una extensión del enfoque de volatilidad implícita empleada para las opciones financieras, la volatilidad de un proyecto es la volatilidad implícita obtenida a partir de la superficie de la volatilidad de empresas comparables, según una determinada fecha de valoración y dada la relación deuda-capital de un proyecto de energía renovable. En este análisis, se utilizó el modelo estocástico 'alfa-beta-rho' para calibrar la superficie de la volatilidad para la valoración mediante opciones reales.

Por último, al final del documento se presentan las conclusiones derivadas de los capítulos mencionados, así como algunas recomendaciones para las futuras investigaciones.
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INTRODUCTION

Financial decisions can be broadly divided in investment and financing decisions. Investment decisions are related to the process followed by firms to select alternatives to employ funds obtained from different sources. Financing decisions concerns the choice of sources to raise funds by the firm (Ross et al., 2002). In investment decisions, the trade-off between risk and return is considered as a central issue to design financial strategies that maximize the firm’s value and the design of investment and hedging strategies by investors. This, considering that financial theory indicates that decisions made by firms and investors should be oriented to minimize risks and maximize rewards (Engle, 2004). In this regard, uncertainty about the future dynamics of financial and economic variables, understood as risk, plays a fundamental role (Bodie et al., 2013). This uncertainty is designated in finance as volatility, which is defined by Andersen et al. (2006, p. 780) as the “fluctuations observed in some phenomenon over time” or, more precisely “the variability of the random (unforeseen) component of a time series”.

Given the importance of volatility in the financial decision-making process, its appropriate estimation and modeling is preponderant for economic agents (Engle, 2004). In consequence, the study of this variable has become one of the most interesting and challenging topics in the discipline of finance. This is explained by the relevance that this important thematic has for firms, investors and regulatory organizations. On the one hand, the increase of volatility may determine the decisions made by regulatory agencies and capital providers in order to maintain the financial markets stability and efficiency. Moreover, is has been shown that volatility affects the markets liquidity considering that an increase in this variable can induce
changes in the spread between the bid and ask prices of the market maker (Daly, 2008). In the case of individual firms, the volatility modeling and measurement is crucial to make decisions related to the start of new projects and the determination of their capital structure. This, taking into account the possible effects that adverse movements in financial markets have in terms of objectives achievement and the sustainability of organizations. In addition, volatility has a notorious role for investors, considering that this variable has a preponderant role in the design of investment and hedging strategies.

In this line, an extensive number of works have focused on volatility analysis from different perspectives. Following the work of Bhowmik (2020), two broad groups can be considered in the literature related to financial volatility. The first group is related to univariate models and the second corresponds to multivariate approaches for volatility analysis. Within the first group, the most prominent proposals are framed in the tradition of the ARCH and GARCH models, proposed by Engle (1982) and Bollerslev (1986), respectively, and their extensions. Most of the models in this research strand model volatility based on historical information. In this regard, one of the approaches that has received attention in recent years is the implied volatility approach. This, considering that implied volatility is believed to be informationally superior to historical volatility because it takes into consideration the markets forecast of future volatility (Canina and Figlewski, 1993).

The second group of works emerges as an innovative research field since the seminal works of Engle et al. (1990) and the subsequent proposals of Ito et al. (1992), Susmel and Engle (1994) and Lin et al. (1994). In this research line, most of the works can be classified in proposals which employ multivariate GARCH models and their extensions (Bollerslev et al.,1988; Ito et al., 1992; Lin et al., 1994), regime switch models (Lamoureux and Lastrapes,
1990; Hamilton and Susmel, 1994; Baele, 2002; Chkili and Nguyen, 2014; BenSaïda et al., 2018) and stochastic volatility models (Harvey et al., 1994; So et al., 1997; Vo, 2011; Ding and Vo, 2012; Jacquier et al., 2004; Shi et al., 2020).

In the tradition of the multivariate GARCH models and their extensions, the Dynamic Conditional Correlation (DCC) model, originally proposed by Engle (2002), and the Baba-Engle-Kraft-Kroner (BEKK) model, proposed by Engle and Kroner (1995), have become some of the most interesting alternatives to analyze volatility transmission (Fallahi et al.; 2014; Fiszeder et al., 2019; Shehzad et al., 2021). Particularly, the DCC model has been widely employed in literature considering that this approach guarantees “the positive definiteness of the conditional covariance matrices and the ability to describe time-varying conditional correlations and covariances in a parsimonious way” (Fiszeder et al., 2019, p. 69). However, the DCC model does not consider the dynamic effects or directional asymmetries of volatility transmission. In consequence, the Diebold and Yilmaz (2012) volatility spillover framework has emerged as an interesting option to analyze volatility spillovers between assets or markets. This approach considers the dynamic and the net directional volatility spillovers effects between variables.

The aim of this document is to address four relevant issues related to volatility in finance. The first chapter examines the volatility transmission effects between an energy index and an equity index for Emerging Markets during turbulence and calm periods. In the second chapter, the volatility spillovers between commodities, Bitcoin and Emerging markets are analyzed and forecasted from a dynamic perspective. In Chapter three, Carbon and Oil prices returns are forecasted through machine learning and traditional econometric models. In
Chapter four, a volatility estimation method, which employs the implied volatility approach, for renewable energy projects through real options is proposed.

Delving into the document content, in the first chapter, the DCC model is employed to analyze the volatility transmission effects between and energy index and a financial index for Emerging Markets during the subprime crisis and the COVID-19 pandemic. Different reasons motivate this exercise. Firstly, the volatility transmission effects between energy and equity volatility are relatively unexplored (Jebabli et al., 2022) despite the increasing interest from investors in commodities as diversification, hedging or safe-haven vehicles and the peculiarities that Emerging Markets have in terms of fragility and complexity (Cheng and Yang, 2021). Secondly, given the growing connectedness between commodities and equity markets in recent years, the analysis of volatility between these markets is pertinent to understand the dynamics of the stock markets and the design of investment, hedging and risk mitigation strategies. Thirdly, literature suggests that the volatility transmission patterns during financial crisis are specific (Goodell, 2020; Laborda and Olmo, 2021; Li, 2021). Hence, the examination of volatility transmission effects in recent financial downturns such as the COVID-19 pandemic and its comparison with previous financial crisis is relevant. The results suggest volatility transmission effects between energy and stock Emerging Markets, during COVID-19, different from the volatility transmission dynamics observed during the subprime crisis period that could be explained by the sector where the crisis was originated.

Considering the limitations of the previous approaches regarding the capture of the dynamic relationship between markets volatility and the directional net volatility effects, in the second chapter of the document, the volatility spillover framework proposed by Diebold and Yilmaz (2012) is employed. This framework is relatively simple, allows the analysis of directional
asymmetries and take into account that volatility spillovers vary over time. In the developed exercise, the volatility spillovers between commodities, Bitcoin and an Emerging Markets index are analyzed. Moreover, machine learning and traditional econometric models are employed to forecast the Total Volatility Spillover (TVS) index proposed by Diebold and Yilmaz (2012). This, to evaluate if it is possible to anticipate high turbulence periods from the forecasted measure. The results show that volatility spillovers can be considered as dynamic relationships, which are time and event dependent (Antonakakis and Kizys, 2015), that present particular effects during turbulent periods such as financial crisis. Moreover, it is shown that Volatility Spillovers measures contain information that can be used to forecast turbulence periods.

On the other hand, one of the topics that is relevant to volatility analysis concerns the asset returns forecasting. In particular, energy assets such as Carbon and Oil have received considerable attention in recent years by academics and practitioners. This is explained by the increasing volatility in these markets (Zhu and Chevallier 2017), the dominance of fossil fuel-intensive industries and the emergency to identify the benefits of the novel energy markets to attract investors to these markets, and the particularities in the price mechanisms of carbon markets, which operate as semi-artificial markets. In consequence, in Chapter three, a hybrid model to forecast Oil and Carbon price returns is proposed. In this model, traditional econometric models and machine learning techniques are employed. Then, the forecasts obtained from the individual models are ensembled by the use of Neural Networks and simple average methods. The results highlight the capacity of hybrid models based on machine learning techniques to forecast financial variables without the limitations imposed by traditional econometric models’ assumptions, unlike previous studies (e.g., Safari and
Davallou 2018; Tsay and Chen 2018), and the advantages of employing nonlinear ensemble methods which contributes to the forecast combination puzzle (e.g. Chan and Pauwels 2018; Diebold and Shin 2019).

Another domain in which volatility analysis is crucial for firms and investors is project valuation. The foregoing considering that high volatility scenarios can increase the risk associated with the flows expected by firms from projects development. In this regard, the valuation of projects through real options emerges as a powerful tool to capture the uncertainty that organizations face in the execution of their initiatives. However, the estimation of volatility in this project valuation approach is challenging. This, as a consequence of the defiances that this approach presents related to the absence of historical and market data and the limitations of alternative approaches to accomplish this task. In consequence, in Chapter four, a method for the estimation of volatility in real option project valuation with the focus on renewable energy projects is presented. In the proposed model, the volatility of the project is the implied volatility obtained from the volatility surface of comparable firms for a certain valuation date and given debt-to-equity relation of a renewable energy project. In this proposal, the stochastic ‘alpha-beta-rho’ model is utilized to calibrate the volatility surface for real option valuation purposes. The results suggest that the developed approach fills the limitations presented by other alternatives employed for the estimation of volatility in projects valued through real options.

Finally, the overall conclusions are summarized at the end of this document. Moreover, some future research and practical implications are discussed in that section.

1.1. Introduction

In recent years, the study of the interrelation between financial markets has received increasing attention from academics and practitioners¹. This increased attention was a consequence of increasingly interconnected markets that, in turn, favor a stronger correlation between the prices of different assets, commodities, and financial instruments. In particular, the analysis of this topic has become a recurrent thematic in finance research since the seminal work of Engle et al. (1990) and the subsequent proposals related to using volatility transmission models based on the GARCH volatility model representation (i.e., Ito et al., 1992; Lin et al., 1994). In this regard, one of the most popular models in this strand of research corresponds to the dynamic conditional correlation model (DCC) originally proposed by Engle (2002). Within the extensive literature related to volatility transmission, special attention deserves the proposals for the specific relationship between energy and stock markets (i.e., Mensi et al., 2017; Zhang, 2017; Boako et al., 2020).

For emerging markets, a reduced number of works examined the volatility transmission between energy and equity markets. However, this topic is relevant for regulatory

organizations and investors, given the fast growth of these financial markets in the last decades, the increase in investment opportunities and capital inflows received from developed countries, and the vulnerability of these markets to global news and events that generate an environment of uncertainty and volatility (Raza et al., 2016). Additionally, it is worth mentioning that there exists evidence in the literature related to the change in the volatility transmission patterns during turbulent periods. (Baur and Lucey, 2010; Farid et al., 2021).

The COVID-19 pandemic can be viewed as a financial meltdown period\(^2\) and, thus, can be analyzed in this way to determine whether the volatility transmission between energy assets and stock markets changes. Along this line, recent proposals have focused on volatility transmission for this episode in developed economies (i.e., Farid et al., 2021; Baek and Lee; 2021; Mensi et al., 2021). However, a minimal number of studies have studied the links between energy and stock returns in emerging markets during the COVID-19 pandemic.

The motivation of this work lies in the following reasons. Firstly, the understanding of the links between the energy and equity markets provides useful information for investors. This is due to the fact that the agents that intervene in the stock markets have increased their interest in grasping the dynamics of the commodity markets by using this type of assets to design diversification, hedging or safe-haven strategies. This interest increases in turbulence periods (Ji et al., 2020; Shaikh, 2021; Urom et al., 2022). Consequently, the connectedness degree between commodities and equity markets have experienced an increase in the last

\(^2\) A financial meltdown can be defined as a day in which a financial market plunges by more than 5% (Wang et al., 2009, Molina et al., 2020). Therefore, the COVID-19 pandemic is considered as a financial meltdown given that the S&P 500 index dropped by more than 6% in a single day in three times during 2020 (-7.6% in 03/09/2020, -9.5% in 03/12/2020 and -12% in 03/16/2020) (Chen and Yeh, 2021).
years (Urom et al., 2022). In this scenario, analyzing the dynamics of volatility transmission between energy and equity markets is pertinent, since the outcome help increase the forecasting capacity of the dynamics of the stock markets, and thus the possibility of forecasting future crises and the appropriate design of market risk mitigation strategies (Elgammal et al., 2021; Gong et al., 2021).

Secondly, despite the ongrowing contributions examining the volatility transmission between different markets, the relationship between energy and equity volatility in emerging markets remains unexplored (Jebabli et al., 2022). This is particularly relevant given the investors’ attraction to commodities, a phenomenon known in literature as commodity financialization (Ding et al., 2021; Natoli, 2021); and the peculiarities that this type of markets present in terms of complexity and fragility. Furthermore, having a better understanding on the volatility spillovers mechanisms in these markets is useful for regulatory organizations to preserve financial stability (Cheng and Yang, 2021).

Thirdly, the consequences of the COVID-19 pandemic still remain in the financial markets and thus are being examined in the financial literature. In this sense, the works related to volatility transmission for this period suggest the presence of specific patterns of connectedness between markets that are the focus of research nowadays (Goodell, 2020; Laborda and Olmo, 2021; Li, 2021).

By using a DCC model, this work contributes to the financial literature in three ways. First, new evidence is found in relation to the changes in the volatility transmission pattern between energy and stock markets for emerging economies in turbulent periods. These volatility
patterns differ from periods of calm/bullish markets to those of turbulence/bearish markets, such as the subprime and COVID-19 crises. Second, using different frequency data enables support for the concept that the conclusions related to the direction of the volatility transmission are sensitive to the periodicity of the data. Finally, as is best known, this study represents one of the first attempts to study, exclusively in emerging markets, volatility transmission between energy and stock markets during the COVID-19 pandemic.

The remainder of this paper is structured as follows. Section 1.2, reviews the literature concerning volatility transmission. Section 1.3 describes the methodology employed to carry out the empirical analyses. The results of the paper are analyzed in Section 1.4, some practical and economic implications are discussed in Sections 1.5 and, finally, Section 1.6 concludes.

1.2. Related Literature

In recent decades, volatility transmission has become extremely relevant in the finance literature. Therefore, an extensive number of proposals have emerged mainly focused on the application of new models to multiple assets and markets. This section presents a non-exhaustive review; nevertheless, it aims to highlight the works that have a prominent impact on this line of research. The proposed classification of models is based on Cardona et al. (2017) and Farid et al. (2021).

1.2.1. Volatility transmission models

The work related to volatility transmission in finance faced a breaking point from the seminal paper of Engle et al. (1990) entitled, “Meteor showers or heat waves? Heteroskedastic intradaily volatility in the foreign exchange market”. The authors pointed out that heat waves
are associated with the notion that most sources of volatility for an asset are specific to its market. In contrast, meteor showers are related to cases in which a given asset’s volatility is influenced by the transmission of shocks that originate in other markets or regions.

Since the abovementioned pioneer work, most of the literature related to volatility transmission is based on extensions or applications of the ARCH model proposed by Engle (1982) and the GARCH model developed by Bollerslev (1986). However, other approaches have been used to analyze volatility transmission. In this regard, the works related to this topic are categorized into three categories: GARCH-based models, regime switch models, and stochastic volatility models.

1.2.1.1. **GARCH-based models**

Despite the fact that there are seminal works employing ARCH-GARCH family models (Bollerslev et al., 1988; Ito et al., 1992; Lin et al., 1994), two approaches dominate the literature related to volatility transmission in this strand: BEKK and DCC models. The BEKK model was originally proposed by Engle and Kroner (1995). The main advantage of this model is that it satisfies the restrictions on the correlations structure (Karali and Ramirez, 2014; Liu et al., 2017). This model has been applied for volatility transmission in different markets and assets (Darbar and Deb, 1997; Kearney and Patton, 2000).

On the other hand, the DCC approach was proposed by Engle (2000). This model guarantees “the positive definiteness of the conditional covariance matrices and the ability to describe time-varying conditional correlations and covariances in a parsimonious way” (Fiszeder et al., 2019, p. 69). These salient characteristics allow the DCC specification to be one of the
most popular alternatives to model volatility transmission between economic and financial variables and risk management (Fallahi et al.; 2014; Fiszeder et al., 2019; Shehzad et al., 2021).

1.2.1.2. **Regime switch models**

Regime switch models have the advantage of being able to detect the differences in the dynamics of volatility transmission for divergent periods (regimes), such as turbulence and calm periods. This type of models permits to integrate in the modeling nonlinearities related to high order moments such as asymmetry and kurtosis (Baele, 2005).

After the initial works (Lamoureux and Lastrapes, 1990; Hamilton and Susmel, 1994; Baele, 2002), which analyze volatility transmission by the use of Regime Switching GARCH models, some proposals have been applied to emerging markets (Edwards and Susmel, 2003; Chkili and Nguyen 2014) and introduced innovations such as the Markov switching models to the volatility transmission study (Chkili and Nguyen, 2014; BenSaïda et al., 2018).

1.2.1.3. **Stochastic volatility models**

The main advantage of this approach is the possibility of including dynamic spillover effects between markets and assets and the dynamic changing path of the spillover effect (Gong et al., 2021). In this regard, the literature has been focused on the analysis of volatility transmission in developed markets (Harvey et al., 1994; So et al., 1997; Vo, 2011; Ding and Vo, 2012) and its application in commodities and equity markets (Jebabli et al., 2014). Also, some extensions include Bayesian volatility approaches (Jacquier et al., 2004; Shi et al., 2020).
1.2.2. Volatility transmission between energy and stock markets

The volatility transmission between energy commodities and stock markets has aroused strong interest from academics and practitioners in recent years. This interest is explained by the drastic and continuous changes in energy assets prices and the high volatility experienced by global stock markets. The relationship between energy and stock prices is interesting but complex. Therefore, the adequate analysis of the volatility transmission between energy assets and stocks allows for better asset valuations and improvements in forecasts performed by market agents not only for investment planning but also for hedging purposes. On the other hand, the relationship between the dynamics of energy prices and stocks is misleading. Whereas in certain time intervals, energy and equity markets follow similar trends, there are other periods when these markets follow opposite trends (Arouri et al. 2011). For these reasons, research related to the volatility transmission between energy and stock markets is necessary in the financial literature.

Most of the literature related to volatility transmission between energy and equity markets have employed the Diebold and Yilmaz and the DCC models and its extensions to analyze volatility connectedness for developed markets. In some cases, these works include other commodities such as metal and gas prices to perform this goal (Mensi et al., 2017; Zhang, 2017; Zhang et al., 2017; Junttila et al., 2018; Al-Yahyaee et al., 2019; Kumar et al., 2019; Wang and Wang, 2019; Uddin et al., 2020; Farid et al., 2021). However, regarding emerging economies, the body of literature related to the volatility transmission between energy and stock markets is smaller and constitutes a topic to be explored, considering the peculiarities that characterize these types of markets and the growing interest of investors. In this scenery, most of the works have analyzed volatility connectedness for specific types of emerging
economies that include Gulf markets (Malik and Hammoudeh, 2007; Arouri et al., 2011), Asian or African emerging markets (Bouri, 2015; Ahmed and Huo, 2020; Boako et al., 2020), but there are studies for more general framework in these markets (Basher and Sadorsky, 2006; Maghyereh, 2006; Basher et al., 2012; Ajmi et al., 2014; Bouri et al., 2017; Mensi et al., 2018).

Overall, the literature on the study of volatility transmission between energy and equites in emerging markets have focused on developed markets using a particular model and a unique frequency data type, despite the relevance the frequency of the employed data in the analyses. Consequently, this study aims to contrast two hypotheses. Firstly, volatility transmission patterns, between stocks and energy in emerging markets are unidirectional, from energy to equity markets, in the COVID-19 period compared to other turbulent (sub-prime crises) and calm intervals. Secondly, the conclusions obtained from the application of volatility transmission models differs depending of the used data type.

1.3. Methodology

This work employs daily, weekly, and monthly data downloaded from Bloomberg for an energy and a stock market index for emerging markets between 2001 and 2021. To compare the performance of the volatility transmission model in different scenarios series were divided in three periods. The first scenario (calm period) covers the periods from January 2001 to November 2007, and between July 2009 and December 2019; the second interval, framed in the subprime crisis, began in December 2007 and ended in June 2009 and the third period, spannig from January 2020 to July 2021, corresponds to the COVID-19 pandemic.
The three phases of the sample were defined according to NBER Business Cycle expansion and contractions classification (NBER, 2021). According to this classification a recession starts at a peak of a business cycle and ends at the bottom of the cycle. In this regard, the period which comprised the subprime crisis occurred from December 2007 to June 2009. The contraction related to COVID-19 pandemic started in the beginning of 2020 (February 2020) and lasted until April 2020. In the case of our classification, we extended the COVID-19 crisis period until June 2021. This, as a consequence of the pandemic economic effects duration, the restrictions that were still present in social matters by the middle of that year, and also, to have a similar period in order to compare results with the subprime crisis period.

From the data, continuously compounded returns of the studied financial indices were computed as follows:

\[ r_t = 100 \log \left( \frac{P_t}{P_{t-1}} \right), \quad (1.1) \]

where \( P_t \) represents the index price at time \( t \).

The DCC model was employed to analyze the volatility transmission between energy and emerging stock markets. As discussed in the previous section, this model is the most commonly used specification to analyze volatility transmission. Particularly, the Nakatani and Teräsvirta (2009) DCC model is employed to analyze the volatility transmission between the energy and financial indices in emerging markets. This model allows to capture the time-varying volatility interdependence between different markets and was recently employed by Broto and Lamas (2020) to analyze the linkage between returns volatility and liquidity volatility using 10-year bond returns and five liquidity indicators. The model comprises two
components: the variance and the conditional correlation. The variance component is traditionally modeled by a GARCH(1,1). Then, if returns on the index $i$ ($r_{it}$) are Gaussian distributed with conditional mean $\mu_{it}$ and conditional variance $h_{it}$, the variance model can be modeled as follows:

$$r_{it} = \mu_{it} + \epsilon_{it},$$

(1.2)

$$\epsilon_{it} = h_{it}^{1/2} z_{i,t}, \ z_t \sim N(0, P_t),$$

(1.3)

$$h_t = a + A \epsilon_{t-1}^2 + B h_{t-1}.$$  

(1.4)

For the bivariate case ($i = 1, 2$), the conditional variance model in Eq. (1.4) can be expressed as follows:

$$\begin{bmatrix} h_{1t} \\ h_{2t} \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t-1}^2 \\ \epsilon_{2,t-1}^2 \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} h_{1,t-1} \\ h_{2,t-1} \end{bmatrix},$$

(1.5)

where $b_{ij}$ captures the volatility transmission from market $i$ to market $j$ and $a_{ij}$ captures the transmission of the shock (for $i \neq j$).

The second component of the model is the conditional correlation. The dynamic correlation $P_t$ is given by the DCC of Engle (2002) and Engle and Sheppard (2001):

$$P_t = (Q_t \odot I_2)^{-1/2} Q_t (Q_t \odot I_2)^{-1/2},$$

(1.6)

$$Q_t = (1 - \alpha - \beta)Q + \alpha z_{t-1} z'_{t-1} + \beta Q_{t-1},$$

(1.7)
where $Q$ is the sample covariance matrix of the innovations $z_t$, with $\alpha + \beta < 1$ and $\alpha, \beta > 0$, and $\odot$ represents the Hadamard product.

Subsequently, a set of diagnostic tests was executed to evaluate the performance of the mentioned model. First, the maximum log-likelihood value is computed. The multivariate version of the Ljung-Box test and the Hosking test were also calculated to examine the presence of autocorrelation in the time series. Moreover, Jarque–Bera’s and Mardia’s tests evaluated whether the analyzed data were normally distributed.

Finally, the value at risk (VaR) and expected shortfall (ES) were computed for an equally weighted portfolio, given that the DCC model with volatility transmission can also be employed to estimate portfolio risk measures in a dynamic setting. In this case, the dynamic portfolio variance is calculated using Eq. (1.8):

$$\hat{\sigma}_{p,t+1}^2 = \sum_{i=1}^{n} w_i w_j \hat{\sigma}_{ij,t+1},$$

where $w_i$ and $w_j$ are the weights assigned to index $i$ and $j$, respectively. The conditional covariance is denoted as $\hat{\sigma}_{ij,t+1}$ and is given by Eq. (1.9). Related to VaR and ES, the formulas used to compute these risk measures (assuming zero mean) are presented in Eqs. (1.10) and (1.11).

$$\hat{\sigma}_{ij,t+1} = \hat{\rho}_{ij,t+1} \hat{\sigma}_{l,t+1} \hat{\sigma}_{j,t+1},$$

where $\hat{\rho}_{ij,t+1}$ is the conditional correlation, and $\hat{\sigma}_{l,t+1}$ and $\hat{\sigma}_{j,t+1}$ are the conditional volatilities for index $i$ and $j$, respectively – all estimated in the DCC model with volatility transmission.
\[
\text{VaR}_{p,t+1}^\alpha = \hat{\sigma}_{p,t+1} \hat{q}_\alpha (r_{p,t+1}), \quad (1.10)
\]

\[
\text{ES}_{p,t+1}^\alpha = \hat{\sigma}_{p,t+1} \bar{E}_\alpha (r_{p,t+1}), \quad (1.11)
\]

where \(\hat{\sigma}_{p,t+1}\) is the portfolio conditional volatility assessed as the squared root of the portfolio variance given in Eq. (1.7). Moreover, \(\hat{q}_\alpha\) is the \(\alpha\)-quantile of a normal distribution and \(\bar{E}_\alpha = \frac{\phi(\psi^{-1}(\alpha))}{\alpha}\) (\(\alpha = 0.025\) is used in the empirical application).

1.4. Empirical analysis

1.4.1. Data

The analyzed data comprises daily, weekly, and monthly prices from the MSCI Emerging Markets Energy Sector Index (Energy Index) and the MSCI Emerging Markets Financials Index (Financial Index) taken from the Bloomberg platform. The energy index comprises 57 securities of companies from 24 emerging markets countries classified in the energy sector according to the Global Industry Classification Standard list. The employed Financial Index includes 239 securities from 24 mid and large emerging markets companies. Most of the companies incorporated in the indices are from India, Brazil, China, Saudi Arabia, Taiwan and Thailand. Data from the two indices are available from January 1, 2001. The sample period ranges from December 29, 2000, to July 30, 2021, for a total of 5,371 daily prices, 1,075 weekly prices, and 248 monthly prices. Table 1.1 displays the descriptive statistics for continuously compounded returns of these series, as defined in the previous section.
Table 1.1 Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Daily</th>
<th>Weekly</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Energy Index</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.036</td>
<td>0.181</td>
<td>0.789</td>
</tr>
<tr>
<td>Median</td>
<td>0.080</td>
<td>0.428</td>
<td>1.299</td>
</tr>
<tr>
<td>Std. deviation</td>
<td>1.549</td>
<td>3.877</td>
<td>8.030</td>
</tr>
<tr>
<td>Skewness</td>
<td>−0.577</td>
<td>−0.710</td>
<td>−0.787</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>11.894</td>
<td>7.625</td>
<td>3.281</td>
</tr>
<tr>
<td>Min</td>
<td>−14.694</td>
<td>−28.517</td>
<td>−42.398</td>
</tr>
<tr>
<td>Max</td>
<td>16.079</td>
<td>25.775</td>
<td>23.018</td>
</tr>
<tr>
<td><strong>Financial Index</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.030</td>
<td>0.151</td>
<td>0.658</td>
</tr>
<tr>
<td>Median</td>
<td>0.073</td>
<td>0.353</td>
<td>1.098</td>
</tr>
<tr>
<td>Std. deviation</td>
<td>1.261</td>
<td>3.192</td>
<td>6.989</td>
</tr>
<tr>
<td>Skewness</td>
<td>−0.420</td>
<td>−0.791</td>
<td>−0.863</td>
</tr>
<tr>
<td>Excess Kurtosis</td>
<td>7.108</td>
<td>5.543</td>
<td>2.846</td>
</tr>
<tr>
<td>Min</td>
<td>−9.184</td>
<td>−23.971</td>
<td>−35.326</td>
</tr>
<tr>
<td>Max</td>
<td>10.153</td>
<td>15.210</td>
<td>18.316</td>
</tr>
</tbody>
</table>

Table 1.1 summarizes the descriptive statistics for the logarithmic returns of the MSCI Emerging Markets Energy Sector Index (Energy Index) and the MSCI Emerging Markets Financials Index (Financial Index). The sample period ranges from December 29, 2000, to July 30, 2021, for a total of 5,371 daily prices, 1,075 weekly prices, and 248 monthly prices.

Table 1.1 shows the common stylized facts for daily financial asset returns, i.e., central tendency measures (mean and median) close to zero, and leptokurtic and negative skewed empirical distributions. The latter feature implies more extreme values at the left tail of the negative returns. Moreover, the “aggregational Gaussianity” property holds (i.e., excess kurtosis decreases with data aggregation); that is, the empirical distribution converges to the
normal as the data frequency declines. In addition, the energy index is more volatile than the financial index for emerging markets. These empirical characteristics are corroborated in Figures 1.1 and 1.2, which depict prices and returns for the indices at the three frequencies.

**Figure 1.1** Prices of energy and financial indexes
Figure 1.2 Log-returns of energy and financial indexes

1.4.2. Transmission effects at different frequencies

Table II summarizes the results of the estimation of the model in Eqs. (1.1)-(1.6) on a daily, weekly and monthly basis. Firstly, strong own GARCH effects exist for the energy index since $a_{11}$ and $b_{11}$ are significant for all analyzed periods (except $a_{11}$ at the monthly frequency). Nevertheless, own GARCH effects are not detected for the financial index beyond the daily frequency ($a_{11}$ and $b_{22}$). Therefore, although a strong own-dependence of volatility exists in the energy index for all frequencies, this evidence is not supported by lower than daily frequency data in the financial index. Secondly, transmission effects between energy and financial markets are captured by the ‘cross persistence volatility’ parameters $b_{ij}$ for $i=1, 2, i \neq j$ (i.e. direct transmission of shocks for both indices is not detected, since $a_{21}$ and $a_{12}$ are not significant). The estimates reveal a bidirectional volatility transmission between the energy and financial indices for daily frequency. However, volatility transmission occurs only from the financial to the energy index for weekly and monthly data. Furthermore, whilst
the propagation of energy markets to financial markets \((b_{12})\) seems to vanish beyond the daily frequency, the intensity of the propagation of financial market instability to energy markets \((b_{21})\) tends to increase with the frequency of the data.

These results exhibit relevant economic consequences. Firstly, in the case of investors, knowing that the transmission between energy and equity emerging markets is bidirectional suggests different ways to establish hedging strategies between these two assets. This is because adverse movements in one of the markets will generate adverse consequences in the other. Therefore, the investment and hedging strategies adopted by these agents have to be adapted to this relationship. Secondly, in the case of regulatory bodies, anticipating potential declines in emerging energy and equity markets is crucial for financial stability in fragile markets such as emerging ones. In sum, our finding of bidirectional transmission of volatility makes it possible to anticipate downturns in the stock and energy markets.

**Table 1.2** Results of volatility transmission for total period

<table>
<thead>
<tr>
<th></th>
<th>Daily</th>
<th>Weekly</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>(A)</td>
<td>0.036 (14.304)</td>
<td>0.046 (5.371)</td>
<td>0.129 (6.337)</td>
</tr>
<tr>
<td>(B)</td>
<td>0.956 (270.850)</td>
<td>0.938 (62.933)</td>
<td>0.080 (0.217)</td>
</tr>
<tr>
<td>(a_{10})</td>
<td>0.011 (0.279)</td>
<td>0.405 (0.409)</td>
<td>11.639 (1.364)</td>
</tr>
<tr>
<td>(a_{20})</td>
<td>0.029 (0.771)</td>
<td>0.669 (9.580)</td>
<td>5.367 (32.303)</td>
</tr>
<tr>
<td>(a_{11})</td>
<td>0.104 (3.335)</td>
<td>0.102 (2.254)</td>
<td>0.161 (0.940)</td>
</tr>
<tr>
<td>(a_{21})</td>
<td>0.036 (0.073)</td>
<td>0.091 (0.056)</td>
<td>0.179 (0.107)</td>
</tr>
<tr>
<td>(a_{12})</td>
<td>0.005 (0.007)</td>
<td>0.000 (0.000)</td>
<td>0.101 (0.049)</td>
</tr>
<tr>
<td>(a_{22})</td>
<td>0.043 (2.946)</td>
<td>0.014 (0.022)</td>
<td>0.004 (0.000)</td>
</tr>
<tr>
<td>(b_{11})</td>
<td>0.237 (13.724)</td>
<td>0.476 (10.515)</td>
<td>0.425 (3.557)</td>
</tr>
</tbody>
</table>
Table 1.2 shows the parameters obtained from the DCC model for the total analyzed period. Results corresponding to \( t \)-Statistics are presented in parenthesis. Significant parameters (volatility transmission) at 5% confidence are highlighted in boldface, where \( b_{ij} \) represents volatility transmission from market \( i \) to market \( j \), and 1 stands for Energy Index and 2 for Financial Index.

Figure 1.3 depicts the fitted conditional volatilities. This picture illustrates the high volatility of both indices, especially during the subprime crisis (2008), the COVID-19 crisis, and the negative West Texas Intermediate (WTI) price effect (2020).

**Figure 1.3** Fitted conditional volatilities

| \( b_{21} \) | 0.121 (5.616) | 0.327 (9.003) | 0.366 (3.607) |
| \( b_{12} \) | 0.938 (3.221) | 0.555 (0.616) | 0.217 (0.163) |
| \( b_{22} \) | 0.710 (1.675) | 0.323 (0.235) | 0.159 (0.098) |

Fitted dynamic correlations are provided in Figure 1.4. Strong (positive) correlations between the energy and financial indices are noted even in ‘relatively’ calm periods. Minimum daily
and weekly correlations are presented in 2001 and 2008, whereas the minimum monthly correlation was noted in 2008. However, this (monthly) correlation is approximately 0.85.

**Figure 1.4** Fitted dynamic conditional correlations

Table 1.3 reports the models’ diagnostic tests. The maximum log-likelihood value is presented for monthly data (−1,513.54), and the Ljung-Box (LB) test fails to reject the null hypothesis of the absence of autocorrelation primarily in the weekly and monthly frequencies, which is confirmed by its multivariate version, the Hosking test. However, for daily data, the LB and Hosking tests reject the absence of autocorrelation. The Hosking test also fails to reject the null hypothesis for weekly data. The Jarque–Bera (JB) test rejects the normality assumption of the residuals for the three analyzed frequencies (daily, weekly, and monthly). Mardia’s tests of multivariate normal are carried out for the three cases, and the results show that the data are not multivariate normal, as expected.
Table 1.3 Diagnostic tests

<table>
<thead>
<tr>
<th></th>
<th>Daily</th>
<th>Weekly</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log-likelihood</td>
<td>−14271.07</td>
<td>−4925.07</td>
<td>−1513.54</td>
</tr>
<tr>
<td>Ljung–Box (Energy)</td>
<td>226.721 (0.000)</td>
<td>14.487 (0.013)</td>
<td>7.382 (0.194)</td>
</tr>
<tr>
<td>Ljung–Box (Financial)</td>
<td>212.197 (0.000)</td>
<td>9.667 (0.085)</td>
<td>3.658 (0.599)</td>
</tr>
<tr>
<td>Hosking (Lag 5)</td>
<td>226.637 (0.000)</td>
<td>33.264 (0.031)</td>
<td>23.851 (0.249)</td>
</tr>
<tr>
<td>Hosking (Lag 10)</td>
<td>237.516 (0.000)</td>
<td>44.035 (0.305)</td>
<td>43.889 (0.310)</td>
</tr>
<tr>
<td>Jarque–Bera (Energy)</td>
<td>469.947 (0.000)</td>
<td>247.457 (0.000)</td>
<td>6.318 (0.042)</td>
</tr>
<tr>
<td>Jarque–Bera (Financial)</td>
<td>317.023 (0.000)</td>
<td>128.261 (0.000)</td>
<td>9.732 (0.008)</td>
</tr>
<tr>
<td>Mardia’s Skewness Test</td>
<td>147.495 (0.000)</td>
<td>108.857 (0.000)</td>
<td>11.018 (0.026)</td>
</tr>
<tr>
<td>Mardia’s Kurtosis Test</td>
<td>32.147 (0.000)</td>
<td>17.641 (0.000)</td>
<td>1.858 (0.063)</td>
</tr>
</tbody>
</table>

Table 1.3 shows the results obtained from diagnostic tests for the total sample. P-values are presented in parenthesis. LB test is performed for 5 lags.

1.4.3. Sub-prime crisis and COVID-19 pandemic effects

In what follows, the volatility transmission during the recent global financial (also called the Great Recession) crisis (GFC) and the ongoing COVID-19 crisis is analyzed, and the results are employed to estimate portfolio risk measures. The starting date of the GFC sample is December 2007, and the end is considered to be June 2009, according to the NBER. From this event, 413 daily prices for each period are employed to obtain the results presented in Table 1.4. The COVID-19 period ranges from January 2020 to July 2021. Weekly and monthly basis are not included because of the few data points for the period under analysis. As for the total sample, transmission effects between the energy index and the financial index are detected in the volatility persistence parameters ($b_{ij}$ for $i=1, 2, i \neq j$), but direct shocks ($a_{ij}$ for $i=1, 2, i \neq j$) do not seem to have a significant impact.
The results show that volatility transmission occurs from the financial index to the energy index \((b_{21})\) during the Great Recession period, but not during COVID-19 crisis. On the contrary, there exists evidence of transmission from the energy index to the financial index, but not the on reverse direction, during the global pandemic period. This finding reflects the different origin of the crises, in GFC instability contagion arises from financial markets, whilst the COVID-19 crisis is an exogenous shock directly impacting to real production sector and the prices of energy inputs. It is remarkable the negative WTI prices during the lockdown phases, but also other factors as the changes in global oil demand and supply, storage risk, geopolitical reasons, OPEC decisions, and futures market dynamics (Sadorsky, 2004; Basher and Saddorsky, 2006; Corbet et al., 2020).

These results are in line with previous works related to this topic. Transmission reversal effects has been observed in earlier contributions with different assets, markets and time intervals (Wang and Wu, 2018; Tu and Xue, 2019). In fact, there is evidence in the literature regarding interruptions or reversals in volatility transmission effects through time, especially in the case of commodities where volatility transmission commonalities seem to be time and event dependent (Antonakakis and Kizys, 2015). Particularly, various sectors may evince this type of effects during market downturns or financial crisis (Liu et al. 2021). In consequence, volatility transmission between markets or sectors are considered as dynamic relationships that changes in direction and intensity over time. (Diebold and Yilmaz, 2012).

The explanations to these volatility linkage direction changes are still an open question. Nevertheless, in most of the related works (Nazlioglu et al., 2015; Nazlioglu et al., 2015; Wang and Wu, 2018), these shifts are explained by a change in the sector where the crisis
originates. For instance, Nazlioglu et al. (2015), explains a change in the volatility transmission direction between oil and equity markets arguing that “it is clear that the direction of volatility spillover between oil and financial markets is reversed after the crisis. Before the crisis, financial markets were led by risk in oil markets; however, after the crisis financial markets seem to become dominant” (Nazlioglu et al., 2015, p. 283). It seems to be the case of our results, where, as previously mentioned, the shift in the volatility transmission direction between subprime crisis and COVID-19 pandemic could be explained by the different causes of the crisis.

Interestingly, Roubini and Mihm (2010) state that “History confirms that [financial] crises are much like pandemics: they begin with the outbreak of a disease that the spreads, radiating outward.” For the GFC case, the beginning was the collapse of subprime mortgages in the U.S. real estate market. Then, the global financial markets were affected through financial innovation (i.e., CDOs financial instruments), and then outweighing the rest of the economy. Thus, in our study, we conjecture that the expected origin of the volatility transmission was the financial industry in emerging markets. On the other hand, the COVID-19 is a health crisis originated in China and rapidly spread to the rest of the world regions. Since the direct consequence of this type of crisis is mortality and respiratory affections, quarantines and lockdowns were the initial solution until a medicine was developed to mitigate the effects of the virus, causing global manufacturing and supply channels disruptions (Chen and Yeh, 2021). Therefore, as suggested by our results, the volatility transmission is originated from the non-financial industry, in particular, from the energy sector.
These conclusions are in line with previous studies which highlight that the GFC started in the financial markets with the collapse of major banks to gradually spread to the rest of the world affecting real economy with a time delay (demand side); while the COVID-19 pandemic crisis affected the real sector and supply of production (the supply side) as a consequence of the disruption in economic activity and supply chain, to posteriorly, impact (rapidly but shortly) the financial sphere (Jebabli et al., 2022; Bouri et al., 2021).

Moreover, there are interesting lessons to be learned from these events. Firstly, not all financial crises originate in a single sector. This suggests the need for regulatory agencies to monitor permanently economic sectors to anticipate this type of events and formulate the appropriate policies to mitigate its possible effects in accordance with the peculiarities of the sector in which these phenomena occur. Secondly, Given the particular dynamics of the transmission of volatility according to the sector in which financial crises occur, there is no single recipe to mitigate the associated effects on financial markets (Cortes et al., 2022). The evaluation of each case in terms of policies aimed at guaranteeing market stability must be carried out in a careful and particular manner, according to the uniqueness of each situation.

**Table 1.4** Volatility transmission for global financial crisis and COVID-19 on a daily basis

<table>
<thead>
<tr>
<th></th>
<th>GFC</th>
<th>COVID-19</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>0.059 (3.925)</td>
<td>0.069 (3.820)</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.915 (43.982)</td>
<td>0.213 (0.436)</td>
</tr>
<tr>
<td>$a_{10}$</td>
<td>0.161 (0.562)</td>
<td>0.101 (0.502)</td>
</tr>
<tr>
<td>$a_{20}$</td>
<td>0.108 (1.323)</td>
<td>0.370 (0.202)</td>
</tr>
<tr>
<td>$a_{11}$</td>
<td>0.142 (1.275)</td>
<td>0.399 (3.390)</td>
</tr>
<tr>
<td>$a_{21}$</td>
<td>0.110 (0.037)</td>
<td>0.059 (0.179)</td>
</tr>
<tr>
<td></td>
<td>a_{12}</td>
<td>a_{22}</td>
</tr>
<tr>
<td>------</td>
<td>---------</td>
<td>---------</td>
</tr>
<tr>
<td></td>
<td>0.031 (0.007)</td>
<td>0.048 (0.072)</td>
</tr>
</tbody>
</table>

Table 1.4 shows the parameters obtained from the DCC model for Global Financial Crisis and COVID-19 periods (turbulence periods). Results corresponding to t-Statistics are presented in parenthesis. Significant parameters (volatility transmission) at 5% confidence are highlighted in boldface, where b_{ij} represents volatility transmission from market i to market j, and 1 stands for Energy Index and 2 for Financial Index.

### 1.4.4. Risk measures with contagion effects

The DCC model with volatility transmission can also be employed to estimate portfolio risk measures in a dynamic setting. With this purpose, the conditional VaR and ES are computed using Eqs. (8), (9), (10), and (11) from the methodology section. In this application, an equally weighted portfolio formed by the energy and financial indices (i.e., \(w_1 = w_2 = 0.5\)) is assumed. VaR is estimated at 99%, and ES is estimated at 97.5% on a daily basis according to the Basel Committee’s consultative document on the Fundamental Review of the Trading Book.

Figure 1.5 depicts the estimated daily ES for the individual energy index (blue line), individual financial index (green line), and the portfolio formed by equal investments in both indices (black line) for the GFC period. Figure 6 depicts this ES for the COVID-19 period. The pictures illustrate how expected losses for the energy index are higher than for the financial index, and the portfolio’s expected losses are between both series for both cases. This result is expected because daily volatility and excess kurtosis for the energy index is
higher than for the financial index (see Table 1.1). Similar results are found for 99%-VaR because the ratio 97.5%-ES/99%-VaR is close to one in the Gaussian case.

**Figure 1.5** 97.5%-ES for (equally weighted) portfolio of energy and financial indexes for GFC
Figure 1.6. 97.5%-ES for (equally weighted) portfolio of energy and financial indexes for COVID-19

As observed, the estimated risk measure decayed faster after the global pandemic effect than after the GFC impact. Similar behavior is observed in VIX index prices for the same periods – an interesting aspect to be analyzed in future research with a short noise model for financial assets (e.g., Altmann et al., 2008).
1.4.5. Further analysis

In order to confirm the results obtained in Section 1.4.3., we performed a similar volatility transmission analysis for ten emerging countries separately. For the subprime crisis, the results presented in Table 1.5 (panel A) confirm that, for the analyzed emerging countries, there is evidence of volatility transmission from financial to energy markets in eight out of ten markets. In this crisis period, the obtained results support volatility transmission effects from energy to financial markets in two countries (Kuwait and United Arab Emirates). The latter confirms that subprime crisis was originated from the financial markets and, subsequently, impacted the energy emerging markets.

Whereas for the COVID-19 pandemic period, the volatility transmission patterns are different (Table 1.5 Panel B). In this case, there are insights of changes in the direction of volatility transmission between energy and financial markets for emerging countries. Particularly, in six out of ten analyzed countries, volatility transmission effects from energy to financial markets become significant. Even when most of the studied markets preserve equity-to-energy volatility transmission effects, it is interesting than in the majority of the cases energy-to-equity effects emerge. These results are in line with previous findings, confirming that there is a shift in the volatility transmission direction and/or dynamics between energy and equity emerging markets.

When reviewing the cases of the analyzed emerging markets, it is possible to observe that the GFC globally affected the vast majority of the studied countries generating significant

---

3 The indices employed for each market in this Section can be found in appendix A. Data were downloaded from Bloomberg database.
equity-to-energy volatility transmission effects. However, for the COVID-19 financial crisis, most of the countries that present significant energy-to-market effects correspond to markets whose national production is concentrated in oil. This is the case of Saudi Arabia, Kuwait, United Arab Emirates and Mexico.

This is reasonable considering the disruption in economic activity and supply chain originated in real sectors production during COVID-19 pandemic which in turn caused falls in the demand and prices of energy assets, including oil, globally. Between 2019 and 2020, oil consumption reduced by 10%, average oil prices dropped by 33% and road traffic decreased by 50%-75% (Ben Hassen, 2022). The above caused a higher impact of the COVID-19 financial crises in Oil exporting emerging markets (Steffen et al., 2020; Priya et al., 2021) that could have triggered a stronger volatility transmission effect from this sector to equity in these countries.

For future research, it would be interesting to examine the volatility transmission effects with special emphasis in the COVID-19 pandemic period due to the fact that in several cases there is evidence of bidirectional volatility transmission effects.

**Table 1.5 Volatility transmission for emerging markets during financial crisis and COVID-19 on a daily basis**

<table>
<thead>
<tr>
<th></th>
<th>Panel A. GFC</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>α</strong></td>
<td>Brazil</td>
</tr>
<tr>
<td></td>
<td>0 (0)</td>
</tr>
<tr>
<td><strong>β</strong></td>
<td>0.14 (0)</td>
</tr>
<tr>
<td><strong>α_{ii}</strong></td>
<td>0 (0)</td>
</tr>
<tr>
<td><strong>α_{ii}</strong></td>
<td>1.91 (34.57)</td>
</tr>
<tr>
<td><strong>α_{ii}</strong></td>
<td>0.15 (2.24)</td>
</tr>
</tbody>
</table>
Table 1.5 shows the parameters obtained from the DCC model for Global Financial Crisis and COVID-19 periods (turbulence periods) for ten emerging markets. Results corresponding to t-Statistics are presented in parenthesis. Significant parameters (volatility transmission) at 5% confidence are highlighted in boldface, where $b_{ij}$ represents volatility transmission from market $i$ to market $j$, and 1 stands for Energy Index and 2 for Financial Index.

### 1.5. Practical and economic implications.

Our results present relevant insights for regulators, policy makers and investors considering their relevant economic implications. To get a better understanding of volatility spillovers and the direction of the transmission effects is crucial for regulators and policy makers as an early warning signal by monitoring of the sectors in which financial crisis emerge. The foregoing is especially relevant for emerging markets considering their fragility and financial instability. The design of policies should be aimed at guaranteeing the stability of the economic system considering the impact that crises originated in the energy markets (equity markets) may influence on the equity markets (energy markets), as analyzed in our paper.
The obtained results are also pertinent for investors given that these agents are continuously monitoring volatility linkages between different markets (Kumar, 2017). The shift in the volatility transmission direction and pattern evidenced in our exercise could suggest changes in their hedging and investing strategies. As a consequence, in the case of the subprime crisis (COVID-19 pandemic), investors should have taken into account that energy markets (equity markets) turbulences are affected by equity markets (energy markets) shocks to design their cross hedging and investing strategies.

Furthermore, an adequate understanding of the volatility transmission dynamics between emerging energy and financial markets can be employed to better estimate financial market risk such as VaR and ES risk measures and for portfolio managers when assessing the variance-covariance matrix.

1.6. Conclusions

Few studies were devoted to an analysis of the co-movements between energy and financial markets for emerging economies. Our study fills this gap with particular emphasis on testing the volatility transmission during the COVID-19 pandemic period compared to other high instability periods and highlighting the impact of the data frequency.

For this purpose, a DCC model that allows for dynamics in the first and second moments, as well as volatility spillovers between both indices, is employed. For a sample ranged from January 2001 to July 2021, the results reveal bidirectional transmission between the energy and financial indices on a daily basis but only found transmission from the financial to the energy indices on weekly and monthly frequencies. Furthermore, volatility persistence of this
transmission from financial markets seems to increase with the data frequency, maybe due to the prolonged impact of the Great Recession.

On a daily basis, our results show clear evidence on the volatility transmission from the financial index to the energy Index for the sample from December 2007 to June 2009, which confirm the GFC contagion. In contrast, volatility transmission occurred from the energy to the financial index during the ongoing COVID-19 crisis – from January 2020 to July 2021. It is remarkable the fact that the reverse effects are insignificant, which indicates the different source and transmission channels in both periods. Moreover, these results constitute empirical evidence about the peculiarities that characterize emerging markets. This, considering that previous studies (Elgammal et al. 2021) highlighted the presence of reciprocal shock spillovers during COVID-19 pandemic.

Moreover, fitted correlations and volatilities are employed to estimate individual and portfolio conditional risk measures, such as VaR and ES. The latter is particularly important for regulators and practitioners because recent regulation suggests switching from 99%-VaR to 97.5%-ES.

The results contribute to the literature on volatility transmission in three ways. First, a change in the dynamics of volatility transmission between energy and stock emerging markets during the COVID-19 period is identified for emerging market indices. This new pattern is different from periods of calm and from other turbulence intervals, such as the subprime crisis period. This finding could be explained by a combination of factors, including global oil demand and supply changes, storage risk, geopolitical reasons, OPEC decisions, and futures market dynamics (Sadorsky, 2004; Basher and Saddorsky, 2006; Corbet et al., 2020). Second, empirical findings support that the conclusions obtained from the application of volatility
transmission models in emerging markets can be affected by the frequency of the employed data. This finding is interesting considering that most of the studies on this topic employ a single type of frequency data. Third, new evidence on volatility transmission patterns was found for emerging markets, which is relevant considering that most studies in this field focused on developed economies.

Future research will focus on the analysis of volatility transmission and conditional correlation with an extension of the DCC model, drawing innovations from a heavy-tailed distribution to allow for a more efficient estimation of the dynamics and more accurate risk measures.

The results of this work are satisfactory in terms of a general understanding of the volatility transmission mechanisms between emerging energy and equity markets. Future research may be focused on the application of the Diebold and Yilmaz (2012) spillover index, which advantages are in terms of the magnitude of volatility transmission, asymmetry effects and the volatility transmission dynamics (Mensi et al., 2021; Naeem et al., 2021; Hung, 2022).

1.7. Appendix

Appendix A. Emerging market indices.

<table>
<thead>
<tr>
<th>Country</th>
<th>Index Bloomberg ticker</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brazil</td>
<td>IBOV index</td>
</tr>
<tr>
<td>Turkey</td>
<td>XU100 index</td>
</tr>
<tr>
<td>Country</td>
<td>Index</td>
</tr>
<tr>
<td>-----------</td>
<td>------------</td>
</tr>
<tr>
<td>India</td>
<td>SENSEX index</td>
</tr>
<tr>
<td>Mexico</td>
<td>MEXBOL index</td>
</tr>
<tr>
<td>Taiwan</td>
<td>TWSE index</td>
</tr>
<tr>
<td>Malaysia</td>
<td>FBMKLCI index</td>
</tr>
<tr>
<td>Russia</td>
<td>IMOEX index</td>
</tr>
<tr>
<td>S. Arabia</td>
<td>SASEIDX index</td>
</tr>
<tr>
<td>Kuwait</td>
<td>KWSEMM index</td>
</tr>
<tr>
<td>UAE</td>
<td>ADSMI index</td>
</tr>
</tbody>
</table>
2.1. Introduction

The study of volatility spillovers effects between assets/markets has recently become one of the most interesting research fields in finance. This is due to factors that include globalization and the subsequent increased interconnectedness of financial markets, but also the rise in volatility and uncertainty in global markets. This has captured the attention of academics and practitioners in understanding the dynamics of volatility spillovers in order to design appropriate investment and hedging strategies. In this context, different proposals have been developed, the most prominent framed within the Dynamic Conditional Correlation (DCC) model, the Baba, Engle, Kraft and Kroner (BEKK) model; the regime switch models and the stochastic volatility models. Nevertheless, the presence of asymmetries and the dynamic behavior of the volatility spillovers have motivated the application of further approaches. In this line, the Diebold and Yilmaz (2009, 2012, 2014) propose a VAR-type methodology to decompose asymmetric and time-varying spillover effects. This model has received increasing attention in the recent years, although most of the works related to the study of volatility spillovers have mainly focused on developed markets and traditional assets such as equity or bonds. Yet, the study of volatility spillovers between Emerging Markets, Bitcoin and commodities has gained relevance and it is pertinent considering the following reasons.

Firstly, there is an increasing interest from investors in commodities to design diversification, hedging or safe-haven strategies, phenomenon known in literature as commodity financialization (Ding et al., 2021; Natoli, 2021), which seems to be increased in turbulent...
periods (Ji et al., 2020; Shaikh, 2021; Urom et al., 2022). In consequence, the relationship between commodities and equity markets has experienced an increment in recent years (Urom et al., 2022).

Secondly, according to Jebabli et al. (2022), the volatility spillovers between commodities, Bitcoin and Emerging Markets remain relatively unexplored despite the particularities that these types of markets have in terms of complexity and fragility. Therefore, understanding volatility spillovers dynamics in this type of markets could constitute a useful tool for regulatory entities to preserve financial stability (Cheng and Yang, 2021).

Finally, the consequences of recent turbulent periods on volatility spillovers between commodities, Bitcoin and Emerging Markets, such as the COVID-19 pandemic, requires further studies analyzing these episodes in view of the related literature, which suggests the presence of specific volatility spillovers patterns in these time intervals (Goodell, 2020; Laborda and Olmo, 2021; Li, 2021). Particularly, recent works imply interruptions or reversals in volatility spillovers effects in the case of commodities, where volatility spillovers dynamics seem to be time and event dependent, specially, during financial crises (Antonakakis and Kizys, 2015; Liu et al. 2021).

Our work fills this gap by analyzing the volatility spillovers between commodities, Bitcoin and Emerging Markets are examined through the Diebold and Yilmaz (2012) approach. Even more, we forecast the volatility spillovers between these markets by the use of econometric and machine learning techniques. This out-of-sample analysis provides investors and regulators with valuable insights about future financial crises, since the presence volatility spillovers are associated with high-instability periods in financial markets (Diebold and Yilmaz, 2012; Laborda and Olmo; 2021).
Our results contribute to literature in the following ways. Firstly, this work is an original attempt to analyze volatility spillovers between commodities, Bitcoin and Emerging Markets from a dynamic perspective. Secondly, we propose the forecasting of the Total Volatility Spillover (TVS) measure (Diebold and Yılmaz, 2012) to examine the embedded information in this variable. Thirdly, the proposed forecasting is estimated by the use of econometric and machine learning techniques to evaluate the capacity of these approaches to forecast financial variables.

The remainder of this paper is structured as follows. Section 2.2 reviews some related literature concerning volatility spillovers and volatility spillovers forecasting. Section 2.3 describes the methodology employed to perform the empirical analyses. The results of the paper are analyzed in Section 2.4, and, finally, Section 2.5 concludes.

2.2. Related literature

Since the seminal work of Engle et al. (1990) decomposed volatility sources of foreign exchange intradaily volatility into idiosyncratic variability (heat waves) and shocks received from other markets (meteor showers), various proposals have emerged in literature analyzing volatility transmission between different types of markets and assets. This is explained by the importance of (i) volatility linkages in terms of market risk, considering that turbulences in a specific market can be originated by shocks in other markets; (ii) market risk contagion, given that volatility connectedness usually incorporate information about cross market risk contagion mechanisms (Cheng and Yang, 2021); and (iii) financial stability, considering that the understanding of volatility transmission dynamics can be used to anticipate possible market stress periods.
Some of the approaches that have received more attention are the models based on the multivariate ARCH-GARCH family specifications. In this line, the DCC and BEKK models are the most popular methods for studying this type of relationship between markets. The BEKK model was originally proposed by Engle and Kroner (1995). The main advantage of this approach lies in its appropriate correlation matrix structure (Karali and Ramirez, 2014; Liu et al., 2017). This class of multivariate GARCH models have been useful for the analysis of volatility transmission for different markets which include stock markets (Cardona et al., 2017; Vo and Ellis, 2018; de Oliveira et al., 2018; Yu et al., 2020), commodities (Jin et al., 2012; Thenmozhi and Maurya, 2020) and innovative assets such as cryptocurrencies (Katsiampa et al. 2019). However, it has been shown that the BEKK model can yield misleading conditional correlations forecasts (de Almeida et al., 2018).

On the other hand, the DCC model, proposed by Engle (2002), emerges as a feasible alternative to model volatility transmission. This approach guarantees “the positive definiteness of the conditional covariance matrices and the ability to parsimoniously describe time-varying conditional correlations and covariances in a way” (Fiszeder et al., 2019, p. 69). In consequence, several works have employed this approach and its extensions to analyze volatility connectedness (Fallahi et al; 2014; Yu et al., 2015; Tsuji, 2018; Hou et al., 2019; Fiszeder et al., 2019; Shehzad et al., 2021). Nevertheless, this model presents limitations, since asymmetries in conditional variances, covariances, and correlations are not considered (Samitas and Tsakalos, 2013). Furthermore, the DCC model does not capture changing volatility transmission effects, which can be significant in some periods.

Other models have been examined in literature and some of the most appealing proposals include regime switch models (Lamoureux and Lastrapes, 1990; Hamilton and Susmel, 1994;
Baele, 2002; Khalifa et al., 2014; Chkili and Nguyen, 2014; BenSaïda et al., 2018), which examine volatility connectedness effects according to regimes (time intervals) allowing the detection of particularities in volatility transmission for certain periods in the economy. Finally, another strand of the literature has focused on the stochastic volatility models (Harvey et al., 1994; Harvey and Shepard, 1996; Vo, 2011; Ding and Vo, 2012, Shi et al., 2020), which are able to capture dynamic changing features of the spillover effects (Gong et al., 2021).

2.2.1. The Dielbold and Yilmaz Spillovers framework

Given the shortcomings of previous models, Diebold and Yilmaz (2009, 2012, 2014), propose a new measure to analyze volatility spillovers between assets or markets. This approach is based on the forecast error variance decompositions from vector autoregressions (see e.g., Diebold and Yilmaz, 2012). One of the advantages of this model is the possibility of capturing the dynamic features of the varying volatility spillovers (including trends and bursts in spillovers). Moreover, the asymmetric effects of the volatility spillovers between assets, sectors or markets can be modeled. It is also possible to obtain the net spillover effect when there is evidence of bidirectional volatility effects. As a result, this proposal is characterized by being simple and intuitive (Diebold and Yilmaz, 2009) and can be used to measure connectedness at a variety of levels that includes assets, firms, sectors, markets, countries, etc. (Diebold and Yilmaz, 2014).

For all these reasons the Diebold and Yilmaz methodology have gained interest by academics and practitioners, which have employed this approach, not only to model volatility spillovers, but also to measure connectedness for other type of variables. The academic contributions related to volatility spillovers have been mainly focused on developed markets which include
studies related to volatility spillovers between sectors of the U.S. and European economies, financial institutions and financial assets (Diebold and Yilmaz, 2014; Alter and Beyer, 2014; Diebold and Yilmaz, 2015; Barunik et al., 2016, Tiwari et al., 2018).

Some recent applications have focused on volatility spillovers in energy markets (Awartani and Maghyereh, 2013; Zhang, 2017; Ma et al., 2019) and cryptocurrencies (Ji et al., 2019; Le et al., 2021). This increasing interest in applications to commodity markets could be largely explained by its use as investment and hedging vehicles, phenomenon known in literature as commodity financialization (Ding et al., 2021; Natoli, 2021). Other works have included extensions or combinations of the Diebold and Yilmaz index to analyze volatility spillovers between different markets (Yang, 2019; Tiwari et al., 2020; Corbet et al. 2020; Liu and Gong, 2020).

2.2.2. Diebold and Yilmaz volatility spillovers in Emerging Markets

Diebold and Yilmaz approach have been also applied to volatility spillovers analysis between developed and Emerging Markets. These contributions have focused on studying volatility spillovers for Asian and African stock markets (Fujiwara and Takahashi, 2012; Chow, 2017; Chevallier et al., 2018; Samitas et al., 2021; Atenga and Mougoué, 2021) and for equity, currencies and derivatives markets (Balli et al., 2015; Prasad et al., 2018; Bostanci and Yilmaz, 2020; Gunay, 2021; Li et al., 2021). Moreover, there is a more recent group of contributions studying volatility spillovers for certain regions of European or Asian emerging countries without a comparison with developed markets (Cronin et al., 2019; Škrinjarić, 2020; Hwang and Suh, 2021, Panda et al., 2021; Zheng et al., 2021).
Various extensions or modifications of the Diebold and Yilmaz approach have been recently proposed in order to capture more precisely volatility spillovers dynamics for Emerging Markets. These proposals include quantile regression approaches, dynamic equicorrelation models and network analysis, among others (Mensi et al., 2017; Su, 2020; Iwanicz-Drozdowska et al., 2021; Li, 2021).

On the other hand, there is a few studies using the Diebold and Yilmaz approach to analyze volatility spillovers between commodities, Bitcoin and Emerging Markets. In particular, some contributions have been devoted to the analysis of volatility spillovers between commodities in Islamic countries; energy, electricity and oil in Turkey; gold and oil in African markets; and energy, metals and equity markets for Emerging Markets (Sugimoto et al., 2014; Mandaci et al., 2020; Bahloul and Khemakhem, 2021; Coskun and Taspinar, 2022).

2.2.3. Volatility spillovers forecasting

Since most of the works do not model changes in the volatility spillovers patterns for different time intervals, there is not a significative amount of studies related to volatility spillovers forecasting. Given that high-volatility periods are correlated with the spillover effects between markets (Diebold and Yilmaz, 2009; 2012), it is pertinent to examine volatility spillovers forecasting. For this purpose, the TVS index seems to be an adequate alternative to detect posterior periods of high volatility and, subsequently, financial crises (Laborda and Olmo, 2021). Our work intends to fill this gap in the literature by forecasting volatility spillovers using the Diebold and Yilmaz index.
2.3. Methodology

This section presents a sketch on the methodology employed in the empirical application to measuring and forecasting volatility spillovers according to the Diebold and Yilmaz methodology.

The procedure is based on the daily estimated variance of the asset $i$ at time $t$ ($\hat{\sigma}_{it}^2$), which, according to Parkinson (1980) and Diebold and Yilmaz (2012), is computed as follows:

$$\hat{\sigma}_{it}^2 = 0.361 \left[ \ln(P_{it}^{max}) - \ln(P_{it}^{min}) \right]^2,$$  \hspace{1cm} (2.1)

where $P_{it}^{max}$ is the maximum price of asset $i$ at time $t$ and $P_{it}^{min}$ corresponds to its minimum price. This measure is annualized according to Eq. 2.2.

$$\hat{\sigma}_{it}^2 = 100 \sqrt{365 \ast \hat{\sigma}_{it}^2},$$  \hspace{1cm} (2.2)

Using the estimated volatilities as inputs, the Diebold and Yilmaz (2012) TVS index and the Net Volatility Spillover for each asset were estimated according to the framework described in Appendix 2.A.

Subsequently, we apply the ARIMA model, the Random Forest and the Support Vector Machine algorithms to forecast the TVS measure as presented in Appendix 2.B. Finally, once the forecasting is performed, results are evaluated according to the mean absolute error (MAE), the root mean-squared error (RMSE) and directional accuracy (DA) measures defined below.

$$MAE = T^{-1} \sum_{t=1}^{T} |Y_t - \hat{Y}_t|,$$  \hspace{1cm} (2.3)

$$RMSE = \left( T^{-1} \sum_{t=1}^{T} (Y_t - \hat{Y}_t)^2 \right)^{1/2},$$  \hspace{1cm} (2.4)
\[ DA = \frac{100}{T} \sum_{t=1}^{T} d_{it}, \]  
\[ d_{it} = 1 \text{ if } (y_{t} - y_{t-1})(\hat{y}_{t} - \hat{y}_{t-1}) \geq 0 \text{ and } d_{it} = 0 \text{ otherwise}. \]

In the case of the three criteria, \( \hat{Y}_t \) (\( Y_t \)) corresponds to the forecasted (observed) value of variable \( Y \) at time \( t \). In consequence, lower values of the MAE and RMSE measures implies better forecasts and higher values of the DA measure denotes a higher accuracy in the direction of the prediction.

### 2.4. Empirical results

This section estimates the static and dynamic spillovers between volatilities of a couple of Commodities, Bitcoin and an Emerging market index employing the Diebold and Yilmaz (2012) methodology. The capacity of the machine learning and traditional econometric models to forecast these volatility spillovers is assessed according to different accuracy criteria.

#### 2.4.1. Descriptive statistics

We use daily prices of two commodities, WTI Oil and Gold, Bitcoin and an Emerging Market index, which traces the behavior of this type of financial markets. Particularly, the MSCI Emerging market index is employed, which includes large and mid companies from 24 Emerging Markets with a higher participation (around 77% of the index) for constituents from China, India, Taiwan, South Korea and Brazil. The data were downloaded from Bloomberg database and comprises the period from April 30th, 2014 to October 6th, 2022 (see the Appendix 2.C for the tickers of the employed series).
Figure 2.1 presents the annualized volatilities for Oil, Gold, Bitcoin and the Emerging market index estimated according to Eq. 2.2. As can be observed, Bitcoin and Oil exhibit higher levels of volatility than Gold and the Emerging market index for the analyzed sample. Moreover, volatility spikes are more abundant for Bitcoin, and the four assets are characterized by volatility clusters and maximum volatility values are observed in 2020 and 2021.

**Figure 2.1** Annualized volatility for the analysed variables.

These features are in line with the descriptive statistics shown in Table 2.1. Average volatility for Bitcoin and Oil are higher than those observed for Gold and Emerging Markets. Likewise, a significantly higher standard deviation is observed for these two variables, confirming the high variability of the observed time series in Figure 2.1. Moreover, the maximum annualized volatility for these two assets is above 480, while for Gold and Emerging Markets is around 90. The four assets present a high excess kurtosis that rules out the normal distribution as an option for their modeling and exhibit positive skewness coefficients, which suggests longer tails to the right. In particular, it is noteworthy that out of the 4 analyzed assets, the lowest kurtosis is presented by Bitcoin.
### Table 2.1 Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>Oil</th>
<th>Gold</th>
<th>Bitcoin</th>
<th>EM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>42.63</td>
<td>14.81</td>
<td>63.99</td>
<td>12.01</td>
</tr>
<tr>
<td>Standard deviation (daily)</td>
<td>34.6</td>
<td>8.41</td>
<td>50.39</td>
<td>7.78</td>
</tr>
<tr>
<td>Median</td>
<td>34.26</td>
<td>12.89</td>
<td>51.38</td>
<td>10.1</td>
</tr>
<tr>
<td>Min</td>
<td>6.84</td>
<td>0.12</td>
<td>0.03</td>
<td>0.61</td>
</tr>
<tr>
<td>Max</td>
<td>522.89</td>
<td>94.76</td>
<td>488.56</td>
<td>83.32</td>
</tr>
<tr>
<td>Skewness</td>
<td>5.32</td>
<td>2.83</td>
<td>2.59</td>
<td>3</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>46.32</td>
<td>15.18</td>
<td>11.17</td>
<td>16.76</td>
</tr>
</tbody>
</table>

Descriptive statistics were obtained from annualized volatility data estimated according to equation 2 and ranges from April 30th, 2014 to October 6th, 2022. Mean, standard deviation, median, minimum and maximum measures are in percentage.

#### 2.4.2. Volatility Spillovers

In this section, a static analysis of the total observations employed in our application is performed. In this regard, each entry $ij$ (referred to the raw $i$ and column $j$) from Table 2.2 can be read as the estimated contribution to the forecast error variance of asset $i$ coming from innovations in asset $j$. The row named as “to others” totalizes the contribution of each asset (column) to the other assets in the table. The “from others” column reports the gross directional spillovers from the other assets to the asset in the corresponding row according to Eqs. 2.A.7 and 2.A.8 in Appendix 2.A. The “Net” row is the net directional volatility spillover which is calculated as the difference between the “to others” and “from others” measures. The TVS measure, estimated according to Eq. 2.A.6, can be found in the lower right corner of the table. The order of the VAR model and the number of days ahead for the
forecast errors are 4 and 10 respectively, following the proposal of Diebold and Yilmaz (2012).

From Table 2.2 it is observed that the Emerging Markets index and Gold present the higher gross directional spillovers to others. It is also noteworthy that Bitcoin does not account for high directional spillovers to the other assets. This result suggests that the Bitcoin volatility does not present high volatility spillovers with Emerging Markets. The “From others” column evidences that the gross directional volatility spillovers to Emerging Markets, Gold and Oil are between 16% and 19% out of 100%, which are considerable high according to Diebold and Yilmaz (2012). This measure is low for Bitcoin, suggesting that there are not considerable directional volatility spillovers to Bitcoin from the other assets.

The net directional volatility spillovers measures, estimated according to Eq. 2.A.9 (Appendix 2.A), indicate that Bitcoin and the Emerging Markets index are net transmitters of shocks to the system and Oil and Gold are net receivers of shocks from other assets. Finally, from the TVS measure it can be concluded that, for the entire sample, 14.61% of the volatility forecast error variance in the considered assets comes from spillovers.

**Table 2.2 Volatility Spillovers.**

<table>
<thead>
<tr>
<th></th>
<th>Oil</th>
<th>BITCOIN</th>
<th>EM</th>
<th>Gold</th>
<th>From others</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil</td>
<td>83.49</td>
<td>1.00</td>
<td>8.38</td>
<td>7.12</td>
<td>16.51</td>
</tr>
<tr>
<td>BITCOIN</td>
<td>0.37</td>
<td>96.63</td>
<td>2.26</td>
<td>0.74</td>
<td>3.37</td>
</tr>
<tr>
<td>EM</td>
<td>7.36</td>
<td>1.91</td>
<td>80.05</td>
<td>10.68</td>
<td>19.95</td>
</tr>
<tr>
<td>Gold</td>
<td>5.64</td>
<td>1.72</td>
<td>11.26</td>
<td>81.38</td>
<td>18.62</td>
</tr>
<tr>
<td>To others</td>
<td>13.37</td>
<td>4.63</td>
<td>21.91</td>
<td>18.54</td>
<td></td>
</tr>
<tr>
<td>Net</td>
<td>-3.14</td>
<td>1.26</td>
<td>1.95</td>
<td>-0.08</td>
<td>14.61</td>
</tr>
</tbody>
</table>
Each entry $ij$ from the table is the estimated contribution to the forecast error variance of the asset in row $i$ coming from innovations of the asset in column $j$. The row named as “to others” totals the contribution of each asset (column) to the other assets in the table. The “from others” column reports the gross directional spillovers from the other assets to the asset in the corresponding row. The row named as “Net” is highlighted in bold and corresponds to the net directional volatility spillover which is calculated as the difference between the “to others” and “from others” measures. The total volatility spillover measure is highlighted in bold and can be found in the lower right corner of the table.

2.4.3. Dynamic volatility Spillovers

Given that volatility spillovers usually exhibit time-varying patterns, the TVS index and the Net Volatility Spillovers are dynamically estimated so as to examine potential changes over the analyzed period. For this purpose, we calculate the volatility spillover measures with a rolling window of 200 daily in-sample observations (April 30th, 2014 to February 2th, 2015) and an out-of-sample period which comprises 2003 observations between February 3th, 2015 and October 6th, 2022. The procedure assumes a VAR order equal to 4, following Diebold and Yilmaz (2012).

Results in Figure 2.2, show that the TVS index varies over time and shows higher values in turbulent periods. Particularly, the higher value for this measure was on March 16th, 2020 reaching a value around 60, which coincides with declines of 12% in the S&P500 index and 6.73% in the Emerging Markets index. In this line, the TVS index presented the highest values for the analyzed sample during 2020, as a result of the COVID-19 pandemic.
It is remarkable that the TVS index presents a positive trend during 2022, reaching levels above its historical average for the analyzed period of 17.8 from March 7th, 2022, suggesting a new period of high volatility in the economy that could be associated with a new financial crisis. Particularly, the value of this measure on March 7th, 2022 was 20.7 which concurred with declines in the S&P500 index and the Emerging Markets index daily returns of 3.2% and 3.34%, respectively. This trend seems to be explained by the COVID-19 crisis effects and the conflict between Russia and Ukraine.

The previous findings give support to the following assessments. Firstly, the TVS index dynamics confirms that the volatility spillovers effects can be considered as dynamic relationships that changes over time (Diebold and Yilmaz, 2012). Secondly, these findings evidence that volatility spillovers effects for commodities, Bitcoin and Emerging Markets are time and event dependent as suggested by Antonakakis and Kizys (2015). Finally, the volatility spillovers dynamics between commodities, Bitcoin and Emerging Markets have an interesting relationship with instability periods in stock markets. Actually, it is noteworthy that this relationship is almost in real time. This suggests that it is possible to predict high volatility periods by the use of volatility spillovers measures as stated by Laborda and Olmo (2021).
The Net Volatility Spillovers, depicted in Figure 2.3, evidence different features related to directional effects on volatility spillovers. In the four analyzed variables, it can be observed that there is a peak in the net volatility spillover at the beginning of the COVID-19 pandemic. Specifically, the higher (lower) value of the net volatility spillovers for the four assets is located between March 10th (March 20th), 2020. This suggests a relationship between this measure and the high volatility periods. Furthermore, it is noteworthy that there are particular changes in the net volatility spillovers during COVID-19 pandemic. Considering Oil and the Emerging Markets index, there is an increase in this measure that could be explained by the origin of the COVID-19 financial crisis.

This crisis emerged from an exogenous shock which impacted real production sectors and the prices of energy inputs. It is notorious the negative WTI prices during the lockdown phases, but also other factors as the changes in global oil demand and supply, storage risk, geopolitical reasons, OPEC decisions, and futures market dynamics (Sadorsky, 2004; Basher and Saddorsky, 2006; Corbet et al., 2020). Regarding Gold and Bitcoin, there is a switch in
the net volatility spillovers trend, which points to a switch from receivers to senders after March, 2020. Finally, since March, and June, 2022, the Emerging Markets index and Oil, respectively, net volatility spillovers changed from positive to negative. This result suggests that these assets are no longer net transmitters of shocks to the system, but are net receivers of shocks from other assets. This can be largely explained by the conflict between Russia and Ukraine.

2.4.4. Volatility Spillovers forecasting

The observed relationship between turbulent periods and high volatility spillovers among commodities, Bitcoin and the Emerging Markets suggests that the forecasting of the dynamics of these spillovers may be a useful tool for investors to design diversification, hedging or safe-haven strategies anticipating high volatility periods (Ji et al., 2020; Shaikh, 2021; Urom et al., 2022). In addition, considering the relationship between high volatility periods and the TVS measure (see Figure 2.4), the volatility spillovers forecasting can be useful to predict future financial crises and the appropriate design of market risk mitigation strategies by regulators (Elgammal et al., 2021; Gong et al., 2021). In particular, given the complexity and fragility of Emerging Markets, this type of application can be especially useful to preserve financial stability in these markets (Chen and Yang, 2021). In spite of this, literature have not explored yet whether there is information embedded in the spillovers measures that helps to predict future market volatility and financial crises (Laborda and Olmo, 2021).
Therefore, we proceed to forecast the TVS index with both traditional econometric methods and machine learning techniques. To this aim, 80% of the data was used as a training set and the remaining 20% as a testing set (Gong et al., 2019; Liu, 2019). In particular, the measure was predicted by the use of ARIMA, Random Forest and Support Vector Machine approaches. For the ARIMA model, the $p$, $d$, and $q$ orders were selected according to the Akaike information criterion and a rolling window of 100 observations.

In the case of the Random Forest technique, we employed parameters based on related works and a grid search tuning process to adequately estimate the hyperparameters. That is, 500 trees (Herrera et al., 2019), a number of variables to randomly sample as candidates at each split (aka mtry), which is equal to one third of the total variables (tv) (Laborda and Olmo, 2021), and a number of lags for the TVS index equal to 25, which was identified as the optimal value to obtain the lowest forecasting scores in the validation procedure. In order to have robust results, we test the outcomes varying the number of trees from 100 to 500, the mtry from 10 to 60, and the number of lags between 5 and 70 based on Herrera et al. (2019). For the Support Vector Machines technique, the best forecast was estimated using 30 lags of the TVS index, the width of the Kernel function (gamma parameter) equal to 8 and a penalty parameter of the error term (cost) of 1.4142. In this case, the gamma and the cost parameters
were obtained by a grid search tuning process and the number of lags were obtained from a trial and error process. As a result, these parameters are close to those used by Liu (2019) and Faldzinski et al. (2020). In addition, based on the abovementioned works, we built different models varying the number of lags from 5 to 32 and the linear, polynomial, radial basis and sigmoid kernels were employed (Yang et al., 2020). The accuracy of the forecasts can be seen in Table 2.3 and Figure 2.5.

Table 2.3 TVS index forecasting

<table>
<thead>
<tr>
<th>Panel A. ARIMA</th>
<th>MAE</th>
<th>RMSE</th>
<th>DA</th>
<th>RW</th>
<th>Max$(p,d,q)$</th>
<th>Criterion</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA</td>
<td>0.3005</td>
<td>0.6331</td>
<td>55.50</td>
<td>100</td>
<td>10</td>
<td>AIC</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B. Random Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAE</td>
</tr>
<tr>
<td>-----</td>
</tr>
<tr>
<td>RF1</td>
</tr>
<tr>
<td>RF2</td>
</tr>
<tr>
<td>RF3</td>
</tr>
<tr>
<td>RF4</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C. Support Vector Machine</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
</tbody>
</table>

56
MAE and RMSE are both based on the difference between the observed and forecasted returns value. The closer the MAE and RMSE to 0, the better the forecasts obtained. The DA measure compares the upward or downward direction of both observed and forecasted values. We obtain the best forecasts when this measure is closer to 100. The best forecasts are highlighted in bold. Table 4 reports the best results between three approaches: ARIMA (Panel A), RF (Panel B) and SVM (Panel C). The ARIMA model was estimated with a rolling window (RW) of 100 observations and a maximum \( p, d \) and \( q \) orders equal to 10. The best ARIMA model was selected according to Akaike information criterion (AIC). In the case of the RF and SVM methods we employed a grid search tuning process to optimize the hyperparameters. The number of lags were selected by a trial and error process.

The results suggest that the best TVS index forecast is obtained through Support Vector Machine (SVM5) followed by ARIMA models and the Random Forest technique. These findings are in line with previous works which highlights the benefits of this machine learning technique to forecast financial variables, considering its relative simplicity in terms of application and optimization of parameters with respect to other machine learning techniques such as neural networks (Gong et al., 2019; Liu, 2019; Faldzinski et al., 2020; Yang et al., 2020). Our evidence points to the possibility to forecast volatility spillovers measures and confirms the advantages of machine learning techniques over traditional econometric techniques to forecast financial variables.
Figure 2.5 Emerging Markets Volatility, Observed TVS index, Forecasted TVS index.

Figure 2.5 depicts the estimated volatility for Emerging Markets, the observed and the forecasted TVS index through the SVM5 model. As can be seen, there is a strong relationship between Emerging Markets volatility and the observed and forecasted TVS index. Especially, there is an increase in the TVS index when Emerging Markets volatility reaches its highest peaks in the second quarter of 2022. This level of the TVS index extends during the rest of the analyzed period, which is consistent with the increase in the Emerging Markets volatility. This confirms the possibility of predicting high-turbulence periods through the TVS index. Finally, Figure 2.5 evidences the satisfactory results obtained from the prediction of TVS index through machine learning techniques, in particular, Support Vector Machine models.

2.5. Conclusions

The analysis of the dynamics of volatility spillovers between commodities, Bitcoin and Emerging Markets and their prediction through different techniques allows us to settle interesting conclusions. Firstly, it can be concluded that volatility spillovers effects between commodities, Bitcoin and Emerging Markets are time-varying and closely related to periods of high volatility in global financial markets. This finding is remarkable considering that it
provides new evidence to the literature about the information embedded in volatility spillovers that can be used to forecast high volatility periods and crisis in financial markets.

In addition, it is featured that turbulent periods, such as COVID-19 pandemic, generate significant changes in the intensity and direction on the volatility spillovers effects in Emerging Markets. In the particular case of Oil and Emerging Markets, it is observed that by March 2020, their role as transmitters of shocks to the system is accentuated. This change could be explained by the fact that the 2020 crisis was caused by shocks that affected the industrial sectors and the prices of energy inputs. Moreover, it is noteworthy that since the first half of 2022, these two assets cease to be transmitters of shocks to the system to become receivers of the aforementioned shocks. This could be explained by the fact that the turbulence in the financial markets for this period is associated with the medium-term effects of Covid-19 pandemic and geopolitical tensions such as the conflict between Russia and Ukraine.

Furthermore, it is also found the superiority of machine learning models with respect to traditional econometric models to forecast Emerging Markets financial variables such as the TVS index. This finding is pertinent considering the close relationship between this index and the Emerging Markets volatility and the fact that, by obtaining accurate forecasts of volatility spillovers dynamics, we may forecast high volatility periods and financial crises.

All in all, our results are meaningful in terms of economic and practical implications. On the one hand, they allow investors to understand and forecast the dynamics of the volatility spillovers between commodities, Bitcoin and Emerging Markets, which constitutes valuable information to design satisfactory investment and hedging strategies. On the other hand, it suggests the possibility of forecasting periods of high volatility and financial crises in
Emerging Markets through volatility spillovers. This information is valuable for regulators who can design policies aimed at anticipating and mitigating market instability and its consequences. This is especially important to guarantee the financial stability, particularly for the most unstable and fragile markets, such as emerging ones.

2.6. Appendix

Appendix 2.A. Diebold and Yilmaz Volatility Spillovers framework.

The TVS index is based on the generalized vector autoregressive (VAR) framework proposed by Koop et al. (1996) and Pesaran and Shin (1998). This framework is employed to cope with the dependence of the traditional VAR model on different orders. In the following equation a stationary N-variable p-order VAR model is represented.

\[ X_t = \sum_{i=1}^{p} \theta_i X_{t-i} + \epsilon_t, \]  

(2.A.1)

where \( X_t \) is the vector of the variables of interest, \( \theta_i \) denotes the matrix with the coefficients associated to \( X_{t-i} \) and \( \epsilon_t \sim (0, \Omega) \) is a vector of zero mean, independent and identically distributed disturbances with variance-covariance matrix given by \( \Omega \). Assuming stationarity in the VAR process, the moving average representation of the VAR model is given by Eq. 2.A.2.

\[ X_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i}, \]  

(2.A.2)

where the \( N \times N \) coefficient matrices \( A_i \) obey the following recursive relations:

\[ A_i = \theta_1 A_{i-1} + \theta_2 A_{i-2} + \cdots + \theta_p A_{i-p} \]  

(2.A.3)

with \( A_0 = I_N \) and \( A_i = 0 \) for \( i < 0 \). The dynamic characteristics of the VAR model are incorporated through the moving average coefficients. These coefficients are essential in the
model since it is possible to decompose the forecast error variance of each variable into parts attributable to various system shocks (Diebold and Yilmaz, 2012). Therefore, the contribution of each variable to the system can be obtained through the variance decomposition method.

Let define own variances (spillovers) as the fractions of the H-step ahead forecast error variances in forecasting $x_i$ that are due to shocks to $x_i$ ($x_j$) for $i, j = 1, 2, ..., N$, with $i \neq j$ and denote the H-step-ahead forecast error variance decompositions by $\Phi_{ij}^g(H)$:

$$
\Phi_{ij}^g(H) = \frac{\sigma_{jj}^2 \sum_{h=0}^{H-1} (e_i' A_h \Omega e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Omega A_h' e_i)^2},
$$

(2.A.4)

where $\Omega$ corresponds to the variance matrix of the forecast error vector, $\sigma_{jj}$ stands for the standard deviation of the forecast error of the $j$-th equation and $e_i$ is a selection vector such that elements are equal to 0 except for the $i$-th term, which is equal to 1. Then, the variance decomposition results can be standardized (Eq. 2.A.5) in order to compare the variance contributions of different variables.

$$
\bar{\Phi}_{ij}^g(H) = \frac{\Phi_{ij}^g(H)}{\sum_{j=1}^{N} \Phi_{ij}^g(H)},
$$

(2.A.5)

where $\sum_{j=1}^{N} \bar{\Phi}_{ij}^g(H) = 1$, and $\sum_{i=1}^{N} \sum_{j=1}^{N} \bar{\Phi}_{ij}^g(H) = N$.

From the previous equation, it is possible to obtain the Total Volatility Spillover index (TVS) according to the following expression.

$$
S^g(H) = \frac{\sum_{i=1}^{N} \bar{\Phi}_{ij}^g(H)}{\sum_{i,j=1}^{N} \bar{\Phi}_{ij}^g(H)} 100 = \frac{\sum_{i=1}^{N} \bar{\Phi}_{ij}^g(H)}{N 100},
$$

(2.A.6)
In addition, we can measure the directional volatility spillovers received by variable $i$ from all other variables $j$ as follows:

$$S_{i\rightarrow j}(H) = \frac{\sum_{j=1}^{N} \tilde{\sigma}_{ij}^g(H)}{\sum_{j=1}^{N} \tilde{\sigma}_{ij}^g(H)} = \frac{\sum_{j=1}^{N} \tilde{\sigma}_{ij}^g(H)}{N} 100,$$  

(2.A.7)

where $S_{i\rightarrow j}(H)$ is equal to the $H$-step-ahead forecast error variance portion in variable $i$ which are explained by shocks in variable $j$. Similarly, the directional volatility spillovers transmitted by variable $i$ to all other variables $j$ is given by equation 2.A.8.

$$S_{j\rightarrow i}(H) = \frac{\sum_{i=1}^{N} \tilde{\sigma}_{ji}^g(H)}{\sum_{i=1}^{N} \tilde{\sigma}_{ji}^g(H)} = \frac{\sum_{i=1}^{N} \tilde{\sigma}_{ji}^g(H)}{N} 100,$$  

(2.A.8)

From equations 2.A.7 and 2.A.8, it is possible to define the Net Volatility Spillover from market $i$ to all other markets $j$ for $i, j = 1, 2, ..., N$ by the equation 2.A.9.

$$S_i^g(H) = S_{j\rightarrow i}(H) - S_{i\rightarrow j}(H),$$  

(2.A.9)

where $S_i^g(H)$ can be defined as the difference between the volatility shocks transmitted to variable $i$ from all other variables $j$ and the volatility shocks transmitted from variable $i$ to all other variables $j$. Additionally, From equation 2.A.9, one may calculate the net pairwise volatility spillovers as follows.

$$S_{ij}^g(H) = \left( \frac{\tilde{\sigma}_{ij}^g(H)}{\sum_{k=1}^{N} \tilde{\sigma}_{ik}^g(H)} - \frac{\tilde{\sigma}_{ji}^g(H)}{\sum_{k=1}^{N} \tilde{\sigma}_{jk}^g(H)} \right) 100 = \left( \frac{\tilde{\sigma}_{ij}^g(H) - \tilde{\sigma}_{ji}^g(H)}{N} \right) 100,$$  

(2.A.10)

where $S_{ij}^g(H)$ is the difference between volatility shocks transmitted from market $i$ to market $j$ and volatility shocks transmitted from market $j$ to market $i$. 

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Appendix 2.B. Forecasting techniques.

The TVS measure is forecasted by using the Autoregressive-Moving Average (ARIMA) model and two well-known machine learning techniques: Random Forest (RF) and Support Vector Machine (SVM) models. The ARIMA model was selected considering its wide use to forecast financial variables and the RF and SVM models were chosen due to their satisfactory results obtained in previous applications to financial variables forecasting (i.e. Khashman and Nwulu, 2011; Gong et al., 2019; Yang et al., 2020).

(i) The ARIMA \((p,d,q)\) model has been widely employed to forecast stationary and non-stationary time series \((y_t)\) as including a \(d\)-order differentiation. It can be represented as follows:

\[
y_t = \mu + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q}, \tag{2.B.1}
\]

where \(e_t\) is the error term at time \(t\), and \(\mu, \phi_i, \) and \(\theta_i\) are the model parameters. One of the most important features to determine in this model are the \(p, d,\) and \(q\) orders. In this work, we identified \(p, d,\) and \(q\) orders using the Akaike information criterion (AIC)

(ii) The RF algorithm, considered as a non-parametric approach, have been proved to have high accuracy to predict financial variables (Basher and Sadorsky, 2022). This approach can be employed for classification and regression exercises, which include financial variables.

Proposed by Breimann (2001), the RF algorithm combines a number of binary decision trees built using several bootstrap samples obtained from learning samples and selecting a subset of explanatory variables for each node (Liu and Li, 2017). In the case of regression exercises, the RF model can be described as follows:

\[
\hat{y}_t = f(y_{t-1} \ldots y_{t-p}) + \varepsilon_t, \tag{2.B.2}
\]
where \( \hat{y}_t \) is the forecasted value for the variable \( y \) at time \( t \), \( y_{t-1} \) is the observed variable value at time \( t - 1 \), \( E[\epsilon_t] = 0 \), and \( f \) denotes the regression function for the RF algorithm.

(iii) The SVM technique was proposed by Cortes and Vapnik (1995) as a supervised learning model used for classification and regression analysis. SVM is a powerful machine learning technique based on the statistical learning theory “that solves the linear constraint quadratic programming problem and obtains the global optimal solution” (Yang et al., 2020). In this sense, this approach does not exhibit the drawbacks of neural networks (related to local solutions), overfitting problems and the selection of the number of nodes/layers (Gong et al., 2019). By the use of this technique is possible to obtain satisfactory results for problems with a small number of training observations. Moreover, SVM allows to handle overfitting problems considering that, in the training data process, the obtained solution is unique (Khashman and Nwulu, 2011). In our application, the linear, polynomial, radial basis and sigmoid kernels are employed to evaluate their performance to forecast the TVS measure.

**Appendix 2.C. Bloomberg tickers**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Index Bloomberg ticker</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil</td>
<td>CL1 Comdty</td>
</tr>
<tr>
<td>Gold</td>
<td>XAU Curncy</td>
</tr>
<tr>
<td>Bitcoin</td>
<td>XBTUSD Curncy</td>
</tr>
<tr>
<td>Emerging Markets index</td>
<td>MXEF Index</td>
</tr>
</tbody>
</table>

Source: Bloomberg LP
CHAPTER 3: Predicting carbon and oil price returns using hybrid models based on machine and deep learning

3.1. Introduction

Climate change has become a challenge in recent years for human development and preservation of natural resources. Since the 2007 Kyoto protocol various governmental and non-governmental organisations have promoted initiatives to mitigate and prevent adverse climate change effects. Among these initiatives, the European Union Emissions Trading System (EU ETS) is considered as one of the most efficient greenhouse gas (GHG) emission reduction strategies employed by the energy and industry sectors. EU ETS aims to achieve a 42% reduction in GHG emissions by the year 2030, with respect to the goal established in 2005. Given that EU GHG levels were 22% lower in 2015 compared to those in the 1990s (European Commission, 2018), this goal still remains realistic. Hence, the modelling and prediction of carbon and oil prices is deemed relevant for the following reasons. Firstly, ‘forecasting carbon prices can contribute to a deep understanding on the characteristics of carbon prices so as to establish an effective and stable carbon price mechanism’ (Zhu et al., 2017, p. 521). Secondly, an accurate prediction of the carbon and oil prices aid investors in designing strategies to maximise benefits and ensure adequate risk management considering carbon and conventional energy markets as alternatives. Thirdly, there has been an increasingly interest of both carbon and oil price volatility in industry and academia recently (Zhu, B., & Chevallier, J., 2017). In consequence, the development of models that are capable of accurately predicting carbon and oil prices may attract investors to the carbon market and mitigate investment-related risk in the oil market. Fourthly, fossil fuel-intensive industries
maintain their dominance in global economies. Therefore, to achieve a successful transition into renewable energy sources, the dynamics of prices in the carbon and oil markets must be clearly understood to identify the possible benefits of novelty energy markets. Finally, predicting carbon and oil prices can contribute to comprehend the dynamics and design of new policies, different from the creation of artificial markets and aimed at reducing GHG emissions.

One strand of the literature related to carbon price forecasting is focused on works that utilise traditional econometric models (Chevallier, 2011; Koop and Tole, 2013; Nademi and Nademi, 2018). On the other hand, machine learning techniques (Chiroma et al., 2015; Zhu et al., 2017; Ramyar and Kianfar, 2019; Xu et al., 2020) has been also employed. A promising methodology for accurately predicting carbon prices is the hybrid models, that combine both conventional econometric models and machine learning techniques (Zhu, 2012; Li and Lu, 2015; Atsalakis, 2016; Zhang et al., 2018; Zhu et al., 2019; Abdollahi and Ebrahimi, 2020; Wang et al., 2021; Zhang et al., 2022; Liang et al., 2022; Lin et al., 2022; Lu et al., 2023).

While traditional econometric models yield accurate results, they are inadequate in capturing the inherent non-linear dynamics of carbon prices. Consequently, machine learning techniques have become an interesting alternative to cope with this limitation (Zhu et al., 2018; Lu et al., 2023). On the other hand, to overcome the drawbacks of single models and improve the carbon price prediction accuracy, hybrid models have been proposed to obtain better results (Liang et al., 2022; Lu et al., 2023). This is due to the fact that hybrid models incorporate the advantages of traditional econometric approaches and machine learning techniques, allowing for the capture of linear and non-linear effects in time series (Tsay and Chen, 2018).
Although several attempts have been employed to predict carbon prices, no specific model has been generally accepted as being the most effective model. Conversely, researchers are continuously testing models that are both simpler and more precise. This study utilises the benefits of hybrid models and aims at predicting carbon and oil price returns by combining conventional econometric models and machine learning techniques through hybrid artificial neural networks. Through this approach, we contribute to literature in different ways. Firstly, we focus on machine and deep learning hybrid models that integrate the autoregressive integrated moving average (ARIMA), random forest (RF), support vector machine (SVM), and non-linear autoregressive (NAR) neural network techniques. Secondly, on the basis of our results, we argue that accurate forecasts can be obtained from combining machine learning techniques unlike previous studies (e.g., Safari and Davallou, 2018; Tsay and Chen, 2018) that highlight the relevance of incorporating traditional econometric models in the construction of hybrid models to capture the linear characteristics of the time series. Thirdly, by the use of artificial neural networks to ensemble traditional and machine learning single models, our results constitute new evidence related to the advantages of non-linear ensemble approaches versus linear ensemble forms (Liao and Tsao, 2006; Alonso et al., 2007; Zhu et al., 2018). Finally, our exercise provides new evidence to the forecast combination puzzle (e.g. Chan and Pauwels, 2018; Diebold and Shin, 2019) which stipulates that the hybrid models usually outperforms more sophisticated ensemble methods.

The remainder of this paper is organised as follows. Section 2 presents a literature overview related to carbon and oil price forecasting. Section 3 develops the methodology for carbon and oil price returns forecasting through the proposed hybrid models. Section 4 evaluates the results obtained from the application of the models. Section 5 presents an additional analysis.
to confirm the results obtained in the previous section. Finally, Section 6 summarises the main conclusions.

3.2. Related works

Literature focusing on the prediction of carbon and oil prices present three main trends: (1) classical econometric models, (2) machine learning techniques, and (3) hybrid models. Within the classical econometric approach, most of the models forecast carbon or oil prices using ARMA or fractionally integrated ARMA specifications (Karia et al., 2013). Additionally, several proposals employ ARCH or GARCH processes to capture the price dynamics of carbon and oil prices (Chevallier, 2011; Koop and Tole 2013; Byun and Cho 2013). More recently, stochastic jump processes (Sanin et al., 2015) or semiparametric Markov switching models (Nademi and Nademi 2018) are also examined.

For models based on artificial intelligence techniques, neural networks have been widely used to forecast oil and carbon prices. In this vein, wavelet neural networks (Yousefi et al., 2005; Huang and Wang 2018) have been considered an appealing alternative for forecasting energy asset prices or returns. Other works have employed different types of neural networks, e.g. evolutionary neural networks (Chiroma et al., 2015), multilayer perceptron neural networks (Fan et al., 2015; Ramyar and Kianfar, 2019) and data fluctuation networks (Wang et al., 2018).

In this research line, alternative proposals based on other machine learning techniques than neural networks have emerged. Among them, Zhu and Wei (2011) predicted international carbon price using an integrated model and particle swarm optimisation to improve the performance of least squares support vector machines; Zhu et al. (2017) proposed a decomposition-based evolutionary least squares support vector regression multiscale
ensemble forecasting model; Cen and Wang (2019) applied the long short-term memory model to predict oil prices; and Xu et al. (2020) developed a network extreme learning machine model to forecast carbon price.

On top of that, hybrid models are motivated by the limitations of previous approaches. Classical econometric models cannot capture non-linear characteristics of time series where artificial intelligence techniques can enter into action by including non-linear features in their modelling (Tsay, 2018; Jing et al., 2021). Hence, hybrid models emerge as a feasible solution to integrate time series linear and non-linear effects. Generally, this technique produces better forecasts than individual models (Timmermann, 2006). Different works have been presented in recent years in this research strand. These studies can be classified into those incorporating econometric and machine learning techniques for constructing the assembled model and those including machine learning techniques, exclusively. The main advantage of the first group of works is the representation of the linear and non-linear effects of time series, characterising asset returns in different time intervals (Safari and Davallou, 2018). In this sense, proposals combining traditional ARIMA models and machine learning approaches exploit features of both approaches on building up hybrid models. These techniques include least squares support vector machine models improved through particle swarm optimisation (Zhu and Wei, 2013), and adaptive neuro-fuzzy inference systems (Abdollahi and Ebrahimi 2020). Furthermore, ARCH-GARCH models and their extensions are assembled with empirical mode decomposition, neural networks, and support vector machine (Li and Lu, 2015; Zhang et al., 2018; Abdollahi 2020; Huang et al., 2021). On the other hand, artificial neural networks and decomposition algorithms have been recurrently employed in literature (Zhu 2012; Zhu et al., 2016; Sun et al., 2016; Zhu et al., 2019; Li et al., 2019; Sun and Huang, 2020, Liang et al., 2022; Lu et al., 2023). In addition,
neural networks have also been combined with adaptive neuro-fuzzy systems and other types of neural networks (Atsalakis 2016, Zhao et al., 2018).

Within these hybrid models, several alternatives have recently been proposed: Hang et al. (2019) use a model that combines a back propagation neural network and a combination-mixed data sampling regression; Lu et al. (2020) combine six machine learning techniques to predict carbon prices; Hao and Tian (2020) consider a multiple influencing factors hybrid model to forecast carbon prices; Zhang et al. (2022) predict carbon prices using ensemble decomposition techniques and deep learning algorithms; and Zhang et al. (2021) propose a hybrid model based on a two-layer decomposition technique and an extreme learning machine to predict oil prices.

When determining the weights of individual predictions, the literature presents different positions. On the one hand, the weights of the predictions obtained from the models separately must be equal according to some proposals (Terui and Van Dijk, 2002; Hendry and Clements, 2004). On the other hand, weights of the individual forecasts must be optimised to improve the models’ prognostic capacity – Guidolin and Timmermann, (2007), Wang et al. (2010) and Safari and Davallou (2018). In this research line, different works have emerged aimed at solve the forecast combination puzzle (e.g. Chan and Pauwels, 2018; Diebold and Shin, 2019).

Our work utilises neural networks to construct hybrid models. This type of approach has been proved successful in the past (Safari and Davallou, 2018; Meifeng and Gouhao, 2015) owing to different features: Simplicity, ability to estimate future values of weights based on historical information, little data required to be performed, and independence from significant information processing (Meifeng and Gouhao, 2015). However, our work
contributes to literature by using machine and deep learning hybrid models built upon the integration of ARIMA, RF, SVM, and NAR models. These models have been proved to be adequate to forecast financial variables (Gong et al., 2019; Yang et al., 2020; Basher and Sadorsky, 2022). However, hybrid models built on these techniques have been less explored in the literature. Moreover, in this study, we also confirm the advantages of non-linear models versus linear ensemble forms (Liao and Tsao, 2006; Alonso et al., 2007; Zhu et al., 2018); and contribute to fill the gap in the forecast combination puzzle debate. We test these models’ performance for carbon and oil price forecasting and argue the appealing benefits derived from combining machine learning techniques.

3.3. Methodology

In this section, we describe the general procedure to predict and evaluate carbon and oil price returns forecasts. Our methodology comprises data collection and depuration, followed by model forecasting using different techniques. Individual forecasts are assembled through multiple hybrid models and the model performance is evaluated in terms of traditionally accuracy indicators, such as the mean absolute error (MAE), the root mean-square error (RMSE) and directional accuracy (DA). This procedure is described in detail as follows.

STEP 1. Data collection. Carbon and oil prices are proxied by the Intercontinental Exchange - Carbon Emission Allowances (ICE-EUA) Phase 3 Futures contract and West Texas Intermediate (WTI) prices, respectively, downloaded from the Bloomberg platform for the period between 7/12/2012 and 06/19/2020. As proposed by Zhao et al. (2018), Xu et al. (2020) and Tan et al. (2022), we employ weekly data, and thus, our sample comprises 394 weekly observations. Subsequently, we obtained the percentage logarithmic returns from the
following expression, $R_t = 100\ln\left(\frac{V_t}{V_{t-1}}\right)$, where $V_t$ corresponds to the carbon or oil prices at time $t$.

**STEP 2. Descriptive statistics and nonlinearity test.** The well-known stylised facts (e.g., non-negligible asymmetry and excess kurtosis) usually observed in financial data are verified. As artificial intelligence time series specifications model non-linear dependencies, we also validated the presence of this type of association through the BDS test (Brock et al., 1987; Brock et al., 1996) implemented in the fNonlinear package in R.

**STEP 3. Forecast carbon price returns using ARIMA, RF, SVM and NAR models.** Carbon and oil price returns are forecasted through ARIMA, RF, SVM and NAR models (see Appendix 3.A for further details). The RF, SVM and NAR models have been selected considering the remarkable results obtained from these techniques in the forecast of financial time series in previous works (Gong et al., 2019; Yang et al., 2020; Basher and Sadorsky, 2022). We conducted the forecast for each model separately with a sample size for the test set comprising the 20% of the data (76 weekly observations), similarly to previous related studies (Safari and Davallou, 2018; Gong et al., 2019; Liu, 2019).

**STEP 4. Ensemble of the hybrid model.** Individual model forecasts are combined in nine hybrid models, the weights of each model being determined through different techniques. Equation (3.1) represents a hybrid model composed of three individual forecasts:

$$\hat{y}_t = w_1\hat{y}_{1t} + w_2\hat{y}_{2t} + w_3\hat{y}_{3t},$$  \hspace{1cm} (3.1)

where $\hat{y}_{it}$ denotes the forecasted value of the variable $y$ (carbon or oil price returns) at time $t$ using the Model $i$ and $w_i$ captures its corresponding weight. In this study, weights were determined through nine techniques classified in three groups which employ either (i) equally
weighted models (EW), (ii) Hybrid artificial neural network models (HANN) or (iii) deep learning models (DL), as explained below.

**Equally weighted models**

This approach assigns equal weights to the individual forecasted values and models are assembled for three different combinations of the individual techniques (named as EW1, EW2 and EW3), as shown in Appendix 3.B. Therefore, hybrid forecasted variable \( \hat{y}_t \) is computed as follows:

\[
\hat{y}_t = \frac{\hat{y}_{1t} + \hat{y}_{2t} + \hat{y}_{3t}}{3}, \tag{3.2}
\]

Where \( \hat{y}_{1t} \), \( \hat{y}_{2t} \), and \( \hat{y}_{3t} \) are the individual forecasts obtained separately from the traditional econometric or machine learning techniques according to the combinations presented in models EW1 to EW3.

**HANN model**

In this technique weights are obtained using a hybrid artificial neural network. In this case, the hybrid model forecast \( \hat{y}_t \) for carbon or oil prices is built upon the basis of a neural network on three combinations of the individual forecasts, according to Equation (3.3):

\[
\hat{y}_t = f(\hat{y}_{1t}, \hat{y}_{2t}, \hat{y}_{3t}). \tag{3.3}
\]

Particularly, the proposed models use the combinations ARIMA-RF-ANR (HANN1), ARIMA-SVM-ANR (HANN2), and the RF-SVM-ANR (HANN3). Considering that no specific technique can determine the number of nodes in the hidden layer, we use a trial-and-error method including 3, 5, 7, 10, and 20 nodes in this layer (see e.g., Safari and Davallou, 2018). In this type of modelling, special attention should be paid to control for overcome
potential overfitting, as the observed data corresponds to the output variable of the training data in the neural network. For this purpose, we employed three different techniques. In the first, we performed a cross-validation (CV) of the errors, which employs a training set whose length is shifted ahead by the forecast horizon after each iteration. This approach is based on the $k$-fold cross-validation methodology. The second technique is the LASSO regularisation ($L1$), which penalises the loss function with a magnitude equal to the absolute value of the weights of the neural network. In this case, the value for some weights can be zero (thus features or explanatory variables are eliminated from the model), or close to zero. In the third technique, overfitting problems were addressed using RIDGE regularisation ($L2$). This regularisation technique penalises the loss function with a penalty equal to the squared value of the magnitude of the weights of the neural network. Therefore, values of certain weights diminish approaching to zero. Unlike the $L1$ technique, ridge regularisation does not contribute to features selection in the model as this technique does not reduce coefficient values to zero. Appendix 3.C presents specifications for $L1$ and $L2$ regularisation techniques.

**Deep learning models**

Deep learning techniques (hereafter DL) ensemble the individual results obtained from the combinations of the models with a higher number of hidden layers than the HANN technique (always considering more than one hidden layer) – see Equation (3.A.4) in Appendix 3.A. Similar to previous ensemble models, we implemented the combinations ARIMA-RF-ANR (DL1), ARIMA-SVM-ANR (DL2), and the RF-SVM-ANR (DL3). In this exercise, we employed two hidden layers with the following mix of nodes: (10,6), (10,4), (10, 10), and (20,6) selected by a trial-and-error process, as is usual in the literature (see e.g., Bucci, 2020; Ma et al., 2021). In this case, the first and second numbers of the combination correspond to
the number of nodes for the first and second layer in the neural network. Figure 3.1 exhibits our proposed methodology for carbon and oil price returns forecasting.

**Figure 3.1** Graphical representation of the proposed methodology.

![Diagram of the proposed methodology]

**STEP 5. Results evaluation.** The forecast evaluation of the different models was performed through the MAE, RMSE, and DA described below:

\[
MAE = T^{-1} \sum_{t=1}^{T} |y_t - \hat{y}_t|, \\
RMSE = (T^{-1} \sum_{t=1}^{T} (y_t - \hat{y}_t)^2)^{1/2}, \\
DA = \frac{100}{T} \sum_{t=1}^{T} d_i_t,
\]

\[d_i_t = 1 \text{ if } (y_t - y_{t-1})(\hat{y}_t - \hat{y}_{t-1}) \geq 0, \text{ and } d_i_t = 0 \text{ otherwise},\]

where \(y_t (\hat{y}_t)\) denotes the observed (forecasted) value of variable \(y\) at time \(t\), and \(T\) corresponds to the total number of observations. According to the definition of each criterion, for the MAE and the RMSE, the lower the value the better the forecast. Whereas, DA a higher value indicates a better forecast, as it provides an idea of the correctness in the predicted direction.
3.4. Results

This section presents the results on carbon and oil returns forecasting using the different individual and hybrid models. After describing the relevant characteristics of the time series, model performance is evaluated and compared.

Descriptive statistics

Figure 3.2 depicts the logarithmic returns of the carbon and oil price returns. Both series exhibit values around 0, but also abundant atypical returns. In particular, negative returns are more extreme than positive ones, the greatest weekly loss being around −40% for carbon price returns and −35% for oil price returns. Conversely, the highest weekly profit is around 23% and 27% for carbon and oil, respectively.

Figure 3.2 Carbon and Oil price returns

Carbon price returns

Oil price returns
The graph shows the weekly carbon price (panel A) and oil price (panel B) logreturns from 12/14/2012 to 06/19/2020.

Table 3.1 reports the basic descriptive statistics and confirms that the mean of the carbon and oil price returns is close to 0. However, as the periodicity of the data is weekly, the mean is not as close to 0 as it would be with daily returns. A standard deviation of 7% for carbon price returns is observed, which is ‘relatively’ high (e.g., compared with stock indices), considering that it would be above 50% when being annualised. This result is around 5.6% for oil returns (39.4% when annualised).

<table>
<thead>
<tr>
<th></th>
<th>Carbon</th>
<th>Oil</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.3381</td>
<td>-0.1962</td>
</tr>
<tr>
<td>Median</td>
<td>0.4494</td>
<td>0.0954</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>7.0869</td>
<td>5.5689</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>8.2744</td>
<td>10.4096</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.9429</td>
<td>-0.6820</td>
</tr>
<tr>
<td>Minimum</td>
<td>-40.9729</td>
<td>-34.6863</td>
</tr>
<tr>
<td>Maximum</td>
<td>23.0405</td>
<td>27.5756</td>
</tr>
</tbody>
</table>

Descriptive statistics were obtained from weekly data from 12/14/2012 to 06/19/2020.
The skewness and kurtosis coefficients shows that the normal distribution does not properly fit the analysed data series. Particularly, skewness coefficients exhibit longer tails to the left for carbon and oil returns. This implies the presence of negative atypical returns (as shown in Figure 1). The kurtosis values indicate much heavier tails than those of a normal distribution, supporting the presence of extreme returns in the two data series, even more pronounced in the case of the oil price returns. Overall, the descriptive statistics indicate the presence of well-known stylised facts for carbon and oil returns, which implies that normal distribution does not fit well the analysed time series.

**Nonlinearity test**

The BDS test was run for the carbon and oil logarithmic weekly returns. The results prove the presence of non-linear effects, mainly for the carbon price returns (Table 3.2, third column). This indicates the relevance of employing models that capture this type of dynamics. We propose the use of machine learning models to address the presence of non-linear effects in the carbon and oil price returns as suggested by Tsay and Chen (2018).

**Table 3.2 BDS test**

<table>
<thead>
<tr>
<th>$\text{eps}$</th>
<th>$M$</th>
<th>Carbon price logreturns</th>
<th>Oil price logreturns</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$m = 2$</td>
<td>0.1179</td>
<td>4.202e-05</td>
</tr>
<tr>
<td></td>
<td>$m = 3$</td>
<td>0.0002</td>
<td>3.269e-10</td>
</tr>
<tr>
<td>2</td>
<td>$m = 2$</td>
<td>0.1804</td>
<td>1.582e-06</td>
</tr>
<tr>
<td></td>
<td>$m = 3$</td>
<td>0.0016</td>
<td>4.692e-11</td>
</tr>
<tr>
<td>3</td>
<td>$m = 2$</td>
<td>0.3178</td>
<td>4.173e-10</td>
</tr>
<tr>
<td></td>
<td>$m = 3$</td>
<td>0.0108</td>
<td>1.516e-14</td>
</tr>
<tr>
<td>4</td>
<td>$m = 2$</td>
<td>0.5754</td>
<td>&lt; 2.2e-16</td>
</tr>
<tr>
<td></td>
<td>$m = 3$</td>
<td>0.0290</td>
<td>&lt; 2.2e-16</td>
</tr>
</tbody>
</table>
P-values for the BDS test in the last two columns; \( m \) corresponds to the embedding dimensions of the BDS test, and \( \varepsilon \) corresponds to a numeric vector of epsilon values for close points. Null hypothesis indicates the presence of non-linear effects.

**Forecast evaluation**

Table 3.3 summarises the performance measures for individual, EW, HANN, and DL models. We present the MAE, RMSE, and DA statistics, as defined in Equations (3.4)–(3.6), for the individual forecasts obtained from the ARIMA, RF, SVM and NAR models. Moreover, the more accurate results obtained from the nine hybrid models, described in Section 3.2, are included in this table. The weights of individual forecasts in the hybrid models are computed either assuming equal weights or optimising them through HANN or DL techniques. In these cases, the forecasts estimated from single models are used as inputs, according to the nine employed models. For the NAR models, we performed 10,000 simulations.

**Table 3.3 Results evaluation**

<table>
<thead>
<tr>
<th>Model</th>
<th>MAE</th>
<th>RMSE</th>
<th>DA</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA</td>
<td>5.1502</td>
<td>6.9236</td>
<td>35.4430</td>
</tr>
<tr>
<td>RF</td>
<td>5.1302</td>
<td>7.1266</td>
<td>51.3158</td>
</tr>
<tr>
<td>SVM</td>
<td>5.1969</td>
<td>7.2036</td>
<td>42.1053</td>
</tr>
<tr>
<td>NAR (5,3)</td>
<td><strong>4.9244</strong></td>
<td><strong>6.7584</strong></td>
<td><strong>56.9620</strong></td>
</tr>
<tr>
<td>EW1</td>
<td>5.0885</td>
<td>6.9271</td>
<td>52.6316</td>
</tr>
<tr>
<td>EW2</td>
<td>5.0640</td>
<td>6.9278</td>
<td>44.7368</td>
</tr>
<tr>
<td>EW3</td>
<td>5.0044</td>
<td>6.9345</td>
<td>48.6842</td>
</tr>
<tr>
<td>HANN1</td>
<td>4.8087</td>
<td>6.6735</td>
<td>55.2632</td>
</tr>
<tr>
<td>HANN2</td>
<td>4.7381</td>
<td>6.6725</td>
<td>65.7896</td>
</tr>
<tr>
<td>HANN3</td>
<td><strong>3.8224</strong></td>
<td><strong>5.6196</strong></td>
<td><strong>71.0526</strong></td>
</tr>
<tr>
<td>DL3</td>
<td><strong>4.4851</strong></td>
<td><strong>6.3752</strong></td>
<td><strong>64.4737</strong></td>
</tr>
</tbody>
</table>
Panel B. Oil price returns results evaluation

<table>
<thead>
<tr>
<th>Model</th>
<th>MAE</th>
<th>RMSE</th>
<th>DA</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA</td>
<td>6.1631</td>
<td>9.6862</td>
<td>51.8987</td>
</tr>
<tr>
<td>RF</td>
<td>5.9141</td>
<td>9.0426</td>
<td><strong>44.7368</strong></td>
</tr>
<tr>
<td>SVM</td>
<td>6.0936</td>
<td>9.4548</td>
<td>40.7895</td>
</tr>
<tr>
<td>NAR (5,3)</td>
<td>5.9832</td>
<td>9.1229</td>
<td>35.4430</td>
</tr>
<tr>
<td>EW1</td>
<td>5.9502</td>
<td>9.2674</td>
<td>43.4211</td>
</tr>
<tr>
<td>EW2</td>
<td>6.0353</td>
<td>9.3845</td>
<td>38.1579</td>
</tr>
<tr>
<td>EW3</td>
<td>5.9746</td>
<td>9.1876</td>
<td>32.9847</td>
</tr>
<tr>
<td>HANN1</td>
<td>6.7871</td>
<td>10.0911</td>
<td>57.8947</td>
</tr>
<tr>
<td><strong>HANN2</strong></td>
<td><strong>5.5773</strong></td>
<td><strong>8.3158</strong></td>
<td><strong>51.3158</strong></td>
</tr>
<tr>
<td><strong>HANN3</strong></td>
<td><strong>5.2960</strong></td>
<td><strong>8.3475</strong></td>
<td><strong>55.2632</strong></td>
</tr>
<tr>
<td>DL1</td>
<td>5.6473</td>
<td>8.0322</td>
<td>50</td>
</tr>
</tbody>
</table>

MAE and RMSE are calculated as the difference between observed and forecasted return values. The best forecasts are obtained when the MAE and RMSE are closer to 0. The DA measure compares the upward or downward direction of the observed and forecasted values; thus, the best forecasts are obtained when this measure is closer to 100. The best individual and hybrid forecasts are highlighted in **bold type font**. Cross-validation and Lasso and Ridge regularisations were performed for HANN and DL models. Only the best results between the three approaches are reported. DL models were built according to models DL1 to DL3 described in the Methodology Section. Table 3 presents the best obtained results by using DL models. These models correspond to the combinations (10,6) and (20,6) for carbon and oil returns, respectively.

The best models are those with the lowest values for MAE, RMSE, and the highest value for the DA. When reviewing the individual models’ performance, the NAR (RF) model presents the more precise results for carbon (oil) price returns. However, considering all the proposed models, we obtained the most accurate results from the HANN3 model with Lasso regularisation for carbon and oil price returns. In terms of accuracy, these models are followed by DL3 model (HANN2 model) for carbon (oil) price returns. These results uncover interesting evidence for the following reasons.

Firstly, previous works (e.g., Safari and Davallou, 2018; Tsay and Chen, 2018) highlight that one of the main advantages of hybrid models is their incorporation of linear and non-linear effects by including traditional econometric methods (linear effects) and machine learning
techniques (non-linear effects). However, our results constitute empirical evidence that, for the analysed data, traditional econometric do not necessarily yield better results than machine learning and/or hybrid techniques, since the best results were obtained by combining machine learning techniques. Considering the assumptions required by the traditional econometric techniques and the values of MSE and RMSE which, in our case, are lower than those obtained in previous related works (Safari and Davallou, 2018; Fan et al., 2015), these results should be of interest.

Secondly, one of the possible disadvantages of employing neural networks as ensemble methods corresponds to the possible overfitting problems. Nevertheless, in the obtained results, the best forecasts for carbon and oil price returns are estimated from the use of Lasso regularisation, which constitutes one of the most established techniques to overcome overfitting problems.

Figure 3.3 confirms these results. since the observed carbon and oil price returns and the forecasted values estimated from a set of the considered hybrid and individual models. As previously mentioned, the best forecasts are obtained through the HANN3 ensemble, which replicates similar dynamics than the observed returns for carbon and oil returns.  

![Figure 3.3 Forecasting through single and hybrid models](image)

*Carbon price returns*

---

4 Though our study focuses on returns, it is possible to recover the carbon prices through the following expression $V_t = V_{t-1} e^{R_t}$.  

81
The graph displays the carbon and oil price observed returns and the forecasted values through the HANN6, DL (HANN5) and NAR (RF) models for Carbon (Oil) returns which presented the higher accuracy in the pool of analyzed models. The number of observations is 76 weeks for this testing sample.

3.5. Further analysis

To confirm the results in the previous section, we performed further analysis by splitting the total sample in an alternative manner. In this section, we assigned 70% (30%) of the dataset to the train (test) subsample, and then we obtained 115 observations for the test subsample; Table 3.4 presents these estimations. In this case, the NAR (7,4) model for carbon price returns and the RF model for oil price returns present the best individual performance. Considering all the proposed models, we obtain the most accurate forecasts from the HANN1 model (HANN2 model) for the carbon (oil) price returns followed by the DL model.
### Table 3.4 Results evaluation

#### Panel A. Carbon price returns results evaluation

<table>
<thead>
<tr>
<th>Model</th>
<th>MAE</th>
<th>RMSE</th>
<th>DA</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA</td>
<td>5.5315</td>
<td>7.2477</td>
<td>27.9661</td>
</tr>
<tr>
<td>RF</td>
<td>5.3653</td>
<td>7.1808</td>
<td>43.4783</td>
</tr>
<tr>
<td>SVM</td>
<td>5.2151</td>
<td>6.9852</td>
<td>39.1304</td>
</tr>
<tr>
<td>NAR (7,4)</td>
<td><strong>5.2441</strong></td>
<td><strong>6.8742</strong></td>
<td><strong>50</strong></td>
</tr>
<tr>
<td>EW1</td>
<td>5.2988</td>
<td>6.9806</td>
<td>34.7826</td>
</tr>
<tr>
<td>EW2</td>
<td>5.2474</td>
<td>6.9316</td>
<td>40.8696</td>
</tr>
<tr>
<td>EW3</td>
<td>5.1921</td>
<td>6.8992</td>
<td>40.1348</td>
</tr>
<tr>
<td>HANN1</td>
<td><strong>4.7012</strong></td>
<td><strong>6.4293</strong></td>
<td><strong>69.5652</strong></td>
</tr>
<tr>
<td>HANN2</td>
<td>5.6939</td>
<td>7.7369</td>
<td>66.0870</td>
</tr>
<tr>
<td>HANN3</td>
<td>5.3830</td>
<td>7.3691</td>
<td>50.4348</td>
</tr>
<tr>
<td>DL1</td>
<td><strong>5.1550</strong></td>
<td><strong>6.9514</strong></td>
<td><strong>54.7826</strong></td>
</tr>
</tbody>
</table>

#### Panel B. Oil price returns results evaluation

<table>
<thead>
<tr>
<th>Model</th>
<th>MAE</th>
<th>RMSE</th>
<th>DA</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARIMA</td>
<td>5.1707</td>
<td>8.2367</td>
<td>52.5424</td>
</tr>
<tr>
<td>RF</td>
<td><strong>4.9697</strong></td>
<td><strong>7.8165</strong></td>
<td><strong>46.0870</strong></td>
</tr>
<tr>
<td>SVM</td>
<td>5.0160</td>
<td>7.9609</td>
<td>44.3478</td>
</tr>
<tr>
<td>NAR (5,3)</td>
<td>5.0665</td>
<td>7.8503</td>
<td>44.0678</td>
</tr>
<tr>
<td>EW1</td>
<td>5.0047</td>
<td>7.9417</td>
<td>45.2174</td>
</tr>
<tr>
<td>EW2</td>
<td>5.0404</td>
<td>7.9829</td>
<td>42.6087</td>
</tr>
<tr>
<td>EW3</td>
<td>4.9835</td>
<td>7.8446</td>
<td>39.1340</td>
</tr>
<tr>
<td>HANN1</td>
<td>5.1603</td>
<td>8.1018</td>
<td>49.5652</td>
</tr>
<tr>
<td>HANN2</td>
<td><strong>4.3493</strong></td>
<td><strong>6.7959</strong></td>
<td><strong>58.2609</strong></td>
</tr>
<tr>
<td>HANN3</td>
<td>5.1834</td>
<td>7.8742</td>
<td>57.3913</td>
</tr>
<tr>
<td>DL2</td>
<td><strong>4.6715</strong></td>
<td><strong>6.7574</strong></td>
<td><strong>57.3913</strong></td>
</tr>
</tbody>
</table>

MAE and RMSE are both based on the difference between the observed and forecasted returns value. The closer that MAE and RMSE to 0, the better the forecasts obtained. The DA measure compares the upward or downward direction of both observed and forecasted values; thus the best forecasts are obtained when this measure is closer to 100. We highlighted the best individual and hybrid forecasts in **bold**. Moreover, we performed cross-validation, lasso, and ridge regularisations for HANN and DL models. Table 4 reports the best results between three approaches. We built DL models according to models seven to nine described in the Methodology Section. Table 4 presents the best obtained results using the DL models. These models correspond to combinations (10,6) and (20,6) for carbon and oil returns, respectively.
Even when the best results are not obtained by combining machine learning techniques without including traditional econometric techniques, the results estimated through the HANN3 model remain satisfactory. Overall, these additional results confirm the benefits of hybrid models based on neural networks and deep learning techniques to forecast carbon and oil price returns. Figure 3.4 exhibits the forecasting dynamics.

**Figure 3.4** Forecasting through single and hybrid models (Further results)

*Carbon price returns*

![Carbon price returns graph](image)

*Oil price returns*

![Oil price returns graph](image)

The graph displays the carbon and oil price observed returns and the forecasted values through the HANN4 (HANN5), DL and NAR (RF) models for Carbon (Oil) returns which presented the higher accuracy in the pool of analyzed models. The number of observations is 115 weeks for this testing sample.
3.6. Conclusions

Considering the efficiency of the EU ETS in reducing GHG emissions and predominance of fossil-energy-intensive industries, the understanding of the dynamics of carbon and oil prices has gained a prominent role. Hence, efficient policies can be formulated to mitigate environmental problems through the correct modelling of carbon and oil prices. The modelling of time series through hybrid models has recently obtained considerable interest. This study has found that non-linear time series models can effectively forecast economic and financial series behaviour without incorporating traditional econometric techniques limitations. Particularly, the forecasts from the hybrid proposals – specifically those obtained from a combination of the individual forecasts through a neural network model – were better off than those obtained from the individual models and the hybrid models ensembled by the use of a simple average calculated from the results obtained from individual models. That is, forecasts obtained using hybrid models based exclusively on machine learning techniques (HANN3 model) presented higher accuracy. These results provide interesting insights about financial time series forecasting considering that previous studies highlight the advantages of modelling financial time series through the combination of traditional econometric models and machine learning techniques enables the capture of both linear and non-linear characteristics of the time series (e.g., Safari and Davallou, 2018; Tsay and Chen, 2018). In contrast to previous studies, our research suggests that satisfactory forecasts can be obtained without including traditional econometric models forecasts in the hybrid models. In other words, traditional econometric models do not offer advantages, in terms of forecasting accuracy, only capturing financial time series linear effects.
Moreover, our findings establish evidence about the importance of employing non-linear ensemble approaches –versus linear ensemble forms– to forecast financial time series (Liao and Tsao, 2006; Alonso et al., 2007; Zhu et al., 2018). Additionally, the outperformance of neural networks as ensemble techniques compared to simple average hybrid models, we contribute with new evidence to the forecast combination puzzle (e.g. Chan and Pauwels, 2018; Diebold and Shin, 2019). Specifically, our results provide insights about the merit of employing sophisticated ensemble methods to forecast financial time series compared to simple average hybrid models.

Furthermore, our proposal constitutes a relatively simple alternative to ensemble individual methods compared to other approaches. In addition, this result suggests further research corresponding to the application of Kalman filters (see, e.g. Safari and Davallou, 2018) and other alternative methods aimed at finding the appropriate weights of the individual forecasts in hybrid models. All in all, this forecasting methodology should be considered in carbon finance models and its implications addressed for analysts, policy makers and regulators. This, considering the relevance that energy returns prediction, particularly carbon returns forecasting, has to establish practical and stable carbon pricing mechanisms, which in turn, offer practical guidance for production, operations and to design hedging and investment strategies. The continued improvement of forecasting techniques for this asset is crucial considering that minimal errors may cause considerable losses for investors and changes in the design of pricing mechanisms by regulators (Zhou et al., 2022).
3.7. Appendix

Appendix 3.A Single models

**ARIMA model.** The ARIMA \((p,d,q)\) model is one of the most popular and established models in time series literature. This model admits non-stationary time series forecasting for order \(d\) differenced variables. Time-varying dynamics of the model is represented in Equation (3.A.1):

\[
y_t = \mu + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + e_t - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q}, \quad (3.A.1)
\]

where \(e_t\) is a white noise random variable and \(\mu, \phi_i (\forall i = 1, 2, \ldots, p)\), and \(\theta_j (\forall j = 1, 2, \ldots, q)\) denote the parameters in the model. In the ARIMA models estimation. The determination of the \(p, d,\) and \(q\) orders can be achieved through different techniques, specifically, we identified \(p, d,\) and \(q\) orders using the Akaike information criterion (AIC).\(^5\)

**RF model.** Random forest algorithm (RF) is commonly used for classification and regression exercises. Random forest (Breiman, 2001) combines different binary decision trees built using several bootstrap samples obtained from learning samples and selecting a subset of explanatory variables for each node (Liu and Li, 2017). The RF model can be expressed according to equation (3.A.2):

\[
y_t = f(y_{t-1} \ldots y_{t-p}) + \varepsilon_t, \quad (3.A.2)
\]

where \(f\) is a regression function on the lagged values of the variable of interest and \(\varepsilon_t\) being a zero mean random variable. In our application we considered 3 and 4 lags as explanatory

\(^5\) Estimation and forecast were performed through the functions `auto.arima` and `forecast` of the forecast package in R, respectively.
variables for the oil and carbon price returns\textsuperscript{6} based on a trial-and-error criteria. The number of terminal nodes is equal to 5, and the employed number of trees was 500.

\textit{SVM model.} Support vector machines (SVM) (Cortes and Vapnik, 1995) are a kind of supervised learning models used for classification and regression analysis. This method is specifically used for solving the problems of a small number of training observations and overfitting, since, in the training data process, the obtained solution is unique (Khashman and Nwulu, 2011). After testing different kernels and according to accuracy measures, we used the polynomial kernel, described in Equation 3.A.3:

\[
K(x_i, x_j) = (\gamma x_i^T x_j + r)^d, \gamma > 0, \tag{3.A.3}
\]

where \(x_i, x_j\) are training vectors and \(\gamma, r, d\) are kernel parameters\textsuperscript{7}.

\textit{NAR model.} Non-linear autoregressive (NAR) neural network is a model of the neural network family wherein input variables correspond to lagged values of the dependent variable. The NAR model can be represented as follows:

\[
\hat{y}_t = f(y_{t-1}, y_{t-2}, y_{t-3}, \ldots, y_{t-o}), \tag{3.A.4}
\]

where the forecasted value for the variable, \(\hat{y}_t\), is obtained from a regression function on the first \(o\) lagged values of the variable, the value of \(o\) being determined in our applications by a trial-and-error method according to previous studies (Safari and Davallou, 2018). Specifically, we used 3, 5, 7, and 10 lags as inputs, and we chose the number of nodes in the hidden layer as half plus one the units of input nodes.

\textsuperscript{6} The number of variables sampled at each node was tuned by the use of the package iRF in R.
\textsuperscript{7} In this exercise, the parameters were selected by a tuning process through the package e1071 in R. The employed parameters comprised \(\gamma = 10, r = 0.1\), and the cost of constraints violation was equal to 10. Similarly to the case of RF, we use 3 and 4 lags as explanatory variables based on a trial-and-error criteria.
Appendix 3.B Hybrid models

Table B.1 gathers the hybrid models considered in the empirical applications.

Table B.1 Combinations of Hybrid models

<table>
<thead>
<tr>
<th>Hybrid model</th>
<th>Individual models combination</th>
</tr>
</thead>
<tbody>
<tr>
<td>EW1</td>
<td>ARIMA, RF, NAR</td>
</tr>
<tr>
<td>EW2</td>
<td>ARIMA, SVM, NAR</td>
</tr>
<tr>
<td>EW3</td>
<td>RF, SVM, NAR</td>
</tr>
<tr>
<td>HANN1</td>
<td>ARIMA, RF, NAR</td>
</tr>
<tr>
<td>HANN2</td>
<td>ARIMA, SVM, NAR</td>
</tr>
<tr>
<td>HANN3</td>
<td>RF, SVM, NAR</td>
</tr>
<tr>
<td>DL1</td>
<td>ARIMA, RF, NAR</td>
</tr>
<tr>
<td>DL2</td>
<td>ARIMA, SVM, NAR</td>
</tr>
<tr>
<td>DL3</td>
<td>RF, SVM, NAR</td>
</tr>
</tbody>
</table>

Abbreviations in the second column of table B.1 denotes techniques ARIMA (ARIMA), random forest (RF), Support vector machine (SVM) and Non-linear autoregressive neural networks (NAR). Combinations between the ARIMA, SVM and NAR models were also examined, but the results obtained from these combinations are not included considering that the performance of the presented ensembles was superior.

Appendix 3.C L1 and L2 regularisation techniques

Assume a neural network with an objective (loss) function $J(\theta, X, y)$ where $X$ corresponds to the input variables, $\theta$ are the weights in the neural network and $y$ is the output variable. Hence, in the case of $L1$ regularisation, the absolute value of the weights of the neural network to the loss function is added to formulate the following cost function:

$$J(\theta, X, y) + \lambda \sum_{j=1}^{p} |W_j|,$$  

(3.C.1)

where $\lambda$ is a tuning parameter to control the bias variance trade-off.
Alternatively, the $L2$ regularisation technique considers the squared value of the weights of the neural network into the loss function, according to the equation (3.C.2),

$$J(\theta, X, y) + \lambda \sum_{j=1}^{p} W_j^2,$$

(3.C.2)

with $\lambda$ being the tuning parameter.
CHAPTER 4: Real options volatility surface for valuing renewable energy projects

4.1. Introduction

Though renewable sources of energy – biomass, hydropower, geothermal, wind power or solar power, among others – are increasing their market share at the expense of other sources, a major concern in this direction is the search of accurate valuation methods for renewable energy projects. The use of real options is gaining in importance since it provides more realistic values for energy projects (Liu et al., 2019; Aquila et al., 2020; Gupta, 2021; Li and Cao, 2022), since real option analysis (ROA) incorporates managerial flexibility in the valuation of projects under uncertainty, especially that of renewable energy projects.

However, one shortcoming that emerges when utilizing real options is the estimation of the volatility parameter. As a matter of fact, for new and renewable energy investments, the absence of historical and market data makes the volatility estimation challenging. Furthermore, the renewable markets uncertainty, high investment costs, and the fossil fuel prices affect the risk of the inflows of this type of projects. The estimation and analysis of volatility is not only important for a more reliable assessment of the project value but also crucial for strategic decision-making due to the fact that higher volatility may delay the investment decision (Dixit and Pindyck, 1994) and increase the owner’s value, but decrease the manager’s value (Cui and Shibata, 2017). As a consequence, the analysis of volatility for renewable energy projects is demanding more research (Li et al., 2018).

A common approach for volatility estimation is the use of the standard deviation of the net present value (NPV) distribution obtained by Monte Carlo simulation; however, several works have evidenced an overestimation of volatility when employing such methodology (Smith, 2005; Godinho, 2006; Brandão et al., 2012). In particular, different studies focused on energy projects employ the volatility of the WTI, electricity, or other commodity prices, either directly or as an input in Monte Carlo simulations (Ritzenhofen and Spinler, 2016; Zhang et al., 2017). Nevertheless, the volatility of some projects is higher than that of
commodity prices (Lima and Suslick, 2006). Another approach considers the volatility of a
stock or commodity as a proxy for the project volatility. This is an appropriate approach
provided that the chosen ‘twin’ asset is highly related to the assets of the project – one
example is the implied volatility of call options on comparable firms (Brach and Paxson,
2001). Nonetheless, it is often difficult to find an asset or similar company with the same
characteristics of the analyzed project. In the same line, the market proxy approach – MPA
(Mun, 2002) consists in adjusting the volatility of stock prices of similar companies by the
financial leverage ratio of their respective companies. The main disadvantage of this method
is that volatility estimation could be distorted by different factors including financial bubbles
and investors’ overreaction.

A more natural technique for estimating volatility is the implied volatility approach,
which employs the volatility that satisfies the Black-Scholes-Merton (BSM) option pricing
formula to value European options. In our case, the implied volatility for real options is the
volatility that makes the value of a company equal to its market value. A similar procedure
was proposed by Brach and Paxson (2001), but the authors suggest that a stock with volatility
similar to the analyzed project should be found. The practical disadvantage, as previously
mentioned, lies in the search of a suitable twin stock. In financial options, it is usual to use
the plot of the implied volatility against the strike price or moneyness. For real options, we
suggest the use of debt-to-equity relation rather than the moneyness or strike price. Therefore,
our methodology relies on Merton’s model (Merton, 1974), where the equity value can be
seen as a call option on the firm’s assets. Under the assumption that the firm value follows a
geometric Brownian motion (GBM), the debt and equity values satisfy the well-known BS
partial differential equation. It is then assumed that the volatility employed for renewable
energy project valuation is comparable to the implied volatility extracted from the firms listed
in an appropriate stock index, and this is the basis of our methodology described in the next
section. For a review and comparison of different methodologies to estimate project volatility
see for instance Lewis et al. (2008), Nicholls et al. (2014), and Godinho (2018).

Thus, the aim of this paper is to provide a suitable methodology to estimate the volatility
parameter for firms that invest in projects of renewable energy sectors and use real options
for valuation purposes. Depending on the debt-to-equity level of the project, the firm may
employ an implied volatility estimated from the market data of peers. Therefore, our procedure to estimate the implied volatility for real options resembles the methodology employed to calculate the implied volatility in financial options. The difference is that we employ levels of ‘debt-to-equity’ rather than values of the ‘moneyness’ to obtain the volatility surface under the real options framework. Given that real option tools are an application of financial option machinery, we consider that our proposal is a natural and straightforward approach to estimate the volatility for real options. Despite the presence of different proposals to estimate the implied volatility for real options, we consider our methodology is straightforward and easily applicable. We expect that this methodology can be applied by practitioners and academics, where the obtained results can be compared with actual methodologies in this field and be considered for valuing investment projects.

4.2. Methodology

The Merton model (Merton, 1974) has been applied in the structural models for credit risk framework, such as the KMV model, and it is useful to estimate the distance-to-default (DD). Since the value of the firm’s assets is unobservable and the face value of debt as well or hard to estimate (Byström, 2011), there are some methodologies in the literature to estimate the necessary variables to assess the DD. One of the first attempts is the proposal of Ronn and Verma (1986). The authors propose two equations to solve two unknowns – the asset volatility and the face value of debt. However, as noted by Milidonis and Stathopoulos (2011), this proposal is not consistent with the Merton’s assumption of stochastic equity volatility. On the other hand, the maximum likelihood proposal of Duan (1994, 2000), which is a data transformation method, is superior to the previous methodology (Milidonis and Stathopoulos, 2011). An approach with similar results is proposed by Vassalou and Xing (2004), which is an iterated procedure – as the one utilized by the KMV model – to find the volatility and drift of the asset value, and it is considered as an expectation-maximization (EM) algorithm according to Duan et al. (2005). More recently, Christoffersen et al. (2022) found that though the maximum likelihood method yields similar results to the iterative approach for the usual levels of firm leverage, there is a remarkable difference when asset values are comparatively lower than the face value of the firm's debt. In addition, the authors
argue that the KMV method cannot be seen as an EM algorithm, in contrast to Duan et al. (2005). The iterative procedure and similar methods have been employed in the literature in different applications. For instance, Lee (2011) estimated the firm value and its volatility to assess the default probability in credit risk applications, followed by Charitou et al. (2013), Doumpos et al. (2015), Afik et al. (2016), and more recently by Andreou et al. (2021) and Levine and Wu (2021). Other similar approximations are applied by Zhang et al. (2020) in the bank’s liquidity risk framework and Lovreta and Silaghi (2020) to obtain the surface of CDS implied firm’s asset volatility. Therefore, we employ the methodology of Vassalou and Xing (2004) in our work to estimate the asset volatility.

As per in Vassalou and Xing (2004), we assume that the market value of the renewable energy firm’s assets follows a GBM:

\[ V = \mu dt + \sigma_V V dB, \]  

where \( V \) is the value of the assets of the renewable company, \( \mu \) and \( \sigma_V \) are the instantaneous drift and volatility, respectively, and \( B \) is a standard Brownian motion. According to the Black-Scholes-Merton formula, the equity’s market value (\( E \)) is given by

\[ E = VN(d_1) - D e^{-r(T-t)}N(d_2), \]

where

\[ d_1 = \frac{\ln(V/D) + (r + \sigma_V^2/2)T}{\sigma_V \sqrt{T}}, \]

\[ d_2 = d_1 - \sigma_V \sqrt{T}. \]

\( N(d_1) \) and \( N(d_2) \) represent the standard normal cumulative distribution functions; \( T \) is the time to maturity; \( D \) is the market value of debt. Then, an iterative procedure is employed to solve the firm’s asset volatility, \( \sigma_V \). More details about the procedure is found in Christoffersen (2020), and it is implemented in our work. In our study, we employ the 10-year treasury bill rate, which is equal to 1.5%, is the proxy for the risk-free rate (although results are not sensitive to the use of other proxies), and the time to maturity is set to 2 years. An important input is the face value of debt, that is unobservable, and we assume that it is equal to the short-term debt plus one half of the long-term debt as per in Vassalou and Xing.
(2004), Bharath and Shumway (2008), and Amaya et al. (2019), therefore, we also employ quarterly data of equity market value, short- and long-term debt due to data availability.

Once the volatilities are estimated, these parameter values are calibrated by employing the Stochastic-Alpha-Beta-Rho (SABR) model. This model (Hagan et al., 2002) is used since it is the most common methodology employed in the financial industry to calibrate the implied volatility for derivatives. The SABR model provides better performance than the BSM for hedging and has been found to predict market volatility accurately — e.g. for foreign exchange option market — as a result of its salient advantages, as described in Vellekoop and Vlaming (2009) and Zhang and Fabozzi (2016), the main benefit being its more realistic volatility dynamics. Following the Kienitz and Wetterau (2013) notation, the SABR model can be expressed through the following differential stochastic equations.

\[
dS(t) = \sigma(t)S(t)^{\beta}dW(t), \tag{4.5}
\]

\[
d\sigma(t) = \nu\sigma(t)dZ(t), \tag{4.6}
\]

\[
dW(t)dZ(t) = \rho dt. \tag{4.7}
\]

Hence, SABR is a CEV model that includes stochastic volatility \(\sigma(t)\), where \(S(0) = S_0\) is the spot price of the underlying asset and \(\sigma(0) = \sigma_0\) is the volatility of the spot value. The parameters \(\nu, \beta,\) and \(\rho\) represent the volatility of the process \(\sigma(t)\), the asymmetry, and the correlation between the Brownian motions \(dW(t)\) and \(dZ(t)\), respectively. These parameters satisfy \(\nu \geq 0; \ 0 \leq \beta \leq 1; \) and \(-1 \leq \rho \leq 1\). By setting \(\beta = 1\) and \(\nu = 0\), we recover the standard BSM model.

Through the application of perturbation techniques (see e.g., Skinner, 2011), it is obtained an expression for the calculation of the implied volatility as follows:

\[
\sigma_{SABR}(K, T) \approx A\left(\frac{z}{x(z)}\right) B, \tag{4.8}
\]

\[
A = \frac{\sigma_0}{(SK)^{1-\beta}\left[1+(1-\beta)^2\frac{\log^2(S/K)}{24}+(1-\beta)^4\frac{\log^4(S/K)}{1920}+\ldots\right]^\frac{1}{2}}, \tag{4.9}
\]

\[\text{A limitation of the SABR model is the fact that it does not fit implied volatilities satisfactorily for small strike values or for long time to maturity. However, this drawback may be solved by the multiple time step Monte Carlo simulation (mSABR) technique proposed by Leitao et al. (2017).}\]
\[ B = \left[ 1 + \left( \frac{(1-\beta)^2 \sigma_0^2}{24(S/K)^{1-\beta}} + \frac{\rho \beta \sigma_0}{4(SK)^{1-\beta}} v + \frac{2-3\rho^2}{24} v^2 \right) T + \cdots \right], \quad (4.10) \]

\[ z = \frac{v}{\sigma_0} (SK)^{1-\beta} \log(S/K), \quad (4.11) \]

\[ x(z) = \log \left( \frac{\sqrt{1-2\rho + z^2 + z - \rho}}{1-\rho} \right). \quad (4.12) \]

The implementation is performed in Matlab by employing the function `blackvolbysabr`, wherein the variable inputs are the implied volatilities estimated in the previous step, and their respective debt-to-equity relations, instead of the moneyness (or strike price) as in the case of financial options. For more details about SABR model, see Hagan et al. (2002), Rebonato et al. (2009), and Kienitz, and Wetterau (2013).

Finally, after the implied volatilities are estimated and calibrated, for each date of valuation, the volatility surface is obtained. For a given date, the graph of implied volatility against the debt-to-equity ratio can be represented and combined to obtain the surface shape. Hence, for a given date of valuation and leverage ratio of a project, the (implied) volatility can be used to estimate the value of the project. It is noteworthy that we employ the date of implied volatility estimation (namely, the valuation date) rather than the time to maturity used in the case of financial options. Though the main purpose of our work is to provide an adequate methodology to estimate volatility in order to valuate new renewable energy projects, the implied volatility may be also used to valuate different strategic options as can be seen in our empirical results. Figure 4.1 depicts our proposed methodology.

**Figure 4.1** The procedure of the proposed methodology for the project volatility estimation
4.3. Empirical results

For sake of general application on renewable energy projects, information about stocks from the S&P/TSX Renewable Energy and Clean Technology Index\(^9\) is used to estimate the implied volatility as of December 2020. From the 17 stocks listed in the index, 11 stocks\(^{10}\) were considered due to information availability. Table 4.1 shows the different renewable firms’ leverage ratios and their respective estimated volatility for each year following the iterated procedure proposed by Vassalou and Xing (2014). The data are sorted according to the leverage ratio, specifically de debt-to-equity relationship.

---

\(^9\) This index measures performance of green technologies and sustainable infrastructure companies listed on the TSX. Constituents are screened by Sustainalytics. Source: us.spindices.com.

<table>
<thead>
<tr>
<th>Year</th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>3.55</td>
<td>13.01</td>
<td>27.33</td>
<td>36.56</td>
</tr>
<tr>
<td>2010</td>
<td>3.48</td>
<td>10.59</td>
<td>23.08</td>
<td>29.36</td>
</tr>
<tr>
<td>2011</td>
<td>24.15</td>
<td>25.65</td>
<td>31.09</td>
<td>35.14</td>
</tr>
<tr>
<td>2012</td>
<td>16.47</td>
<td>26.76</td>
<td>36.15</td>
<td>38.52</td>
</tr>
<tr>
<td>2013</td>
<td>13.43</td>
<td>22.79</td>
<td>27.04</td>
<td>38.96</td>
</tr>
<tr>
<td>2014</td>
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<td>22.84</td>
<td>24.75</td>
<td>38.47</td>
</tr>
<tr>
<td>2015</td>
<td>19.13</td>
<td>29.22</td>
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</tr>
<tr>
<td>2016</td>
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<td>30.35</td>
<td>33.59</td>
<td>36.71</td>
</tr>
<tr>
<td>2017</td>
<td>20.02</td>
<td>23.42</td>
<td>27.14</td>
<td>36.39</td>
</tr>
<tr>
<td>2018</td>
<td>20.56</td>
<td>26.76</td>
<td>28.25</td>
<td>31.43</td>
</tr>
<tr>
<td>2019</td>
<td>20.75</td>
<td>26.68</td>
<td>30.24</td>
<td>37.45</td>
</tr>
<tr>
<td>2020</td>
<td>1.83</td>
<td>18.28</td>
<td>24.12</td>
<td>24.47</td>
</tr>
</tbody>
</table>

Table 4.1 Implied volatility estimation for the analyzed renewable companies
As observed, the minimum volatility is 3.37% (when the debt-to-equity ratio is 62.7% in 2013) and the maximum is 113.38% (when the debt-to-equity proportion is 20.7% in 2019); however, the median of the estimated volatility ranges between 16.42% (2013) and 47.10% (2009). For renewable energy data, the volatility surface at annual basis is mapped in Figure 4.2. Different values of implied volatility are obtained based on the analyzed period and the leverage ratio of the analyzed sample.

**Figure 4.2** Volatility surface for renewable energy data (annual basis)

The dynamics of the estimated parameters of the SABR model are presented in Fig. 4.3. The $\nu$ parameter (referred to as ‘volvol’) is relatively stable during the sample period but has its peak (around 20) in 2009.
To illustrate the utility of our methodology for the valuation of renewable energy projects, this section presents a case study, which analyzes the adoption of solar photovoltaic project for 2013. Torani et al. (2016) examine the adoption of solar photovoltaic by employing a stochastic dynamic model. The authors extend the Bellman equation to consider two variables, which are the long-term price of electricity ($P$) and cost of solar ($C$). The dynamics for each of these variables are given by

\begin{align}
    dP &= \alpha_P Pdt + \sigma_P Pdz_P, \quad (4.13) \\
    dC &= \alpha_C Cdt + \sigma_C Cdz_C, \quad (4.14)
\end{align}

where $\alpha_P$ ($\alpha_C$) is the drift of the electricity price (cost of solar) process, $\sigma_P$ and $\sigma_C$ are the volatilities of the respective processes, and $dz_P$ and $dz_C$ are the increments of a Wiener process or Brownian motion. Thus, the Bellman equation considering the two variables is

\begin{equation}
\frac{1}{2}(\sigma_P^2 P^2 F_{PP} + 2\gamma \sigma_P \sigma_C P C F_{PC} + \sigma_C^2 C^2 F_{CC}) + \alpha_P P F_P + \alpha_C C F_C - r F = 0, \quad (4.15)
\end{equation}

where $\gamma$ is the correlation between $P$ and $C$. The solution for $F$ is analogous to the previous case (one variable), and $\beta_1$ is given by

\begin{equation}
\beta_1 = \frac{1}{2} - \frac{\alpha_P - \alpha_C}{\sigma^2} + \sqrt{\left(\frac{\alpha_P - \alpha_C}{\sigma^2} - \frac{1}{2}\right)^2 + 2 \frac{r - \alpha_C}{\sigma^2}}, \quad (4.16)
\end{equation}

and
\[ \sigma^2 = \sigma_P^2 - 2\gamma \sigma_P \sigma_C + \sigma_C^2. \] (4.17)

Interestingly, the authors find that

\[ P_{ROA}^* = \left( \frac{\beta_1}{\beta_1 - 1} \right) P_{NPV}^*, \] (4.18)

where \( P_{NPV}^* \) and \( P_{ROA}^* \) are the threshold electricity price at which a residential or commercial consumer will adopt solar photovoltaic according to NPV and ROA rule, respectively. Once again, we are interested in the valuation result and more details are found in Torani et al. (2016). Table 4.2 presents the comparison of the results obtained by using the volatility extracted from the volatility surface for real options and \( r = 3\% \) discount rate.

\begin{table}
\caption{Results comparison on option valuation of the Case Study}
\begin{center}
\begin{tabular}{cccc}
\hline
 & Calculations based on Torani et al. (2016) & Mean Vol in 2013 (our study) & Median Vol in 2013 (our study) \\
\hline
\( \sigma \) & 0.2007 & 0.2269 & 0.1642 \\
\( \alpha_P \) & 0.0289 & 0.0289 & 0.0289 \\
\( \alpha_C \) & -0.0441 & -0.0441 & -0.0441 \\
\( \beta_1 \) & 1.0118 & 1.0111 & 1.0127 \\
\( P_{NPV}^* \) & 0.0102 & 0.0102 & 0.0102 \\
\( P_{ROA}^* \) & 0.8760 & 0.9285 & 0.8137 \\
\hline
\end{tabular}
\end{center}
\end{table}

The authors employ \( \sigma_P = \sigma_C = 0.1409 \) and \( \gamma = 0 \); therefore, their volatility estimation is 20.07\% according to Eq. (4.17). Instead of implementing the previous assumptions, we apply our proposal, which yields a more appropriate volatility estimation for this renewable energy case study. Since there is no information about the leverage ratio of the project, we employ the information provided in Table 4.1, with a mean (median) implied volatility of 22.69\% (16.42\%). Otherwise we could extract the implied volatility corresponding to the debt-to-equity relation in 2013 from the volatility surface.
4.4. Conclusions

Renewable energy project valuation requires accurate tools to estimate volatility, a problem that has not been satisfactorily addressed in the literature. We cover this remarkable gap by suggesting a method to estimate volatility for new and renewable energy projects that follows the ROA and thus is based on the concept of implied volatility for financial options. As the framework is based on the concept of implied volatility for financial options, we employed the debt-to-equity ratio for real options instead of the moneyness or strike price used in the case of financial options. To this end, we applied the SABR model to calibrate the implied volatilities. Future research should be focused on applying the proposed methodology to conventional energy projects, such as the oil-based projects, which have been extensively studied in the literature, and other types of projects for which market data is available.
CONCLUSIONS

The four chapters presented in this document suggest interesting conclusions about financial volatility and the specific topics that are developed throughout the text. In this line, the main conclusions, practical implications and some recommendations for future research related to the analyzed subjects are presented in this section.

The first chapter results contribute to literature, significantly, through the study of the volatility transmission effects between energy and financial markets in Emerging Markets. This study fills some gaps observed in literature related to this thematic, with a special emphasis on the comparison between financial crisis periods, such as the COVID-19 pandemic and the subprime crisis, and calm intervals. Based on a DCC model, the results find volatility transmission effects from the financial index to the energy index during the subprime crisis. In contrast, there is a reversal in the transmission effects patterns during COVID-19 pandemic, when volatility transmission effects from the energy index to the financial index are observed. Moreover, the results reveal bidirectional volatility transmission effects between the energy and the financial indices on a daily basis, but on weekly and monthly frequencies, only volatility transmission from the financial to the energy indices is evidenced.

The reversal in the volatility transmission effects can be explained by the sector in which COVID-19 pandemic crisis originated. This is, whereas the subprime crisis originated in the financial sector, the COVID-19 crisis originated in the real sector of the economy. This, considering that a combination of different factors, which include global oil demand and
supply changes, storage risk, geopolitical reasons, OPEC decisions, and futures market dynamics (Sadorsky, 2004; Basher and Saddorsky, 2006; Corbet et al., 2020), triggered the emergence of the second crisis.

The most interesting result of this chapter confirms that volatility transmission effects are time and event dependent in emerging markets, as suggested by Antonakakis and Kizys (2015). Particularly, this type of volatility transmission effects changes may be evidenced during market downturns and financial crisis (Liu et al. 2021). In consequence, volatility transmission between markets or sectors are considered as dynamic relationships that change in direction and intensity over time (Diebold and Yilmaz, 2012).

The results of the second chapter of the document confirm these findings. Through the use of the Diebold and Yilmaz (2012) framework, the volatility spillovers between commodities, Bitcoin and Emerging Markets are examined. This framework is employed considering that it allows to capture the changes and the net directional effects of volatility spillovers over time. The results confirm changes in direction and intensity of volatility spillovers during the analyzed period. Particularly, changes in volatility spillovers effects between commodities, Bitcoin and Emerging Markets are evidenced, specially, during turbulent periods such as COVID-19 pandemic. In the case of Oil and Emerging Markets, their role as transmitters of shocks to the system is accentuated since March 2020 to the first quarter of 2022, when these assets cease to be transmitters of shocks to the system to become receivers of shocks from the system. This could be explained by the fact that turbulence in financial markets in this period is associated with the medium-term effects of COVID-19 pandemic and geopolitical tensions such as the conflict between Russia and Ukraine.
Moreover, it is remarkable that the intensity of volatility spillovers among these markets seems to be related to high volatility periods. This suggests that these periods in Emerging Markets could be anticipated by the increase in volatility spillovers between commodities, Bitcoin and Emerging Markets. In this line, traditional econometric models and machine learning techniques were employed to forecast the TVS index proposed by Diebold and Yilmaz (2012). The results confirm the adequate performance of machine learning techniques to forecast financial variables and the possibility to employ the TVS index as a measure to anticipate turbulence periods.

Considering the relevance that machine learning models have gained in financial literature in recent years and the importance of returns forecasting in volatility analysis, in Chapter three, Carbon and Oil price returns are forecasted through machine learning techniques and traditional econometric models. Particularly, ARIMA, Random Forest, Support Vector Machines and Neural networks are employed to obtain individual returns forecasts, which posteriorly are combined by the construction of hybrid models based on machine learning and deep learning techniques. This, taking into account the increasing volatility in energy returns and the relevance that the adequate understanding of carbon prices has to attract investors to these semi-artificial markets.

The results confirm the superiority of hybrid models which combines machine learning forecasts exclusively, unlike previous studies (e.g., Safari and Davallou 2018; Tsay and Chen 2018) that highlight the advantages of incorporating traditional econometric models in the construction of hybrid models to capture the linear features of financial time series. Moreover, the advantages of non-linear ensemble approaches versus linear ensemble forms are evidenced, which contributes to the forecast combination puzzle (e.g. Chan and Pauwels...
that stipulates that the hybrid models built through simple average methods tend to outperform the more sophisticated ensemble approaches.

Finally, Chapter four contributes to the literature by addressing some of the shortcomings of the usually employed methods to estimate volatility in real options valuation and providing an application of the implied volatility approach to estimate volatility in renewable energy projects valuation through real options. This, through a suitable method which employs the SABR model to calibrate the volatility surface by the use of comparable firms data.

The conclusions derived from the presented exercises have remarkable practical implications for investors and regulatory organisms. The adequate understanding of volatility transmission and spillovers is crucial to the design of mechanisms oriented to maintain stability in financial markets. This, considering that the volatility relationships between different markets could be used to anticipate possible market crashes or turbulent periods. This result is particularly relevant for emerging markets given their fragility and instability issues.

Investors can also benefit from the presented findings, since these agents are continuously monitoring volatility linkages between different markets for the design of hedging and investment strategies. Moreover, firms which are interest in renewable energy project valuation through real options can employ the proposed method to obtain accurate and satisfactory volatility estimations which are crucial to make financial decisions.

Finally, the advantages of hybrid and machine learning models to forecast financial variables evidenced in the document can be of special interest to regulators and investors. This, considering that the obtained results can be used as a reference to build models oriented to
anticipate high-volatility periods which are relevant for the design of policies and hedging and investment strategies.

Future research can be focused on the use of alternative deep learning techniques, such as LSTM model, or hybrid models ensembled through innovative methods such as Kalman or particles filters to forecast energy assets returns or volatility spillovers. In addition, the proposed volatility estimation method for project valuation through real options may be tested in conventional energy projects or projects related to other type of sectors. Finally, it could be interesting to examine volatility spillovers in Emerging Markets from different perspectives. For instance, the quantile connectedness and the Barunik et al. (2016) approaches could be employed in future works.
CONCLUSIONES

Los cuatro capítulos presentados en este documento sugieren interesantes conclusiones sobre la volatilidad financiera y los temas específicos que se desarrollan a lo largo del texto. En este apartado, se presentan las principales conclusiones, implicaciones prácticas y algunas recomendaciones para futuras investigaciones relacionadas con los temas analizados.

Los resultados del primer capítulo contribuyen de forma significativa a la literatura, a través del estudio de los efectos de transmisión de volatilidad entre mercados energéticos y financieros en mercados emergentes. Este estudio cubre algunos vacíos observados en la literatura relacionada con esta temática, con especial énfasis en la comparación entre periodos de crisis financieras, como la pandemia del COVID-19 y la crisis subprime, e intervalos de calma. Con base en un modelo DCC, los resultados sugieren la presencia de efectos de transmisión de volatilidad del índice financiero hacia el índice energético durante la crisis subprime. En cambio, se produce una reversión de los patrones de transmisión durante la pandemia del COVID-19, cuando se observan efectos de transmisión de volatilidad desde el índice energético hacia el índice financiero. Además, los resultados revelan efectos bidireccionales de transmisión de volatilidad entre los índices energético y financiero usando datos diarios, pero en las frecuencias semanal y mensual, sólo se evidencia transmisión de volatilidad desde el índice financiero hacia el energético.

La reversión de los efectos de transmisión de volatilidad puede explicarse por el sector en el que se originó la crisis del COVID-19. Es decir, mientras que la crisis subprime se originó en el sector financiero, la crisis del COVID-19 se originó en el sector real de la economía. Esto, teniendo en cuenta que una combinación de diferentes factores, entre los que se
incluyen los cambios en la oferta y la demanda mundiales de petróleo, el riesgo de almacenamiento, las razones geopolíticas, las decisiones de la OPEP y la dinámica del mercado de futuros (Sadorsky, 2004; Basher y Saddorsky, 2006; Corbet et al., 2020), desencadenaron la aparición de la segunda crisis.

El resultado más interesante de este capítulo confirma que los efectos de transmisión de volatilidad dependen del tiempo y de los acontecimientos ocurridos en los mercados emergentes, como sugieren Antonakakis y Kizys (2015). En particular, este tipo de cambios en los efectos de transmisión de volatilidad pueden evidenciarse durante caídas de mercado y crisis financieras (Liu et al. 2021). En consecuencia, la transmisión de volatilidad entre mercados o sectores se considera una relación dinámica que cambia de dirección e intensidad con el tiempo (Diebold y Yilmaz, 2012).

Los resultados del segundo capítulo del documento confirman estas conclusiones. Mediante el uso del método propuesto por Diebold y Yilmaz (2012), se examinan los efectos en los spillovers de volatilidad entre materias primas, Bitcoin y mercados emergentes. Este marco se emplea teniendo en cuenta que permite capturar los cambios y los efectos direccionales netos de los spillovers de volatilidad a lo largo del tiempo. Los resultados confirman cambios en la dirección e intensidad de los spillovers de volatilidad durante el periodo analizado. En particular, se evidencian cambios en los spillovers de volatilidad entre materias primas, Bitcoin y Mercados Emergentes, especialmente, durante periodos de turbulencia como la pandemia del COVID-19. En el caso del petróleo y los mercados emergentes, su papel como transmisores de choques al sistema se acentúa desde marzo de 2020 hasta el primer trimestre de 2022, momento en el que estos activos dejan de ser transmisores de choques hacia el sistema, para convertirse en receptores de choques desde el sistema. Esto podría explicarse
por el hecho de que la turbulencia en los mercados financieros en este periodo está asociada a los efectos a medio plazo de la pandemia COVID-19 y a tensiones geopolíticas como el conflicto entre Rusia y Ucrania.

Además, se destaca que la intensidad de los spillovers de volatilidad entre estos mercados parece estar relacionada con periodos de alta volatilidad. Esto sugiere que estos periodos en los mercados emergentes podrían estar precedidos por un aumento en los spillovers de volatilidad entre materias primas, Bitcoin y Mercados Emergentes. En este sentido, se emplearon modelos econométricos tradicionales y técnicas de machine learning para predecir el índice TVS propuesto por Diebold y Yilmaz (2012). Los resultados confirman el desempeño adecuado de las técnicas de machine learning para predecir variables financieras y la posibilidad de emplear el índice TVS como medida para anticipar periodos de turbulencia.

Considerando la relevancia que los modelos de machine learning han adquirido en la literatura financiera en los últimos años, y la importancia del pronóstico de rentabilidades en el análisis de la volatilidad, en el capítulo tres, se pronostican las rentabilidades de los precios del carbono y del petróleo mediante técnicas de machine learning y modelos econométricos tradicionales. En particular, se emplean modelos ARIMA, Random Forest, Support Vector Machine y de redes neuronales para obtener pronósticos de rentabilidades individuales, que posteriormente se combinan mediante la construcción de modelos híbridos basados en técnicas de machine learning y deep learning. Esto, teniendo en cuenta la creciente volatilidad en los retornos de activos energéticos y la relevancia que tiene el adecuado entendimiento de los precios del carbono para atraer inversionistas a estos mercados semi-artificiales.
Los resultados confirman la superioridad de los modelos híbridos que combinan exclusivamente pronósticos obtenidos a partir de técnicas de machine learning, a diferencia de estudios anteriores (p. ej., Safari y Davallou 2018; Tsay y Chen 2018) que destacan las ventajas de incorporar modelos econométricos tradicionales en la construcción de modelos híbridos para capturar las características lineales de las series temporales financieras. Además, se evidencian las ventajas de los modelos híbridos construidos mediante métodos no lineales frente a las aproximaciones lineales usadas para construir este tipo de modelos, lo que contribuye al *forecast combination puzzle* (por ejemplo, Chan y Pauwels 2018; Diebold y Shin 2019) que estipula que los modelos híbridos construidos mediante promedios simples tienden a superar a los métodos de combinación más sofisticados.

Por último, el capítulo cuatro contribuye a la literatura abordando algunas de las deficiencias de los métodos empleados habitualmente para estimar la volatilidad en la valoración de opciones reales. Lo anterior mediante una aplicación del enfoque de volatilidad implícita para estimar la volatilidad en la valoración de proyectos de energías renovables mediante opciones reales. Esto se realiza a través de un método que emplea el modelo SABR para calibrar la superficie de la volatilidad mediante el uso de datos de empresas comparables.

Las conclusiones derivadas de los ejercicios presentados tienen notables implicaciones prácticas para los inversionistas y los organismos reguladores. La adecuada comprensión de la transmisión y los spillovers de volatilidad es crucial para el diseño de mecanismos orientados a mantener la estabilidad en los mercados financieros. Esto, considerando que las relaciones de volatilidad entre distintos mercados podrían utilizarse para anticipar posibles caídas de mercado o periodos de turbulencia. Este resultado es particularmente relevante para los mercados emergentes dados sus problemas de fragilidad e inestabilidad financiera.
Los inversionistas también pueden beneficiarse de los hallazgos presentados, ya que estos agentes están continuamente monitoreando los vínculos de volatilidad entre diferentes mercados para el diseño de estrategias de cobertura e inversión. Además, las empresas interesadas en la valoración de proyectos de energías renovables mediante opciones reales pueden emplear el método propuesto para obtener estimaciones precisas y satisfactorias de la volatilidad, que son cruciales para la toma de decisiones financieras.

Por último, las ventajas de los modelos híbridos y de machine learning para predecir variables financieras evidenciadas en el documento pueden ser de especial interés para los organismos reguladores e inversionistas. Esto, considerando que los resultados obtenidos pueden ser utilizados como referencia para construir modelos orientados a anticipar periodos de alta volatilidad, lo cual es relevante para el diseño de políticas y estrategias de cobertura e inversión.

La investigación futura puede centrarse en el uso de técnicas alternativas de deep learning, como el modelo LSTM, o modelos híbridos construidos a través de métodos innovadores como los filtros de Kalman o de partículas para predecir los rendimientos de los activos energéticos o los spillovers de volatilidad entre diferentes mercados. Además, el método de estimación de la volatilidad propuesto para la valoración de proyectos mediante opciones reales puede probarse en proyectos de fuentes de energía convencional o relacionados con otro tipo de sectores. Finalmente, podría ser interesante examinar los spillovers de volatilidad en mercados emergentes desde diferentes perspectivas. Por ejemplo, las propuestas de quantile connectedness y el método de Barunik et al. (2016) podrían emplearse en futuros trabajos.


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