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Dynamic co-movement analysis among oil prices, green bonds, and CO_2 emissions, 2014-2022

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2023

This thesis is dedicated to God and my family,
especially to my lovely husband and daughter.

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Resumen

Análisis de las relaciones dinámicas entre los precios del petróleo, los bonos verdes y las emisiones de CO_2, 2014-2022

Esta investigación aborda el vacío en la literatura existente sobre cómo se relacionan entre sí los precios del petróleo, los bonos verdes y las emisiones de CO_2. Además, se investigan las relaciones a corto y largo plazo de los co-movimientos entre estas importantes variables en el contexto de la transición energética mundial, utilizando un modelo de aprendizaje automático. Por lo tanto, el objetivo principal de este estudio es analizar los resultados de los co-movimientos a corto y largo plazo y las implicaciones para investigadores, inversores y responsables de política. Para validar el análisis, utilizamos datos diarios de los precios del petróleo, los bonos verdes y las emisiones de CO_2 desde 2014 hasta 2022. Además, se realiza un análisis cienciométrico de las principales metodologías para medir los co-movimientos entre los mercados financieros, utilizando técnicas como el análisis de (i) fuentes, (ii) autores, (iii) documentos, y (iv) análisis de *clusters*. De este modo, esta investigación aplica metodologías como la prueba de causalidad de Granger, la correlación condicional dinámica *(Dynamic Conditional Correlation*, DCC-Garch), el espectro de potencia wavelet (*Wavelet Power Spectrum*, WPS) y el análisis de coherencia wavelet (*Wavelet Coherence Analyses*, WCA). Además, este estudio emplea un modelo de aprendizaje automático para medir las relaciones entre las variables seleccionadas. En concreto, se implementó el autoencoder logístico difuso (*Fuzzy Logistic Autoencoder,* FLAE). Además, los resultados del modelo de aprendizaje automático se validaron y compararon con los modelos estimados. Por último, este estudio representa un avance en la explicación de la relación entre estas variables.

Palabras clave: co-movimientos, dependencia, precios del petróleo, bonos verdes, Emisiones de CO_2, análisis cienciométrico, machine learning.

Abstract

Dynamic co-movement analysis among oil prices, green bonds, and CO_2 emissions, 2014-2022

This research addresses the problem of the coverage gap in the extant literature to know how oil prices, green bonds, and CO_2 emissions are related to each other. Additionally, to research the short and long-term relations using a machine learning model for measuring co-movements among these important variables in the global energy transition context. Therefore, this study's primary objective is to analyze the results of the short- and long-term co-movements and the implications for researchers, investors, and policy-makers. To validate the analysis, we use daily data from oil prices, green bonds, and CO_2 emissions from 2014 to 2022. In addition, a scientometric analysis of the principal methodologies for measuring the co-movements among financial markets, using techniques such as the analysis of (i) sources, (ii) authors, (iii) documents, and (iv) cluster analysis. In this way, this research applies methodologies like Granger Causality Test, Dynamic Conditional Correlation (DCC-Garch), Wavelet power spectrum (WPS), and wavelet coherence analyses (WCA). Additionally, this study employs a machine learning model for measuring the relationships among the selected variables. Specifically, the Fuzzy Logistic Autoencoder (FLAE) was implemented. Furthermore, the results of the machine learning model were validated and compared with the estimated models. Finally, this study represents a breakthrough in explaining the relationship among these variables.

Keywords: co-movements; dependence; oil prices; green bonds, CO_2 emissions, scientometric analysis; energy markets; machine learning.

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List of Symbols and Abbreviations

Abbreviation	Concept
ADF	Augmented Dickey-Fuller
AE	Autoencoders
ANNs	Artificial Neural Networks
AR	Auto-Regressive
ARIMA	Auto-Regressive Integrated Moving Average
ARIMAX	Auto-Regressive Integrated Moving Average with exogenous variables
ARMA	Auto-Regressive Moving Average
BB-P	Brent oil returns
BiLSTM	Bidirectional Long Short-Term Memory
BSE	Bombay Stock Exchange
CNN	Convolutional Neural Networks
CNN	Convolutional Neural Networks
CO2	Carbon dioxide
CO2-E	CO_2 futures' returns
COVID-19	Coronavirus Disease, 2019
CWT	Continuous Wavelet Transforms
DCC	Dynamic Conditional Correlation
DCDNNs	DCC-GARCH-DNNs model
DL	Deep Learning
DNNs	Deep Neural Networks
DWT	Discrete Wavelet Transform
ESG	Environmental, Social, And Governance
ESN	Echo State Network
ETS	Emissions Trading
EU	European Union
EU ETS	European Union Emissions Trading System
EUAs	European Union Allowances
F	Fair
FAC2	Factor of Two
FB	Fractional Bias
FL	Fuzzy Logistic
FLAE	Fuzzy Logistic Autoencoder
FNLM	Fuzzy Neural Logistic Maps
G	Good
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GBP	Green Bond Principles
GB-V	Green Bond Index
GCC	Gulf Cooperation Council
GRU	Gated Recurrent Unit
ICE	Intercontinental Exchange Group
ICMA	International Capital Markets Association
IOA	Index of Agreement
JB	Jarque–Bera
LBQ	Ljung–Box Q-statistics
LSTM	Long Short-Term Memory

LT	Long-Term
MG	Geometric Mean Bias
ML	Machine Learning
MLP	Multi-Layer Perceptron
MRE	Mean Relative Error
MT	Medium-Term
OECD	Organisation for Economic Co-operation and Development
OF	Over-Fair
OPEC	Organization of Petroleum Exporting Countries
P	Poor
RBRENT	Brent oil returns
RDNNs	Recurrent Deep Neural Networks
RF	Random Forests
RGBEUTREU	Green Bond Index
RMO1	CO2 futures' returns
RNNs	Recurrent Neural Networks
RV	random variables
S-ANFIS	Stochastic Neural Fuzzy Integrated System
SDGs	Sustainable Development Goals
SLSTM	Stacked Long Short-Term Memory
ST	Short-Term
SVM	Support Vector Machines
TMLE	Targeted Maximum Likelihood Estimation
TSC	Time Series Classification
TVP-VAR	Time-Varying Parameter Vector Auto Regression
UAPC2	Unpaired Accuracy of the Peak Concentration
UF	Under-Fair
VAR	Vector Auto Regression
VG	Variance Mean Bias
WD	Wasserstein Distance
WDI	Wasserstein Distance Index
WHO	World Health Organization
WoS	Web of Science
WTO	World Trade Organization

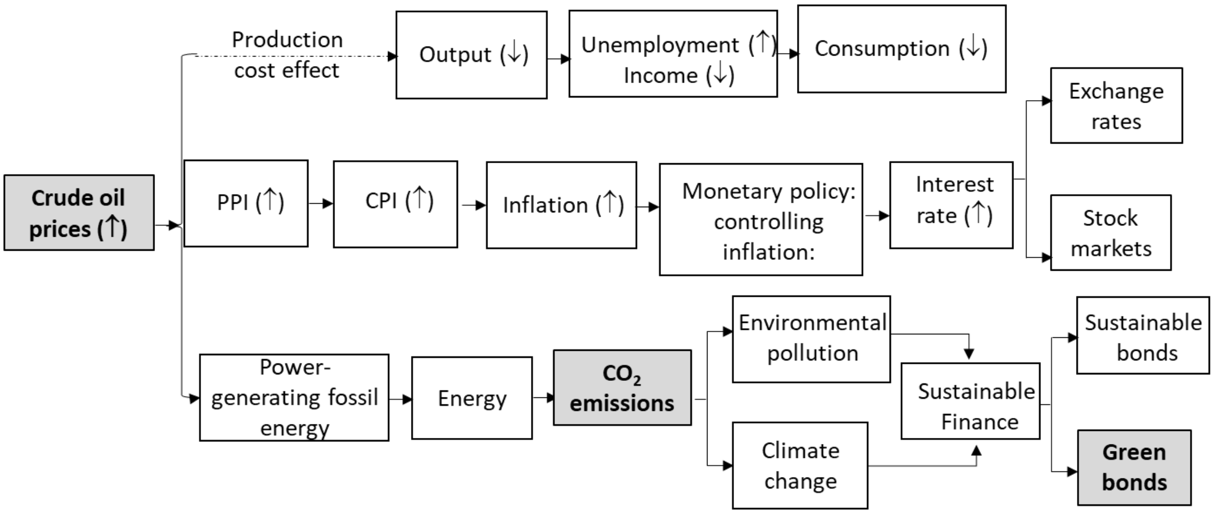
Introduction

The profound globalization interdependence among financial variables and economic and political environment increases the co-movements between financial markets. The word co-movement is an abbreviation of joint movement or correlated movement between different time series. Mitra & Bhattacharjee (2015) argued that there are two main channels through which financial series show interdependence with each other. Firstly, there are the macroeconomic benefits, linked to the effective management of the countries' monetary policies, tending towards low inflation and stability of interest rates and exchange rates, which is why there is a transmission of monetary policies to the financial markets via asset prices. Secondly, due to the management of international portfolios, in the search for better returns with less exposure to risk, there is an increase in the integration of financial markets that gradually aligns international prices, thus reducing the benefits of portfolio diversification in the international context.

In this global scenario, oil price has an important role. Oil prices play a significant role in the global economy as oil is a major source of energy and is used in various industries such as transportation, manufacturing, and agriculture. Fluctuations in oil prices can have a major impact on the economies of countries that are major producers or consumers of oil, as well as on the profits of companies in the oil and gas industry. Additionally, changes in oil prices can also affect inflation, currency exchange rates, and global trade (Sadorsky, 2009; Tang et al., 2010). According to Tang et al. (2010) the main transmission channels of crude oil in the production are: (i) supply-side shock effect, (ii) wealth transfer effect, (iii) inflation effect, (iv) monetary policy effect, (v) industrial adjustment, and (vi) uncertainty effect.

Additionally, oil price has a significant effect on green bonds issuances and CO_2 emissions. To understand the connections is necessary to understand their roles. Oil price is the primary indicator in the energy market, and almost all other energy product prices are influenced by it, including natural gas and coal (Ma et al., 2021). Thus, energy prices are correlated with carbon emissions rights and green bonds because this last financial mechanism represents firms' attention to environmental protection, which promotes the development of a low-carbon economy (Wang and Wang, 2022; González-Ruiz et al., 2023). Figure 0-1 presents the connection among crude oil, economic and financial variables including sustainable finance.

Figure 0-1: Linkages among crude oil, economic and financial variables including sustainable finance.



Source: author based on Ma et al. (2021) and Tang et al. (2010).

Thus, to understand the co-movement between sustainable variables like oil prices, green bonds, and CO_2 emissions acquires importance in a context of energy transition that the world is currently experiencing. Furthermore, to know if the co-movements change in the short and long term, acquires importance for the practical purposes of this investigation. The necessity of one methodology for its modeling is due to the practical need of different countries to measure the dependence of their financial and economic variables for the formulation of economic policy by policy-makers and for hedging and financial planning decisions by investors. All these topics are expanded in detail in this thesis.

Objectives

General:

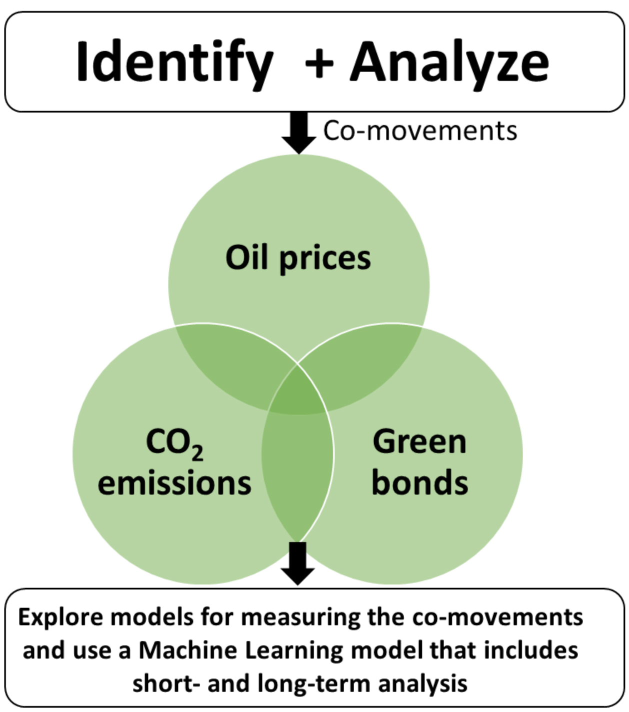
To develop a co-movement methodology that includes short- and long-term time series analysis using machine learning and data from oil prices, green bonds, CO_2 emissions in the period 2014-2022.

Specific:

1. To conduct a comprehensive scientometric study of the dynamic co-movements among oil prices and financial markets (including energy markets and assets related to sustainable finance) to provide researchers, investors, and policy-makers with a broad understanding of the status quo of the literature on this topic. Additionally, it identifies research trends that provide a framework driving further research.
2. To provide an in-depth analysis of the co-movements among the green bonds, CO_2 emissions, and oil prices, using Granger Causality Test and the Dynamic Conditional Correlation Garch (DCC-Garch).
3. To perform an in-depth analysis of the time-frequency relationship among oil prices, green bonds, and CO_2 emissions using wavelet coherence.
4. To propose a co-movement methodology analysis that includes short- and long-term time series using machine learning and data from oil prices, green bonds, CO_2 emissions.
5. To analyze the results of the developed methodology, searching for formulating economic and investment policy recommendations that help mitigate the impact of oil shocks on green bonds issuances and CO_2 emissions.

A graphical representation of the objectives is shown below:

Figure 0-2: Research objectives.



Scope of Research

The objective of this research is to analyze the co-movements among oil prices, green bonds, and CO_2 emissions in the period 2014-2022, using a machine learning model that includes short- and long-term time series analysis. Additionally, analyze the implications of the results for researchers, investors, and policy-makers.

Thesis Organization

The methodology begins by exploring a scientometric analysis of the existent literature in the area of study. This activity is constantly repeated in the development of each stage. The methodology primarily consists of four stages divided into chapters, each of which follows the format of the paper and refers to the respective specific objective. Each stage provides the elements for establishing the proposed financial mechanism. Finally, chapter five describes the main conclusions and recommendations. Each step is described below.

Stage 1→ Chapter 1

Through a bibliographic analysis of the primary specialized and high-impact sources we examined the extant literature on the dynamic association between oil prices and financial assets with special emphasis on the methodologies for measuring the dependence among oil prices, exchange rates, stock prices, energy markets, and assets related to sustainable finance. We performed a scientometric review of the structure and global trends of the dynamic association among oil prices and financial assets, based on research from 1982 to 2022 (September) using techniques such as the analysis of (i) sources, (ii) authors, (iii) documents, and (iv) cluster analysis. A total of 746 bibliographic records from Scopus and Web of Science databases were analyzed to generate the study’s research data through scientometric networks. The visualization of the research results was performed using the VOSviewer software version 1.6.18 developed by van Eck & Waltman (2017) and the Bibliometrix package for R conceived by Aria & Cuccurullo (2017).

Stage 2→ Chapter 2

In order to better understand the dynamic relationships among green bonds, CO_2 futures’ prices and oil prices, Granger Causality Test and the Dynamic Conditional Correlation (DCC-Garch) Model were employed using a daily data set that includes 2206 observations corresponding to daily information from January 1, 2014 to June 15, 2022. The Granger Causality Test results present a unidirectional causality running from the Green Bond Index to the oil price returns. Also, there is a unidirectional causality running from the Green Bond Index to the CO_2 futures' returns. Additionally, a unidirectional causality runs from the oil price returns to the CO_2 futures' returns. The results for the DCC-Garch indicate a positive dynamic correlation between the Brent oil price return and the CO_2 futures' returns. Finally, the Green Bond Index shows a negative dynamic correlation to the oil return and the CO_2 futures' returns presenting a strong correlation in uncertainty periods.

Stage 3→ Chapter 3

A methodology to analyze the time-frequency co-movements among oil prices, green bonds, and CO_2 emissions was implemented. Thus, Wavelet power spectrum (WPS) and wavelet coherence analyses (WCA) were used on daily data from January 2014 to October 2022. The WPS results show that oil returns exhibit significant volatility at low and medium frequencies, particularly in 2014, 2019-2020, and 2022. Also, the Green Bond Index, presents significant volatility at the end of 2019-2020 and the beginning of 2022 at low, medium, and high frequencies. Additionally, CO_2 futures' returns present high volatility at low and medium frequencies, expressly in 2015-2016, 2018, the end of 2019-2020, and 2022. WCA's empirical findings reveal (i) that oil returns have a negative impact on the Green Bond Index in the medium term. (ii) There is a strong interdependence between oil prices and CO_2 futures' returns in short, medium, and long terms, as inferred from the time–frequency analysis. (ii) There also is evidence of strong short, medium, and long terms co-movements between the green bond Index and CO_2 futures' returns, with the green bond Index leading.

Stage 4→ Chapter 4

A machine learning model that includes the analysis in the short-, medium and long-term was developed identify the co-movements among oil prices, green bonds, and CO_2 emissions. Thus, The Fuzzy Logistic Autoencoder (FLAE) model was used to examine the co-movements among oil prices, green bonds, and CO_2 emissions on daily data from January 2014 to October 2022. The results indicate that in the short and medium-term, the Green Bond Index (GB-V) influenced the CO_2 futures' returns (CO2-E), and the Brent oil returns (BB-P) with a negative relationship (category - High). Additionally, the BB-P and the

CO2-E returns series are also important to forecast the BB-P and the CO2-E returns in the short and medium-term but in a smaller proportion. Finally, in the case of the Green Bond Index (GB-V) return series forecasts (category - Positive High), their own lags ordered from zero to 251 are included, which indicates that the series is mainly random as it is highly dependent on impacts close to zero, but the BB-P, and the CO2-E returns have a negative but smaller impact on its forecast. This study represents a breakthrough in explaining the relationship among these variables.

Expected results

Contribution to the Financial Area

This research contributes to the knowledge area on the measuring the co-movements among oil prices, CO_2 emissions, and green bonds as important variables in a context of energy transition. Furthermore, the proposed model base on deep learning techniques is innovative and procures for a most accurate measure of the relations among financial variables. The proposed contribution, according to the revised literature, is unprecedented and innovative.

Contribution to Sustainable Development

To obtain a robust model to quantify the co-movements among oil prices, CO_2 emissions, and green bonds. Thus, this study's outcomes can help researchers, managers, policymakers, and decision-makers to understand the importance of the oil price shocks on the design of assets and policies that tend to improve sustainability practices. It is also mandatory to gain a better understanding of decision-makers perspectives in designing investment portfolios.

Academic Contributions

The findings within this dissertation will contribute to literature including the publication of scientific papers and presentations at international academic events. The following table indicates the results obtained during the research process.

Table 0-1: Academic contributions

Product	Title	Journal/Event	Authors
Paper 1 **(Chapter 1)**	Dynamic Co-Movements among Oil Prices and Financial Assets: A Scientometric Analysis	Sustainability 2022, 14, doi:10.3390/su141912796. Indexed by: Scopus. SJR: 0.664 Quartile: Q1. A1 Category - Minciencias.	Nini Johana Marín-R., Juan D. González, Sergio Botero
Paper 2 **(Chapter 2)**	Dynamic Relationships among Green Bonds, CO_2 Emissions, and Oil Prices	Frontiers in Environmental Science 2022, 10, doi:10.3389/fenvs.2022.992726. Indexed by: Scopus. SJR: 1.233 Quartile: Q1. A1 Category – Minciencias.	Nini Johana Marín-R., Juan D. González, Sergio Botero
Paper 3 **(Chapter 3)**	A wavelet analysis of the dynamic connectedness among oil prices, green bonds, and CO_2 emissions	Risks 2023, 11(1), 15; https://doi.org/10.3390/risks11010015. Indexed by: Scopus. SJR: 0.398 Quartile: Q2. A2 Category – Minciencias.	Nini Johana Marín-R., Juan D. González, Sergio Botero
Paper 4 **(Chapter 4)**	Analyzing dynamic co-movements among oil prices, green bonds, and CO_2 emissions using the fuzzy logistic autoencoder model	Journal of Cleaner Production. Indexed by: Scopus. SJR: 1.92 Quartile: Q1. A1 Category - Minciencias. In Peer Review Process.	Nini Johana Marín-R., Juan D. González, Sergio Botero, Alejandro Peña
Conference 1 **(Chapter 1)**	Dynamic co-movements between assets in financial markets: A Scientometric Analysis	World Finance Conference (WFC22), Turin (Italy), August 2022.	Nini Johana Marín-R., Juan D. González, Sergio Botero
Conference 2 **(Chapter 2)**	Dynamic linkages between green bonds, CO_2 emissions, and oil prices	International Conference on Sustainable Finance (ICSF22), Madrid (Spain), September 2022.	Nini Johana Marín-R., Juan D. González, Sergio Botero

This thesis proceeds as follows. Each chapter contains an introduction that references the literature review regarding the respective topic and presents some stylized facts about the phenomenon of co-movements analyzed. After the introduction, each chapter outlines a different approach to measure the interdependence in financial markets and presents the results obtained for every estimation using empirical data from green bonds, CO_2 emissions, and oil prices. Finally, we present some conclusions and some recommendations for the findings in every chapter.

1. Chapter 1. Dynamic Co-Movements among Oil Prices and Financial Assets: A Scientometric Analysis

In this study, we examined the extant literature on the dynamic association between oil prices and financial assets with special emphasis on the methodologies for measuring the dependence among oil prices, exchange rates, stock prices, energy markets, and assets related to sustainable finance. We performed a scientometric review of the structure and global trends of the dynamic association among oil prices and financial assets, based on research from 1982 to 2022 (September) using techniques such as the analysis of (i) sources, (ii) authors, (iii) documents, and (iv) cluster analysis. A total of 746 bibliographic records from Scopus and Web of Science databases were analyzed to generate the study's research data through scientometric networks. The findings indicate that the most promising areas for further research in this field are represented by co-movement, copula, wavelet, dynamic correlation, and volatility analysis. Furthermore, energy markets and assets related to sustainable finance emerge as crucial trends in investigating dynamic co-movements with oil prices. They also suggest a research gap in analyzing by means of machine learning, deep learning, big data, and artificial intelligence for measuring dynamic co-movements among oil prices and assets in financial and energy markets, especially in emerging countries. Thus, these methodologies can be implemented in further research because these methods could more robustly quantify the association among such variables. The analysis provides researchers and practitioners with a comprehensive understanding of the existing literature and research trends on the dynamic association among oil prices and financial assets. It also promotes further studies in this domain. The identification of these relations presents benefits in risk diversification, hedges, speculation, and inflation targeting.

Keywords: co-movements; dependence; oil prices; stock prices; exchange rates; bibliometric analysis; energy markets; sustainable finance

1.1 Introduction

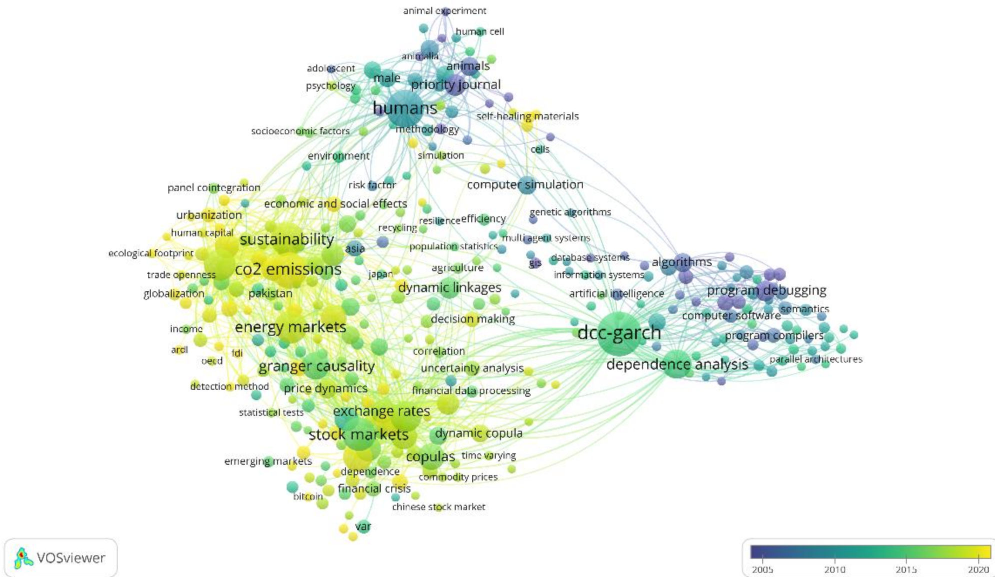
As globalization advances, economic issues and societal shifts are influencing economic, social, and governance aspects in scenarios where sustainability plays a pivotal role. Analyzing changes in the relationships among the principal financial markets provides new and enriched studies regarding the importance of cross-border cooperation, strategies, synergies, and transactions that are already reshaping the global economic and socioeconomic panorama. Regarding financial markets, it is crucial to analyze the link between oil prices and financial assets because identifying these relationships provides benefits in terms of risk diversification, hedging, speculation, and inflation targeting, especially in a global decarbonization scenario toward more sustainable energy sources (Burandt, 2021). Among the financial assets, we can primarily mention exchange rates, stocks, bonds, and commodities, but we focus our analysis on the foreign exchange and stock markets because both mainly reflect the impacts of shocks on oil prices. The evidence suggests that much of the co-movements across markets are driven by the energy market, principally oil and natural gas (Mensi et al., 2021). Thus, it has been found that oil has a leading role in the global economy (Hamilton, 1983). It has been estimated that oil is the most common energy source, with approximately one-third of the total energy consumption. In this way, oil is the most used energy source and is a natural resource that gives political and economic power to countries that have abundant reserves (Bashir, 2022; Bashir et al., 2020, 2021). Thus, oil prices are expected to be correlated with changes in financial markets' prices (Huang et al., 1996), energy markets, assets related to sustainable finance, and other variables in the real economy.

Among the main studies that have analyzed the relationship between oil shocks and financial markets, Refs. (Huang et al., 1996; Jones & Kaul, 1996; Sadorsky, 1999) can be mentioned. The results indicate that changes in oil returns had an impact on stock markets. Conversely, the literature also proposes different channels connecting international oil prices and exchange rates (Albulescu et al., 2019; Amano & van Norden, 1998a, 1998b; Chen & Rogoff, 2003; Darby, 1982; Sadorsky, 1999). For example, fluctuations in the price of oil will affect supply and demand channels of the economy, causing inflationary pressures, which will be reflected in changes in interest rates (Darby, 1982). These changes will finally be reflected in the value of the national currency (Darby, 1982). Furthermore, according to the International Trade Theory, fluctuations in oil prices and real exchange rates are related through their effects on the terms of trade and parity conditions caused by arbitrage forces (Amano & van Norden, 1998a, 1998b). Other studies examine the linkages among oil prices, energy markets, and assets related to sustainable finance (Lee et al., 2021; Li et al., 2022; Marín-Rodríguez, González-Ruiz, & Botero, 2022; X. Ren et al., 2020; Sahu et al., 2022). For example, Marín-Rodríguez, González-Ruiz, & Botero (2022) studied the dynamic relationships among green bonds, CO_2 emissions, and oil prices. They found that green bonds have a negative dynamic correlation to the oil return and the future CO_2 return and present a strong negative correlation in uncertainty periods.

Co-movements can be approached from the concepts of contagion and interdependence. Contagion refers to short-term dependence and interdependence to long-term interrelationship. Thus, it is important to analyze what is meant by the concepts of financial contagion and financial interdependence and if there is a consensus among the authors for these concepts. There are different types of co-movements among oil prices and financial markets (including energy markets and assets related to sustainable finance). However, this paper focuses on financial interdependence and financial contagion because we are interested in knowing the short- and long-term relationships between a country's most important financial variables and oil prices. According to Beirne & Gieck (2014), the difference between these two concepts is that financial interdependence is defined as the relationship between asset classes on average during the sample period, and financial contagion is specified as a change in the transmission mechanism among different types of assets in times of crisis. Beirne & Gieck (2014) found that interdependence is more notable in advanced and emerging economies in the case of the stock market, and financial spillovers are more evident within the stock market in Latin America and emerging Asia. The response to shocks differs depending on the source of the disturbance. Then, the methodologies to measure financial contagion and interdependence play an important role due to the globalization process that increases the bond or correlated movement of the different financial variables of the markets in the international context.

When first searching for "dynamic linkage*" OR "dynamic co-movement*" OR "dynamic dependence*" OR "dynamic interdependence*" in Scopus and Web of Science (WoS), four significant themes appeared, as shown in Figure 1-1. The first topic is related to biological models in humans and animals. The second is associated with computational methods and algorithms. The third deals with CO_2 emissions, energy markets, sustainability, and renewable energies. Thus, in this scenario, energy markets and sustainable finance emerge as crucial trends in investigating dynamic co-movements with oil prices. Finally, a fourth one is related to financial markets, stock markets, oil prices, and time series analysis. These topics are the central focus object of research due to the importance and development in recent times in the financial arena.

Figure 1-1: Network of co-occurring keywords for the search “dynamic linkage*” OR “dynamic co-movement*” OR “dynamic dependence*” OR “dynamic interdependence*”.



Source: Authors’ own research using VOSviewer, as well as Scopus and WoS databases.

Then, identifying the methodologies used to quantify the co-movements between oil prices and financial markets (including energy markets and sustainable finance) appears as an opportunity for understanding the financial impact of the energy transition in the global economy to more sustainable energy sources. Moreover, the energy transition promotes the use of clean energy resources and discourages fossil fuel energy consumption from ensuring sustainability (Rasheed et al., 2022). Thus, due to oil having an essential impact on the financial and economic markets, this change in the source of energy will affect the assessments of global change and development of the countries.

1.1.1 Knowledge Gap, Objective, and Contributions

Few literature review articles have been published on dynamic co-movements among oil prices and assets in financial markets (including energy markets and assets related to sustainable finance). For instance, Lin & Su (2020) conducted one about the relationship between oil prices and the stock markets. The review applied a scientometric analysis of 1342 academic publications that provided a broad understanding of the state of research and trends on this subject. Thus, Lin & Su (2020) divided their research hotspots into three segments: (i) basic relationships analysis, (ii) analysis based on updated econometric methods, and (iii) expanded analysis combining other financial sectors and market characteristics.

Moreover, Patel et al. (2022) conducted a meta-literature review of financial market integration research, including 260 articles from 1981 to 2021. This study identified five research groups in the analysis of financial market integration: (i) portfolio diversification with financial market integration, (ii) general equity market integration, (iii) financial market relationship concerning crises and events, (iv) time-varying financial market integration, and (v) co-movements and spillovers between commodities and financial markets; they also presented possible further research directions.

Similarly, Bashir (2022) undertook a bibliometric analysis of papers related to oil price shocks, stock market returns, and volatility spillovers. This author examined 684 studies in order to identify research trends in oil price shocks, stock market returns, and volatility spillover effects. Among the findings, the co-occurrence and keyword analysis highlighted that oil price shocks, equity returns, and volatility spillover are the most significant terms in the current literature. Likewise, the joint citation analysis divided the literature into three groups: (i) oil price shocks, stock market activity, and the emerging economies; (ii) oil volatility behavior and spillover effects in oil exporting and importing countries; and (iii) oil prices, stock market returns, and portfolio management.

This research aims at conducting a comprehensive scientometric study of the dynamic co-movements among oil prices and financial markets (including energy markets and assets related to sustainable finance) to provide researchers, investors, and policy makers a broad understanding of the status quo of the literature on this topic. Additionally, it identifies research trends that provide a framework driving further research.

According to this paper’s inquiry, there is no previous research in the body of knowledge about dynamic co-movements among oil prices and assets in financial markets (including energy markets and assets related to sustainable finance) that employ maps and working relationships employing networks using VOSviewer and Bibliometrix. Although the analysis of Bashir (2022) is the most similar to this research, there are three fundamental differences: (i) our purpose is to study the nexus between oil prices and financial markets in general, not only stock markets but also to extend the analysis to the impact that oil prices can have on exchange rates. (ii) Our analysis uses two databases, Scopus and WoS, whereas Bashir (2022) only use WoS, but the author admits that the inclusion of additional databases will increase the robustness of findings from further studies. Finally, (iii) this study uses the VOSviewer and Bibliometrix tools, but Bashir (2022) only uses Bibliometrix.

This study's findings will allow understanding the trends on this topic and thus establish the bases for the research processes on this field. We also outline strategies to provide data to expand the knowledge frontier in analyzing co-movements among oil prices and assets in financial markets (including energy markets and sustainable finance). This study is also expected to help investors and policy makers have more information for making decisions. For investors, knowing the co-movements among oil prices and assets (particularly correlation) provides insights into their investments' potential diversification and hedging benefits. For policy makers, such as central banks, knowing the links between these variables will help them have a better frame of reference for making monetary policy decisions.

Then, this study strives to make three considerable contributions to the existing body of literature and practice. Primarily, it is the first to integrate a scientometric analysis using the VOSviewer and Bibliometrix tools into the research topic. These tools provide an appropriate framework for articulating and understanding co-movement among oil prices and financial assets (including energy markets and sustainable finance). Second, this study compiles and classifies a broad range of documents about the topic of research on dynamic linkages among oil prices and assets in financial markets. Third, it reveals how opportunities for further research can be identified by applying maps of networks and topic cluster reviews, and thus, it is possible to find emerging themes from empirical and theoretical literature.

This study is organized as follows. In Section 2, the research approach utilized, and the literature search strategy are discussed. Section 3 presents the results of the different scientometric methods used in this study with different knowledge maps of links and tables along with their interpretation. Section 4 outlines the discussion of the main topics of the findings. Finally, Section 5 indicates the main findings and conclusions.

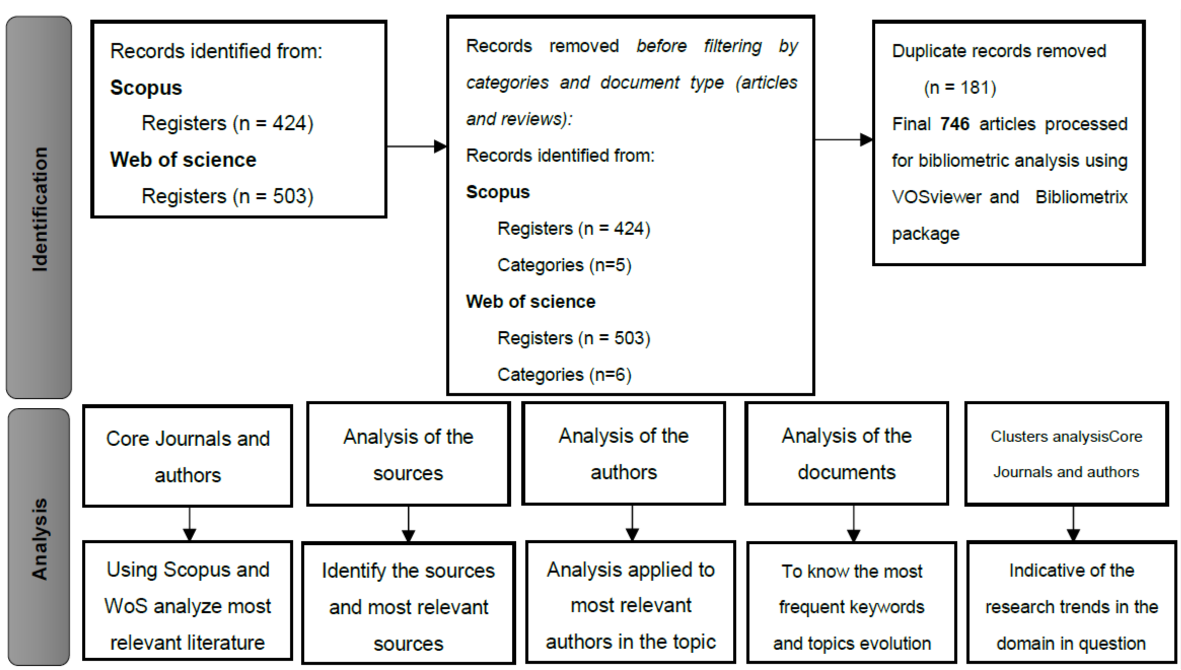
1.2 Materials and Methods

We analyzed the dynamic association among oil prices and assets in financial markets with a special focus on the methodologies for measuring the dependence among the oil prices, exchange rates, stock prices, energy markets, and assets related to sustainable finance variables using network analysis based on word diagrams and maps provided by scientometric techniques. Four scientometric techniques were implemented, which analyze

(1) sources, (2) authors, (3) documents, and (4) cluster analysis. The visualization of the research results was performed using the VOSviewer software version 1.6.18 developed by van Eck & Waltman (2017) and the Bibliometrix package for R conceived by Aria & Cuccurullo (2017). The four scientometric techniques selected are employed to (i) track the frontier of knowledge of the research area; (ii) identify the principal researchers, institutions, countries, and key subject categories; (iii) research keywords and co-citation clusters; and (v) infer the emerging research topics in the area.

The academic databases used for publication search and selection were Scopus and Web of Science (WoS). The search equation was: (TITLE-ABS-KEY ("stock market*" OR "Exchange rate*" OR "foreign exchange*" OR "financial market*" OR "asset market*") AND TITLE-ABS-KEY ("oil price*") AND TITLE-ABS-KEY ("contagion" OR "interdependence*" OR "co-movement*" OR "correlation*")). A total of 927 studies were obtained from Scopus and WoS as far as September 2022. All these were downloaded and indexed into the Mendeley reference manager for reading and content analysis. Figure 1-2 illustrates the framework implementation of the current review. The process of document analysis and screening consisted of the removal of duplicate records in the screening. After the screening process, a total of 746 articles were included in the analysis.

Figure 1-2: Literature search strategy.



Source: Authors' own research.

1.3 Scientometric Analysis

1.3.1 Analysis of the Sources

- General Information

Among the 746 documents selected for this study, 1358 authors were identified. The average number of citations per document is 26.79, which is highly regarded in academe. The annual growth rate increased by 11.54% per year. The main document type is article (672). A total of 1778 KeyWords Plus and 1792 author keywords were identified. Table 1-1 summarizes the general information about the examined papers in this study.

Table 1-1: Summary of the descriptive information.

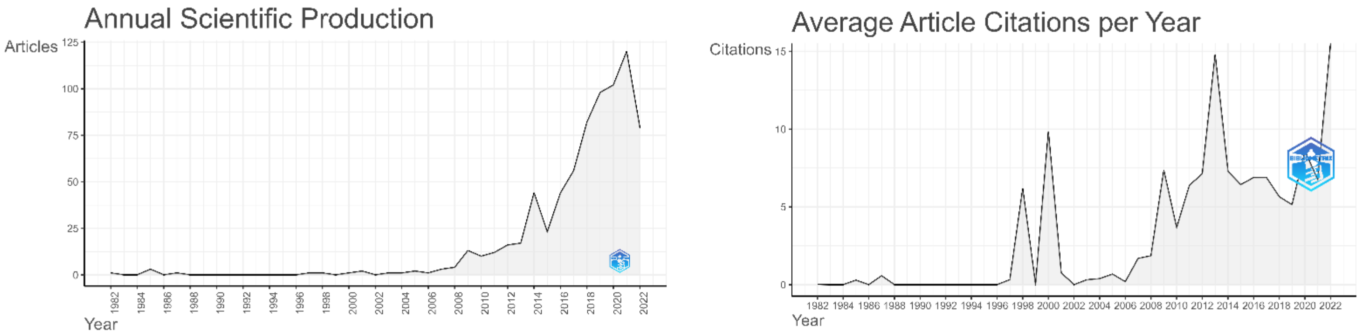
Description	Results	Description	Results
MAIN INFORMATION		DOCUMENT TYPES (continued)	
Timespan	1982:2022	Conference review	1
Sources (journals, books, etc.)	289	Erratum	2
Documents	746	Note	1
Annual growth rate %	11.54	Retracted	2
Document average age	4.37	Review	8
Average citations per doc	26.79	DOCUMENT CONTENTS	
References	27,756	KeyWords Plus (ID)	1778
DOCUMENT TYPES		Author keywords (DE)	1792
Article	672	AUTHORS	
Article; book chapter	1	Authors	1358
Article; early access	8	Authors of single-authored docs	91
Article; proceedings paper	2	AUTHORS COLLABORATION	
Book	1	Single-authored docs	112
Book chapter	13	Co-authors per doc	2.71
Conference paper	35	International co-authorships %	14.08

Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

- Publication Output

Figure 1-3a shows an important increase in studies published over the previous years, indicating the academic community's increasing interest. The annual growth rate changed from 1 document in 1982 to 120 documents in 2021. In 2022 (September), there are 79 published studies about this topic thus far, so this trend is expected to continue through 2022 and into the future. However, annual publication trends can be divided into two time periods. During the first one, until 2014, there were limited research contributions. The second period is from 2014 on (September 2022), when there was a significant increase in the research contributions due to the advance in the methodologies to address the issue. Figure 1-3b illustrates the average number of citations per year, indicating that 2014 was the year with the highest average number of citations (14.8%).

Figure 1-3: Publication output. (a) Publication output and (b) average number of citations per year.



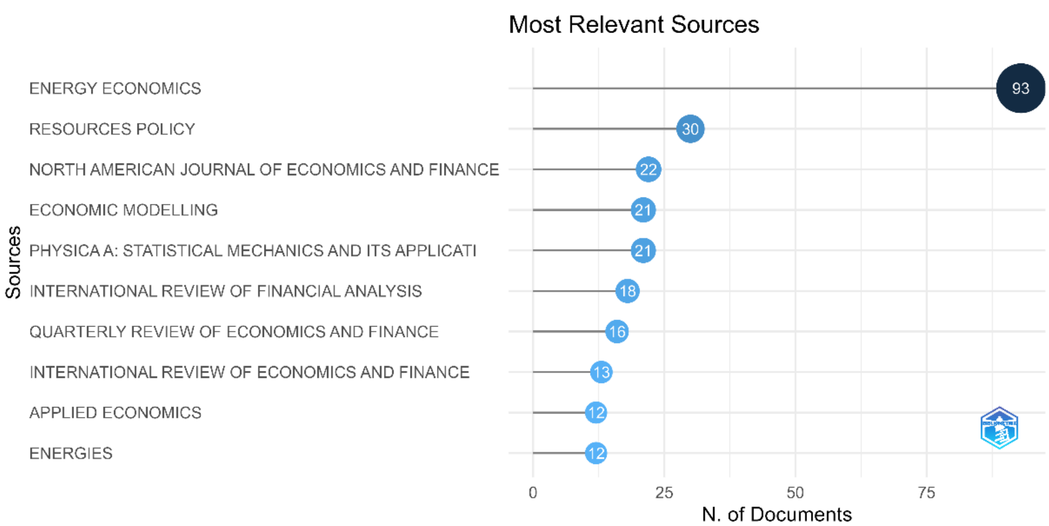
(a) (b)

Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

- <u>Discipline-Wise Analysis</u>

Figure 1-4 shows the articles published by each source in order of importance in researching dynamic co-movements among oil prices and financial assets (including energy markets and assets related to sustainable finance). It was found that this topic has been extensively studied, mainly in the journal Energy Economics (93). The second leading journal in occurrences was Resources Policy (30), and the third and fourth most relevant journals were the North American Journal of Economics and Finance (22) and Economic Modelling (21), respectively. This shows that these are essential sources for the associated research.

Figure 1-4: Distribution of documents across sources.

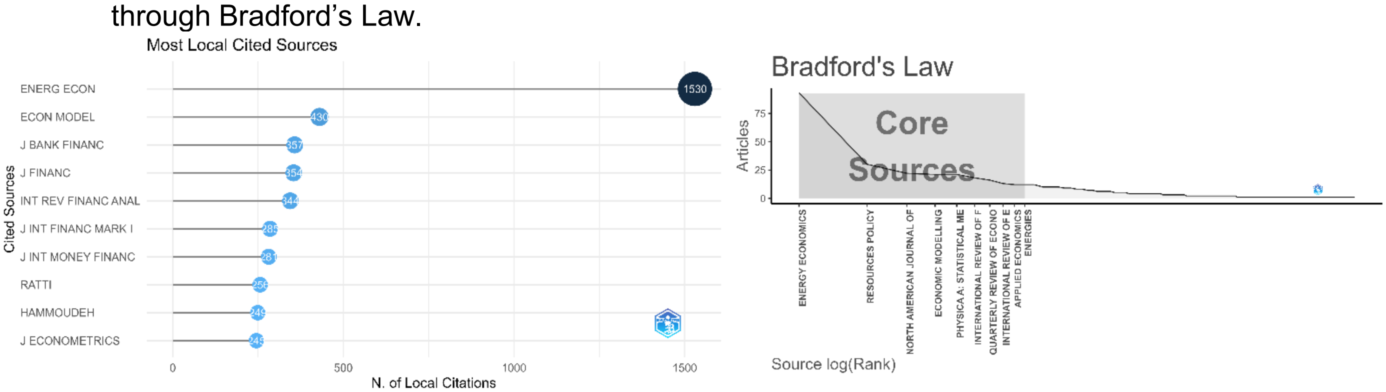


Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

- <u>Most Relevant Sources</u>

This section discusses the most significant and influential sources in the research of dynamic co-movements among oil prices and assets in financial markets (including energy markets and sustainable finance). Figure 1-5a illustrates the distribution of the most cited sources. According to the number of citations, Energy Economics with 1530 citations is ranked at the top, followed by Economic Modelling (430) and Journal of Banking & Finance (357). These results agree with (Bashir, 2022), showing that Energy Economics is the most significant platform in our research area, focusing on analyzing the oil prices–stock market relationship. Bradford's Law (Bradford, 1934) (Figure 1-5b) includes only ten journals in zone 1 or the core area that is the most frequently cited in the literature of this subject. These, along with their frequency, are Energy Economics (93), Resources Policy (30), North American Journal of Economics and Finance (22), Economic Modelling (21), Physica A: Statistical Mechanics and Its Applications (21), International Review of Financial Analysis (18), Quarterly Review of Economics and Finance (16), International Review of Economics and Finance (13), Applied Economics (12), and Energies (12). Zones 2 and 3 have 55 and 224 journals, respectively. The dominance of two open access journals in the core of this research discourse emphasizes the importance of scientific knowledge being freely and openly accessible.

Figure 1-5: Effect of the sources. (a) Most cited sources and (b) source clustering through Bradford's Law.



(a) (b)

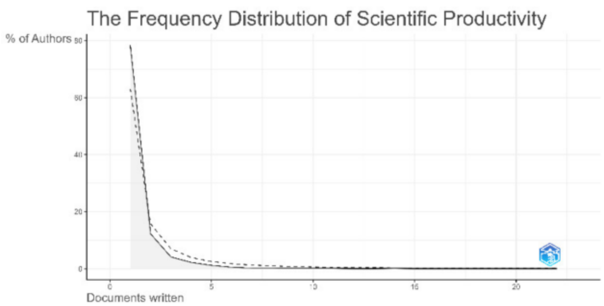
Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

1.3.2 Analysis of the Authors

- <u>Authors' Productivity</u>

Lotka's Law (Lotka, 1926) identifies and describes researchers with a higher production frequency in a given knowledge area. Figure 1-6 presents the results for papers on dynamic co-movements among oil prices and financial assets (including energy markets' sustainable finance) alongside the predicted distribution according to Lotka. For this study, the results indicate a Lotka's index in which 78.4% of the authors would write one article, 12.2% would write two, 4.1% would write three, and 2.2% would write four. This indicates that dynamic co-movements among oil prices and assets in financial markets authorship do not currently comply with Lotka's Law. The dashed line in the figure depicts the graph that should be in accordance with Lotka's Law.

Figure 1-6: Authors' productivity according to Lotka's Law production of research about dynamic co-movements between assets in financial markets from 1982 to (September) 2022.



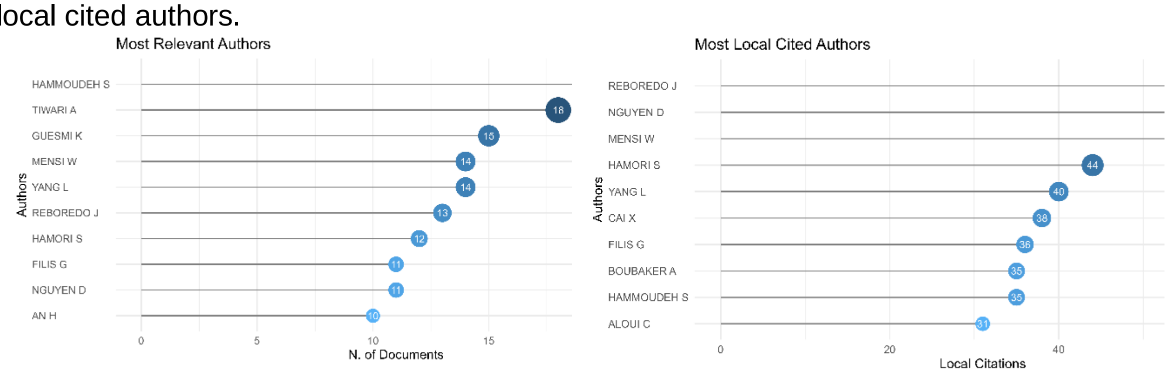
Documents written	No. of Authors	Proportion of Authors
1	1064	78.4%
2	166	12.2%
3	56	4.1%
4	30	2.2%

Source: Authors' own research using the Bibliometrix tool as well as Scopus and WoS databases.

- <u>Most Relevant Authors and Authors' Impacts</u>

Figure 1-7 illustrates the top five most relevant authors based on the number of published articles: (i) Hammoudeh, (ii) Tiwari, (iii) Guesmi, (iv) Mensi, and (v) Yang. Based on the number of local citations, the top five authors concerning the impact on dynamic co-movements among oil prices and assets in financial markets publication outputs are (i) Reboredo, (ii) Nguyen, (iii) Mensi, (iv) Hamori, and (v) Yang. Table 1-2 shows the top 20 most relevant authors in publications on dynamic co-movements among oil prices and financial assets between 1982 and 2022 based on the H_index.

Figure 1-7: Effect of the authors. (a) Number of publications by authors and (b) most local cited authors.



(a) (b)

Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

Table 1-2: Top 20 most relevant authors on dynamic co-movements between assets in financial market outputs.

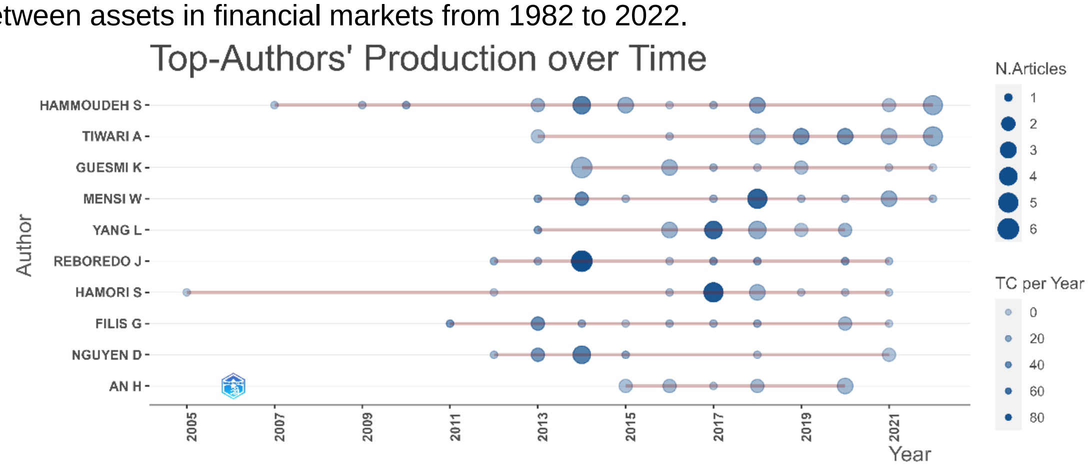
	Element	H_index	G_index	M_index	TC	NP	PY_start
1	Hammoudeh, S.	16	22	1	1549	22	2007
2	Reboredo, J.	13	13	1.18	1680	13	2012
3	Mensi, W.	12	14	1.2	1104	14	2013
4	Tiwari, A.	12	18	1.2	478	18	2013
5	Yang, L.	11	14	1.1	783	14	2013
6	Hamori, S.	10	12	0.56	454	12	2005
7	Filis, G.	9	11	0.75	1299	11	2011
8	Nguyen, D.	9	11	0.82	1101	11	2012
9	An, H.	8	9	1	247	10	2015
10	Kang, S.	8	10	1.14	321	10	2016
11	Guesmi, K.	7	14	0.78	359	15	2014
12	Wang, Y.	7	8	0.7	508	9	2013
13	Zhang, Y.	7	8	1	343	8	2017
14	Aloui, C.	6	7	0.55	856	7	2012
15	Cai, X.	6	6	0.86	352	6	2016
16	Huang, S.	6	6	0.86	170	7	2016
17	Al-Yahyaee, K.	5	5	1	242	5	2018
18	Antonakakis, N.	5	5	0.5	632	5	2013
19	Ftiti, Z.	5	5	0.56	157	5	2014
20	Ghorbel, A.	5	6	0.455	59	6	2012

Notes: TC = total citations; NP = number of publications; PY start = publication year start.
Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

- <u>Authors' Production over Time</u>

The top authors' documents on dynamic co-movements among oil prices and assets in financial markets analysis over the years are presented in Figure 1-8.

Figure 1-8: Top authors' production over time in researching the dynamic co-movements between assets in financial markets from 1982 to 2022.



Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

The color intensity in the Figure 1-8 is related to the citation year, and the bubble dimension represents the various authors' yearly publications. For example, in 2007, Hammoudeh published his first article about this topic. Later, in 2017, four papers were published, and in 2022, five documents were published.

- The Leading Countries and Institutions

The world's leading countries and institutions were analyzed as part of the research. In first place, China appears as the most prolific country in the production of documents on this theme, with a total of 160 publications. In second place is the United States (50), and in third place is France (33). Table 1-3 presents a list of other top nations. Drexel University in the United States leads the top 10 institutions with the publication of 22 articles. In the following position, there is the Ipag Business School (France) with 15 articles; next are Hunan University (China) and Pusan National University (South Korea) with 12 articles. Other distinguished institutions are shown in Table 1-4.

Table 1-3: The top 10 corresponding author countries.

	Country	No. of Articles
1	China	160
2	United States	50
3	France	33
4	India	30
5	Turkey	30
6	Korea	25
7	United Kingdom	22
8	Japan	21
9	Saudi Arabia	20
10	Tunisia	18

Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

Table 1-4: The top 10 institutions publishing articles.

	Affiliation	No. of Articles
1	Drexel University	22
2	IPAG Business School	15
3	Hunan University	12
4	Pusan National University	12
5	Kobe University	10
6	Montpellier Business School	10
7	South Ural State University	10
8	University of Sfax	10
9	Chiang Mai University	10
10	Zhongnan University of Economics and Law	9

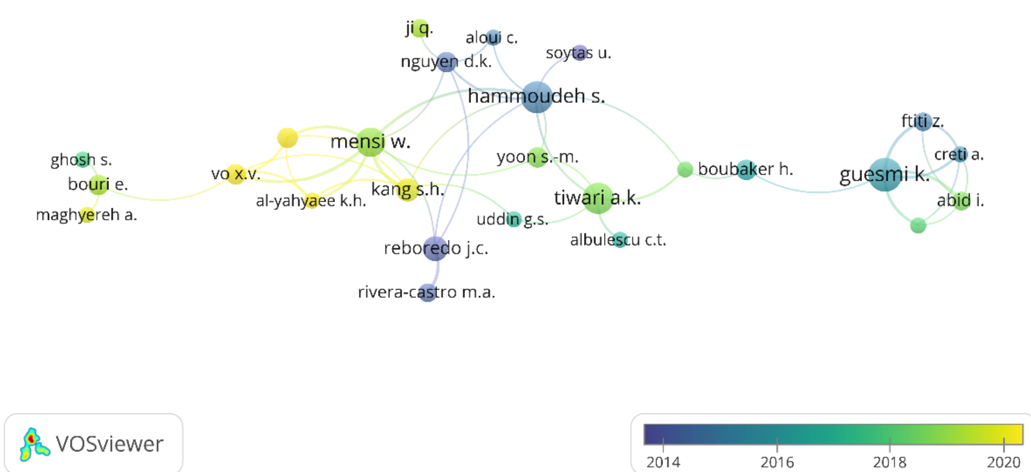
Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

- <u>Co-Author Analysis</u>

In the co-author analysis, the number of documents in which two or more researchers are co-authors is an important issue. The map visualization shows the links as colored lines among the items. The weight attributes reveal the importance of the identified network, which is reflected in the item's size. Finally, the number of lines among the co-authors indicates their relevance within the bibliographic data analysis (B. Lin & Su, 2020).

Figure 1-9 presents the connections between researchers according to the conjointly elaborating documents. Thus, this figure allows us to examine the existence and characteristics of collaboration networks and possible established groups of authors that center on studying the dynamic association between assets in financial markets. The network obtained reveals the existence of 966 authors and 56 links that are formed in eight clusters. These clusters are very dispersed, but several research co-authorships can be identified, such as Reboredo and Rivera-Castro, Hammoudeh and Tiwari, Nguyen and Aloui, Guesmi and Chevallier, Bouri and Maghyereh, and Mensi and Kang, among others.

Figure 1-9: Co-authorship network.



Source: Authors' own research using VOSviewer, as well as Scopus and WoS databases.

1.3.3 Analysis of the Documents

- <u>The Most Impactful Documents</u>

Table 1-5 shows the 10 most globally cited documents in the research of dynamic co-movements among oil prices and assets in financial markets, with worldwide citation counts ranging from 246 to 865. Kilian and Park (2009); Sharif, Aloui, and Yarovaya (2020); and Filis, Degiannakis, and Floros (2011) have the most citations worldwide, receiving 865, 517, and 403, respectively, and their papers are listed as the top three most referenced publications.

The most cited 10 articles mainly focus their analysis on three aspects: (i) the impact of oil price shocks on the financial markets, (ii) global factors that impact stock markets, and (iii) correlations and volatility spillovers between commodities and stock markets. These three aspects reflect how oil price shocks and other shocks on macroeconomic fundamentals affect the dynamics of commodity and stock markets.

Kilian and Park (Kilian & Park, 2009) presented how the U.S. real stock returns reacted to an oil price shock, differing depending on whether the oil price change was driven by demand or supply shocks in the oil market. Sharif, Aloui, and Yarovaya (2020) explored the time–frequency relationship between the COVID-19 (Coronavirus Disease, 2019) outbreak, oil price, geopolitical risk, economic uncertainty, and the U.S. stock market using the continuous wavelet transform, the wavelet coherence, and the wavelet-based Granger causality tests. This study shows that the COVID-19 pandemic caused an outcome disruption, a notable increase in U.S. economic policy uncertainty, and an unprecedented response from the stock market.

Table 1-5: Top 10 cited documents in the research of dynamic co-movements between assets in financial markets.

	Author	Source	Total Citations	TC per Year	Normalized TC
1	Kilian and Park (Kilian & Park, 2009)	*International Economic Review*	865	61.79	9.07
2	Sharif, Aloui, and Yarovaya (Sharif et al., 2020)	*International Review of Financial Analysis*	517	172.33	30.15
3	Filis, Degiannakis, and Floros (Filis et al., 2011)	*International Review of Financial Analysis*	403	33.58	5.74
4	Sari, Hammoudeh, and Soytas (Sari et al., 2010)	*Energy Economics*	315	24.23	7.19
5	Wang, Wu, and Yang (Y. Wang et al., 2013)	*Journal of Comparative Economics*	314	31.40	2.36
6	Antonakakis, Chatziantoniou, and	*Economics Letters*	307	30.70	2.31

	Author	Source	Total Citations	TC per Year	Normalized TC
	Filis (Antonakakis et al., 2013)				
7	Mensi et al. (Mensi et al., 2013)	*Economic Modelling*	264	26.40	1.99
8	Basher and Sadorsky (Basher & Sadorsky, 2016)	*Energy Economics*	263	37.57	6.37
9	Creti, Joëts, and Mignon (Creti et al., 2013)	*Energy Economics*	252	25.20	1.90
10	Mensi et al. (Mensi et al., 2014)	*Emerging Markets Review*	246	27.33	4.23

Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

Filis, Degiannakis, and Floros (2011) studied the time-varying correlation between the stock market prices and oil prices for oil-importing and oil-exporting countries using the DCC-GARCH-GJR approach on data from six oil-exporting countries. Their findings of contemporaneous correlation show that although the time-varying correlation does not differ for oil-importing and oil-exporting economies, the correlation increases positively (or negatively) in response to significant aggregate demand-side (precautionary demand) oil price shocks, which are caused due to fluctuations of the global business cycle or world turmoil. Moreover, supply-side oil price shocks do not influence the relationship between the two markets. The lagged correlation results show that oil prices negatively affect all stock markets, regardless of the oil price shock origin.

Three of the top 10 most cited documents were published in the journal Energy Economics, followed by the International Review of Financial Analysis with two documents published, showing that these are two essential sources for the related research.

- Most Frequent Keywords

The most frequent keywords (author keywords and KeyWords Plus) in the 1982–2022 (September) period are presented in Table 1-6. Author keyword analysis offers information about research trends under the researchers' points of view (Garfield, 1970). The KeyWords Plus are terms extracted from titles or abstracts (Aria & Cuccurullo, 2017). In the two keyword analyses presented, "oil prices" and "stock markets" are the most common. Meanwhile, "exchange rates", "volatility spillovers", and "volatility" were also found in both categories. The author keywords give clues about the main methodologies that have been used to measure the co-movements among the variables analyzed. In this way, wavelet analysis is located in first place, with 84 occurrences, followed by volatility spillover, with 75 occurrences. In third place, there is DCC-GARCH methodology, with 71 occurrences. Finally, in the fourth and fifth places, there are hedge ratios and copula, with 39 and 37 occurrences, respectively. KeyWords Plus covers the basic literature related to oil prices and the link with the variables of financial markets and energy markets. Then, according to these keywords, the main topics that are explored when researching the dynamic co-movements among oil prices and financial assets (including energy markets sustainable finance) are volatility spillovers, price dynamics, and volatility.

Table 1-6: Most frequent words (author keywords and KeyWords Plus) found in the research of dynamic co-movements between assets in financial markets.

	Author Keywords	Occurrences	KeyWords Plus	Occurrences
1	oil prices	314	oil prices	465
2	stock markets	156	stock markets	317
3	wavelet analysis	84	financial markets	158
4	exchange rates	83	volatility spillovers	143
5	volatility spillovers	75	exchange rates	134
6	DCC-GARCH	71	commerce	132
7	COVID-19	43	costs	119
8	volatility	42	energy markets	113
9	hedge ratio	39	price dynamics	110
10	copula	37	volatility	100

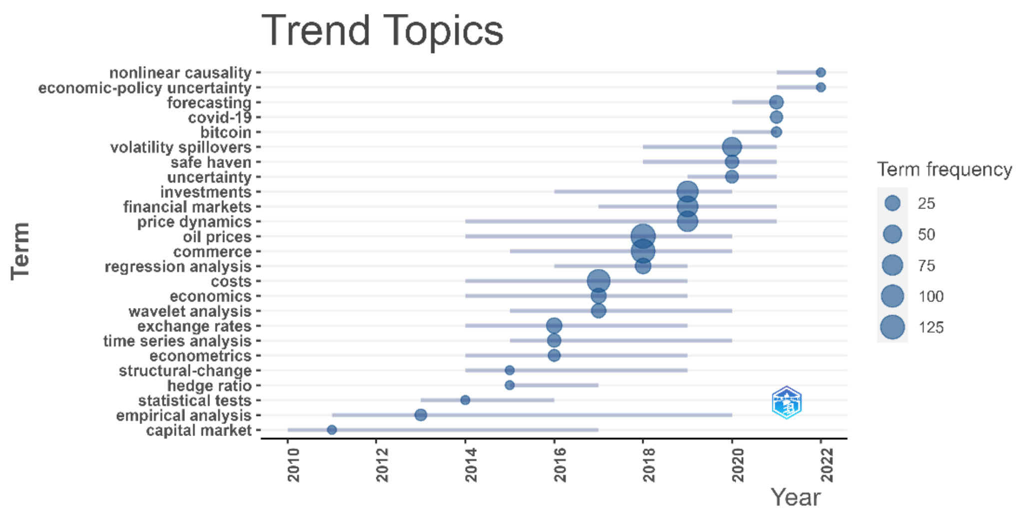
Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

- Trend Topics over the Years

A trending topic analysis is an important mapping tool that helps demonstrate the evolution of literature. Figure 1-10 depicts the topics that have been identified when examining the author keywords and maintaining a minimum five-word frequency per article three times a year.

In the past few years (2021, 2022), there have been prominent topics, namely nonlinear causality, economic policy uncertainty, forecasting, COVID-19, and bitcoin, which illustrate the new trends in studies searching for nonlinearities in the linkages between variables and uncertainty due to COVID-19 and the recent changes at economic and political levels globally. Between 2019 and 2020, the common topics were volatility spillovers, safe heaven, uncertainty, investments, financial markets, and price dynamics. This reveals the strong interconnection among the world economies and the quest for investment opportunities; thus, the explanation for these keywords was also the global uncertainty. The most frequent quests in the 2016–2018 period were oil prices, commerce, regression analysis, wavelet analysis, exchange rates, and econometrics. During this period, research was focused on the impact of the oil markets on the real economy. In 2015, the popular keywords were structural change and hedge ratio. According to the results, there is a significant research gap in the use of machine learning or deep learning, big data, and artificial intelligence for measuring dynamic co-movements among oil prices and assets in financial markets. The use of these could improve the findings by offering a better understanding of the co-movement among financial and energy markets.

Figure 1-10: Trend topics over the years.



Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

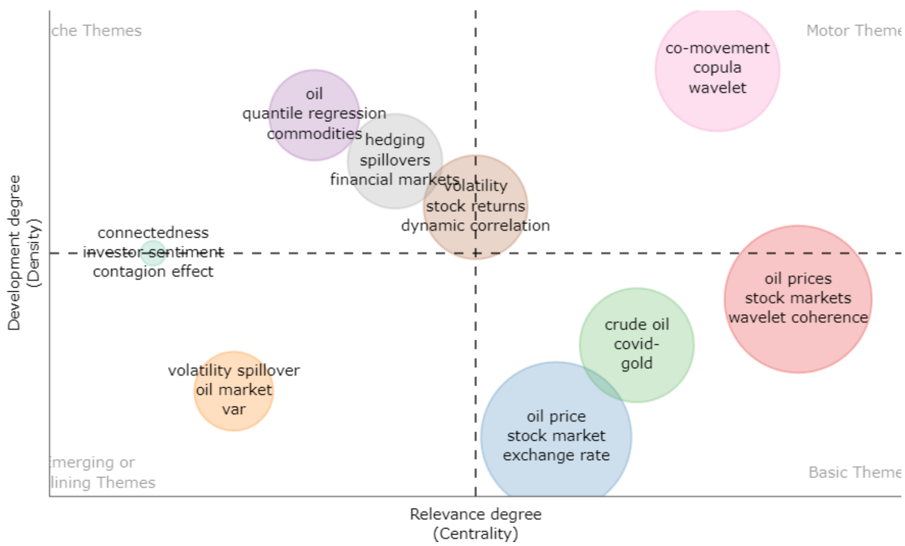
Furthermore, due to the importance of emerging economies in global finance, it is important to extend the existent literature about this kind of analysis involving data from those economies and to analyze the impact of oil shocks on their financial assets, energy markets, and assets related to sustainable finance.

- Thematic Map

This analysis presents a thematic map by dividing it into four topic quadrants based on the density and centrality of the issues (Figure 1-11). The themes in the upper-right quadrant should be examined and studied more profoundly due to their high density and centrality (Chansanam & Li, 2022). Nine major keyword clusters were identified.

Figure 1-11 shows that the first and most promising areas for further research in analyzing dynamic co-movements among oil prices and financial assets are represented by the following keywords: co-movement, copula, and wavelet. Thus, considering the results of Figures 1-1 and 1-11, further research will lead to quantifying the co-movements between CO_2 emissions, renewable energy instruments, and assets related to sustainable finance or financial markets and oil prices using the copula or wavelet methodologies. Figure 1-11 also shows the second highest relevance for the keywords oil prices, stock markets, and wavelet coherence; this confirms that an analysis of this type should be included in further research. The third topic with high relevance and density is the use of dynamic correlation and volatility analysis, which are methodologies that could also be applied to data from CO_2 emissions and renewable energy instruments or financial markets and oil prices. In the fourth theme, the principal keywords are crude oil, COVID-19, and gold. Then, using the methodologies identified before, an analysis may emerge as further research. The fifth theme is represented by the keywords hedging, spillovers, and financial markets. Finally, the sixth group includes quantile regression and commodities, emerging as further topics than can be analyzed due to the high density of the topics.

Figure 1-11: Thematic map.

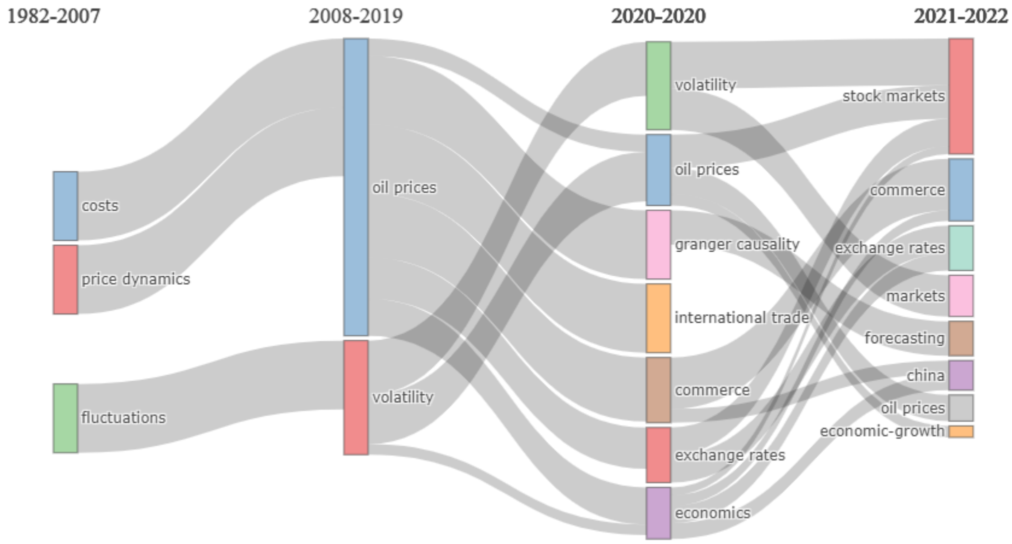


Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

- <u>Thematic Evolution</u>

Thematic evolution is a technique in bibliometrics for introducing a historical perspective on research and contributing to a science-based paradigm for directing further research themes (Moral-Munoz et al., 2018). It emphasizes the most significant research themes of evolution across time, presenting insights into the area's further path (X. Chen et al., 2019). Figure 1-12 illustrates the progression of the most frequently used terms in studying dynamic co-movements among oil prices and assets in financial markets based on the co-occurrence network from 1982 to 2022. Based on the different events of the sample, three periods were chosen as cut-off points: 2007, 2019, and 2020. These points cover the global crisis of 2008, the global COVID-19 pandemic, and recent times 2021–2022 (September).

Figure 1-12: Thematic evolution of KeyWords Plus.



Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

Furthermore, KeyWords Plus are utilized to comprehensively understand the keywords corresponding to documents' contents. The dimensions of the boxes in Figure 1-12 suggest the frequency of keyword appearance and topics. From 1982-2007, the most popular keywords were cost, price dynamics, and fluctuations. In that period, the explorations were directed toward the macroeconomic impacts caused by changes in oil prices. These three topics were merged into the next time slice (2008–2019) as oil prices and volatility. Thus, these keywords appear as the other two topics of interest in that period. The term volatility is commonly associated with risk, and in the period next to the subprime crisis in 2008, risk (particularly the financial risk) was the main accessed topic. The term "oil prices" is divided into five branches in the next time slice (2020–2020): volatility spillover, oil prices, granger causality, international trade, and exchange rates. Precisely, at the origins and evolution of the COVID-19 pandemic (2020), one of the main concerns, due to the decrease in the world trade occasioned by the total or partial closure of the major economies, was the key theme of the research due to the significant global macroeconomic repercussions.

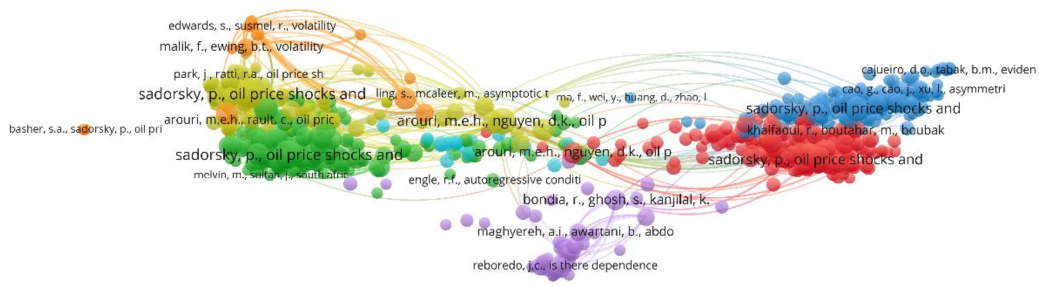
The keyword "volatility" is divided into three branches: volatility spillovers, markets, and exchange rates. This is because the researchers were more concerned about the impact of the global pandemic on their markets and the exchange rates. Finally, in 2021–2022 (September) "volatility" appears divided into two branches: stock markets and energy markets, due to the singular uncertainty moment provoked by the global inflation and polity tensions experimented in the period. The keyword “oil prices” appears divided into stock markets and oil prices due to the interest in knowing the impact of oil prices on stock markets in developed economies. Finally, China, with its important role in global economic growth, appears as a new topic that is driven by recent research in this area.

1.3.4 Clusters Analysis

- <u>Co-Citation Networks Analyses</u>

The co-citation map presents the structure of a body of literature by the frequency of conjunct mention of two or more documents in a third publication (Mumu et al., 2021). This study includes 18,868 citations in the quest for dynamic co-movements among oil prices and financial assets. This study includes citations mentioned at least three times, and the co-citation analysis was conducted on 746 articles in the research area of dynamic co-movements among oil prices and assets in financial markets (including energy markets and assets related to sustainable finance). The dimension of its node represents the article’s normalized number of citations, while the thick line shows the co-citation’s interaction strength among the nodes in the network. The box color indicates the article’s cluster; the nodes with the same color are grouped. According to Figure 1-13, each box is labeled with the document’s first author’s name and year of publication.

Figure 1-13: Co-citation network of references.



Source: Authors’ own research using VOSviewer, as well as Scopus and WoS databases.

As shown in Table 1-7, the map of co-citations is grouped into five clusters. Each cluster is based on the most included references. A single critical concept connects all five groups in the research of dynamic co-movements among oil prices and assets in financial markets that serve as the theoretical groundwork for this study.

The first cluster (red) shows the concern about the oil price shocks and the volatility spillovers analysis across markets. For example, Diebold and Yilmaz (2012) characterize daily volatility spillovers across the U.S. stock, bond, foreign exchange, and commodity markets from January 1999 to January 2010. The authors found important spillovers from the stock market to other markets taking place after the collapse of the Lehman Brothers in September 2008. Jammazi and Reboredo (2016) analyzed the dependence structure and portfolio risk management issues for daily Brent oil and stock returns using a flexible wavelet–copula approach. They concluded that wavelet decomposition is decisive in analyzing risk for the different investment horizons. In this first cluster, wavelet analysis methodologies and volatility spillovers predominate in analyzing markets.

In the second cluster (green), the dynamic conditional correlation (DCC-GARCH) and cointegration models emerge as the main elements of financial co-movement analysis. In this way, Chiang, Jeon, and Li (2007) applied a DCC-GARCH model to nine Asian daily stock-return data series from 1990 to 2003. The empirical evidence confirms a contagion effect, identifying two phases of the Asian crisis. The first shows an increase in correlation (contagion); the second shows a continued high correlation (herding). Furthermore, Narayan and Narayan (2010), using daily data from Vietnamese markets for the period 2000–2008, carried out a cointegration analysis of oil prices, stock prices, and the nominal exchange rate. They found that oil prices and the nominal exchange rates are cointegrated. Additionally, oil prices have a positive and statistically significant impact on stock prices in Vietnam's markets.

Table 1-7: Co-citation clusters as theoretical fundamentals.

Cluster	Relevant Citations
Cluster 1 (Red)	Basher, Haug, and Sadorsky (2012); Diebold and Yilmaz (2009, 2012); Hamilton (1983); Jammazi and Reboredo (2016); Jammazi (2012); Kilian and Park (2009); Mensi and Hammoudeh (2015); Park and Ratti (2008), Reboredo and Rivera-Castro (2014); Sadorsky (1999) and Torrence, and Compo (1998); Wu and Yang (2013).
Cluster 2 (Green)	Aloui, Hammoudeh and Nguyen (2013); Arouri, Jouini, and Nguyen (2012); Basher, Haug, and Sadorsky (2012); Bollerslev (1986); Chiang, Jeon, and Li (2007); Dutta (2018); Engle (2002); Engle and Granger (1987); Golub (1983); Kang and Ratti (2013); Mensi (2019); Narayan and Narayan (2010).
Cluster 3 (Blue)	Apergis and Miller (2009); Andrews (2003); Bai and Perron (2003); Basher and Sadorsky (2006); Chen (2010); Engle and

Cluster	Relevant Citations
	Kroner (1995); Jones and Kaul (1996); Kilian and Park (2009); Ma et al. (2013); Park and Ratti (2008); Sadorsky (1999).
Cluster 4 (Yellow)	Amano and Van Norden (1998b); Chen and Roll 1986); Ciner (2001); Cong et al. (2008); Elder and Serletis (2010); Golub (1983); Hamilton (1983); Hammoudeh, Dibooglu and Aleisa (2004); Kilian (2009); Lee, Ni and Ratti (1995); Park and Ratti (2008); Sadorsky (1999, 2001, 2014).
Cluster 5 (Purple)	Apergis and Miller (2009); Hamilton (1983, 2003); Henriques and Sadorsky (2008); Jones and Kaul (1996); Reboredo and Rivera-Castro (2014); Sadorsky (1999, 2001, 2014).

Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

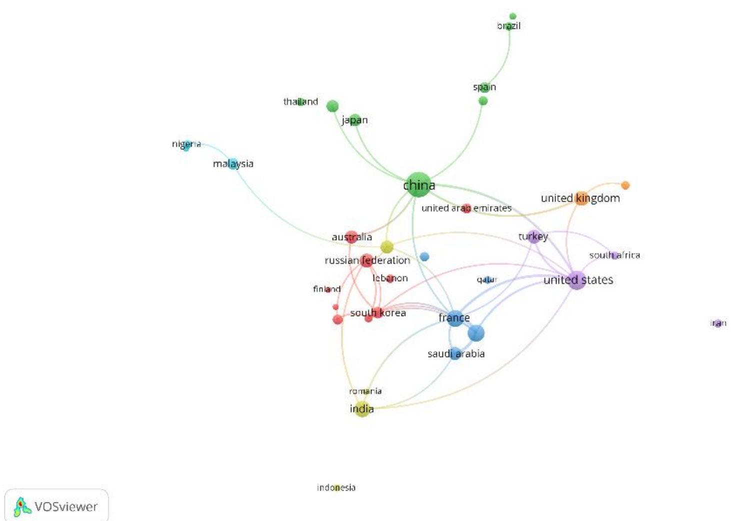
The third cluster (blue) discusses the structural models for explaining how oil shocks affect the markets. Apergis and Miller (2009) studied how explicit structural shocks that characterize the endogenous character of oil price changes affect stock market returns in a sample of eight countries—Australia, Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States—using a vector error–correction model to decompose oil price changes into three components: oil supply shocks, global aggregate demand shocks, and global oil demand shocks. The authors found that international stock market returns do not respond significantly to oil market shocks. Likewise, in this cluster, some studies analyzed the structural change of time series, such as Bai and Perron (Bai & Perron, 2003) and Andrews (2003).

Finally, the fourth and fifth clusters (yellow and purple) include (in their analysis of researching dynamic co-movements among oil prices and assets in financial markets) issues such as nonlinearities among variables and the importance of incorporating uncertainty in modeling. For example, Ciner (2001), relying on nonlinear causality tests, provides evidence that proves how oil shocks affect stock index returns; it is consistent with the documented influence of oil on economic output. Moreover, Elder and Serletis (2010) considered the relationship between oil price and investment, focusing on the role of uncertainty of oil prices. The authors found that volatility in oil prices has had a negative and statistically significant effect on several measurements of investment, durables consumption, and aggregate output.

- <u>Countries and Regions Network</u>

The analysis of co-authorship can be implemented to identify leading countries' distribution regarding the production of knowledge and collaboration networks among them in the research field analyzed. The countries and regions' networks showed a result of 50 items and 47 links. This is shown in Figure 1-14. The network predominates in clusters highlighted in green, red, and blue. The green cluster includes China, which has many relationships with other countries including Spain, Brazil, Japan, and Thailand, among others. Red, for its part, includes Russia, Australia, Lebanon, Finland, and South Korea. Finally, blue includes France, Canada, Tunisia, Saudi Arabia, and Qatar. These three principal clusters show a relationship between countries and collaboration among authors.

Figure 1-14: Network of countries.



Source: Authors' own research using VOSviewer, as well as Scopus and WoS databases.

- <u>Co-Word Analysis</u>

The co-word or co-occurring keywords analysis identifies the principal keywords in the analyzed bibliographic records. It helps determine which categories of analysis are most relevant in the field of study, where a larger size indicates a higher frequency. (See Figure 1-15.) This analysis is useful because the research has the possibility of focusing on the most relevant words presented in the research results. In concordance with Bashir (2022), oil price and stock markets are the most frequent author keywords in the analyzed documents (Figure 1-15a). One of the reasons for this is the wide number of documents that study the nexus between these two markets. The author keywords financial markets, volatility spillovers, wavelet analysis, DCC-GARCH, Granger Causality, exchange rates, and co-movements have also led to a strong research contribution in the literature, as their focus is to analyze the most frequently used methodologies to model the co-movement among oil prices and financial markets. In contrast, KeyWords Plus (Figure 1-15b) show energy markets and sustainability as crucial keywords in the analysis. Furthermore, the methodologies of volatility spillovers, wavelet analysis, DCC-GARCH, Granger Causality, and time series analysis appear as essential keywords.

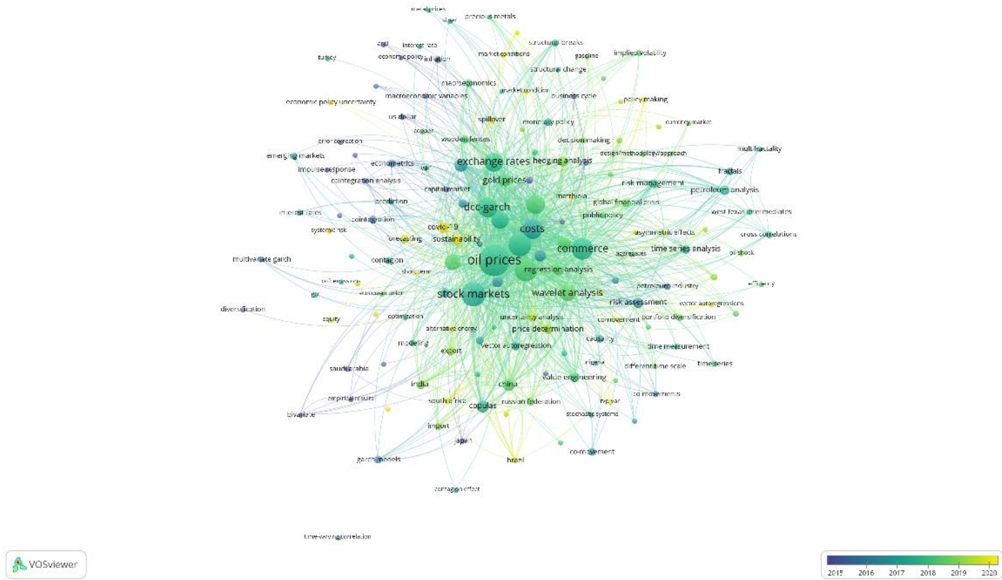
Figure 1-15: Word cloud. (a) Author keywords and (b) KeyWords Plus.

(a) Author keywords (b) KeyWords Plus

Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

In addition to identifying research topics, the keyword analysis allows studying their evolution over time. In this sense, Figure 1-16 shows the overlay visualization of the keyword network. The color corresponds to the average year of publication (avg. pub. year). Older documents have a violet color, and the more recent documents have a color close to yellow. Some of the most recent keywords are "volatility spillovers", "hedge ratio", "sustainability", and "renewable energy". Then, energy markets and sustainable finance emerge as crucial trends in analyzing dynamic co-movements among oil prices and financial assets.

Figure 1-16: Network of co-occurring keywords.



Source: Authors' own research using VOSviewer, as well as Scopus and WoS databases.

1.4 Discussion

1.4.1 Co-Movements: Contagion or Interdependence?

There are different kinds of co-movements among oil prices and financial assets. This paper focuses on interdependence and contagion. According to Beirne & Gieck (2014), the difference between these two concepts is that interdependence is defined as the relation among asset classes on average over the sample period, and contagion is defined as a change in the transmission mechanism among asset classes in times of crisis. Beirne & Gieck (2014) found that interdependence is most notable across advanced and emerging economies in the case of the equity market, and contagion effects within the stock market are most evident in Latin America and Emerging Asia. The response to shocks differs according to the origin of the disturbance. Then, the methodologies for measuring contagion play important roles because globalization increases the interdependence across the markets in the international context.

According to Bodart & Candelon, (2009 and Orlov (2009), the terms contagion and interdependence are defined in terms of the frequency domain, that is, low scale (high frequency) and high scale (low frequency). Following Dewandaru et al. (2014), a low scale can be defined as a period of less than one year (short term) and a high scale as a period greater than one year (long term). Therefore, an increase in co-movement on the low scale may be associated with contagion, while an increase in co-movement on the high scale may be associated with interdependence.

Pericoli & Sbracia (2003) described five definitions for financial contagion: (i) financial contagion is a significant increase in the probability of a crisis in one country, conditioned by a crisis occurring in other countries; (ii) contagion is a transmission that occurs when volatility spills over from the country in crisis to the financial markets of other countries; (iii) contagion is a significant increase in co-movements on prices in different markets, affected by a crisis occurring in one market or group of markets; (iv) contagion occurs when a different channel causes the transmission of a crisis to those that occurred in the other market; and (v) the contagion happens when macroeconomic fundamental causes cannot explain ordinary movements of prices and quantities. Meanwhile, Forbes & Rigobon (2002) and Forbes & Rigobon (2001) argue that financial contagion can be defined as the transfer of a financial crisis from one country to another as a result of the interdependence present in non-crisis periods, which may be associated with any of the previous definitions, since according to the literature, the high association among the variables of the economies, without taking into account their origin, is what generates a high-dependency relationship between their markets and therefore the spread of the financial crisis. Thus, as mentioned above, supported by Forbes & Rigobon (2001) and Pericoli & Sbracia (2003), financial contagion is defined as an increase in correlations between markets after an economic shock in an individual country or group of countries.

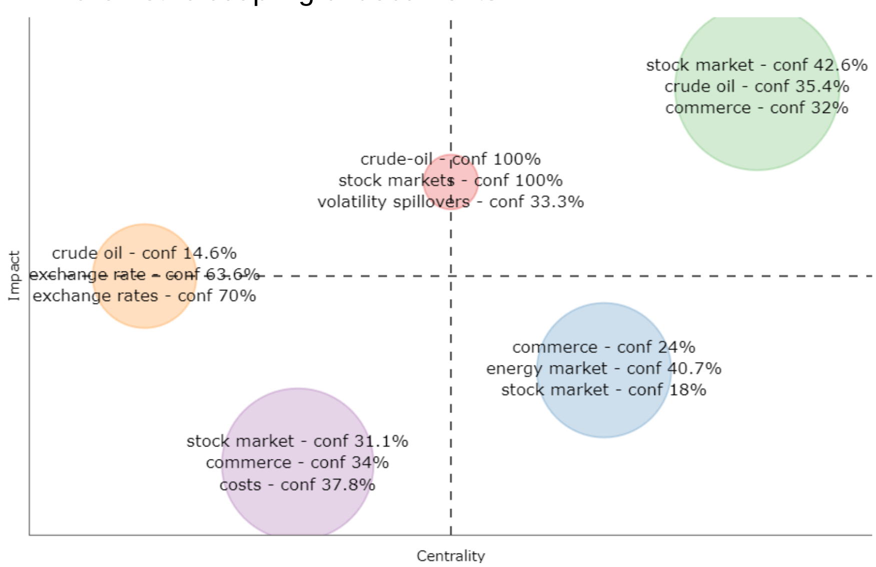
According to Vayá-Valcarce & Frexedas (2005), channels of contagion among economies can be commercial, financial, political, regional, and macroeconomic fundamentals. Thus, they argue that there are five possible transmission channels of contagion from one country to another: (i) being subjected to a common shock, such as movements in interest rates by the Federal Reserve in the U.S.; (ii) the similarity among the macroeconomic fundamentals of the economies; (iii) maintaining trade relations since the devaluation in one country would be reflected in the macroeconomic fundamentals of its trading partners; (iv) maintaining political ties among countries, as this may influence the actions of policy makers in both countries, e.g., policies of joint devaluation, which are also known as a channels for regional transmission of contagions; and (v) maintaining financial relations among countries such as having the same lender or maintaining foreign direct investment among countries, as this would be a channel of liquidity that could generate common financial behaviors. These common causes could explain why financial crises usually occur in clusters.

Mitra & Bhattacharjee (2015) argued that there are two main channels through which financial series show interdependence with each other. Firstly, there are the macroeconomic benefits, linked to the effective management of the countries' monetary policies, tending towards low inflation and stability of interest rates and exchange rates, which is why there is a transmission of monetary policies to the financial markets via asset prices. Secondly, due to the management of international portfolios, in the search for better returns with less exposure to risk, there is an increase in the integration of financial markets that gradually aligns international prices, thus reducing the benefits of portfolio diversification in the international context.

1.4.2 Measuring the Co-Movements: Bibliometric Coupling of Documents

The bibliometric coupling of documents examines prior researchers' writings on a topic, identifies significant ideas, and illustrates the character of scholarly argument (Chansanam & Li, 2022). Figure 1-17 represents a scientific map that identifies critical documents (impact) and their relationships (centrality) using k-means clustering as an unsupervised learning algorithm to solve clustering problems (Chansanam & Li, 2022). The number of local citation scores quantified the document's effect. Five clusters were created depending on the topic's significance, each with a distinct color scheme: red, blue, green, blue, purple, and orange.

Figure 1-17: Bibliometric coupling of documents.



Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

Among these, the red cluster has a centrality of 0.5405, an impact of 2.177, and 15 documents containing the topics of crude oil, stock markets, and volatility spillovers. The documents in this cluster include Nagayev et al. (2016), Antonakakis, Chatziantoniou, and Filis (2017), Shahzad et al. (2018), Roy and Roy (2017), Disli et al. (2021), and others. Nagayev et al. (2016) explored whether commodities offer potential diversification benefits for Islamic equity index investors. The authors used MGARCH-DCC and wavelet coherence analyses. Their findings reveal that correlations between commodity markets and the Dow Jones Islamic Market World Index were time-varying and highly volatile throughout the January 1999–April 2015 period. A substantial and persistent increase was observed in the return correlations between commodities and Islamic equity at the onset of the 2008 financial crisis. However, recent trends suggest that this association is heading towards its pre-crisis levels, again offering diversification benefits for Islamic equity holders. Disli et al. (2021) studied the role of gold, crude oil, and cryptocurrency as a haven for traditional, sustainable, and Islamic investors during the COVID-19 pandemic crisis. The authors use the wavelet coherence analysis and the spillover index methodologies in bivariate and multivariate settings, examining the correlation of these assets for different investment horizons. The findings suggest that gold, oil, and bitcoin exhibited low coherency with each stock index across almost all considered investment horizons until the onset of COVID-19. Conversely, given the pandemic outbreak, the return spillover was more intense across financial assets, and a significant pairwise return connectedness between each equity index and the hedging asset was observed.

The blue cluster with a centrality of 0.576, an impact of 1.516, and 39 documents contains the topics of commerce, energy market, and stock markets. The studies in this cluster include Pal and Mitra (2019), Ftiti, Guesmi, and Abid (2016), Bouri et al. (2017), Maghyereh and Abdoh (2022), and others. Pal and Mitra (2019), explore the co-movement between oil price and automobile stock return using the Wavelet Coherence for daily price series from August 1, 1996, to June 20, 2017. The results indicate that the co-movement between oil price and automobile stock return was strong from November 2000 to December 2002 and from March 2006 to December 2009. The co-movement is found to be more prominent in the long term, and stock return is sensitive to the higher oil price emanating from the demand shock. Maghyereh and Abdoh (2022) examine the extreme co-movements (tail dependence) between the different sources of oil price shocks and stock market returns of major oil-exporter countries (Gulf Cooperation Council (GCC) countries) directly by testing the tail dependence of the joint distribution across frequencies.

Their methodology incorporates an oil shock decomposition with a novel quantile cross-spectral dependence approach and the wavelet coherence analysis from June 1, 2006, to February 28, 2020. These two approaches enable the detection of the dependence structure during extreme market conditions (bearish and bullish markets) and/or at different time horizons (frequencies).

The green cluster with a centrality of 0.614, impact of 2.564, and 56 documents contains the topics of stock markets, crude oil, and commerce. The research in this cluster includes studies conducted by leading researchers. (Filis et al., 2011) studied the time-varying correlation between stock market prices and oil prices for oil-importing and oil-exporting countries using a DCC-GARCH-GJR approach based on data from six oil-exporting (Canada, Mexico, Brazil) and oil-importing (USA, Germany, The Netherlands) countries. The findings suggested that (i) the contemporaneous correlation, although it is a time-varying correlation, does not differ for oil-importing and oil-exporting economies, and (ii) the correlation increases positively (negatively) in response to important aggregate demand-side (precautionary demand) oil price shocks, which are caused by fluctuations of the global business cycle or world turmoil (i.e., wars). Supply-side oil price shocks do not influence the relationship between the two markets. Furthermore, the lagged correlation results show that oil prices negatively affect all stock markets, regardless of the origin of the oil price shock. Boldanov, Degiannakis, and Filis (2016) examined the time-varying conditional correlation between oil price and stock market volatility for six major oil-importing and oil-exporting countries using data from January 2000 to December 2014 and a Diag-BEKK model. Their findings report the following regularities. (i) The correlation between the oil and stock market volatilities changes over time, fluctuating at both positive and negative values. (ii) Heterogeneous patterns in the time-varying correlations are evident between the oil-importing and oil-exporting countries. (iii) Correlations are responsive to major economic and geopolitical events, such as the early 2000 recession, the 9/11 terrorist attacks, and the global financial crisis in 2007–2009.

Studies conducted mainly by Belhassine (2020), Ali et al. (2022), and Ren (2022) are included in the purple cluster with a centrality of 0.5108, an impact of 1.266, and 48 documents containing the topics of stock markets, commerce, and costs. Belhassine (2020) and Ren (2022) employ a bivariate VAR-BEKK-GARCH model to explore the dynamic relationships between oil prices and other assets in the Eurozone. Belhassine's findings (2020) show that both mean and volatility spillovers among the oil market and the different Eurozone sectors are time-varying and heterogeneous. Meanwhile, Ren (2022) found stronger shock and volatility contagions from the European stock market to oil and gold markets. For the volatility nexus between oil and gold, weak and moderate evidence of shock and volatility transmission from gold to oil markets is reported by this author.

Finally, studies conducted mainly by Aloui, Aïssa, and Nguyen (2013), and Feng and Cui (2022) are included in the orange cluster with a centrality of 0.388, an impact of 1.649, and 27 documents. Aloui, Aïssa, and Nguyen (2013) and Feng and Cui (2022) used a copula–GARCH approach to analyze the conditional dependence structure among crude oil prices and foreign exchange rates. Aloui, Aïssa, and Nguyen (2013) found evidence of significant and symmetric dependence for almost all the oil–exchange rate pairs considered. The rise in the price of oil was found to be associated with the depreciation of the dollar. On the other hand, Feng and Cui (2022) studied the dual hedge of integrated risks among oil prices and foreign exchange rates. Their results showed that a dual hedge cannot outperform the single hedge in the direct hedging background. However, in the cross-dual hedging setting, a dual hedge performs much better, possibly because the dual hedge brings different levels of advantages and disadvantages in the two different settings, and the superiority of the dual hedge is more evident in the cross-dual hedging setting.

1.5 Conclusions

This paper presents a scientometric study that, through various analysis such as (i) sources, (ii) authors, (iii) documents, and (iv) cluster analysis, examined the existing frontier of knowledge in the field of dynamic association between oil prices and assets in financial markets, with a special emphasis on the methodologies for measuring the dependence among the variables oil prices, exchange rates, stock prices, energy markets, and assets related to sustainable finance. We identified and analyzed the configuration of the research on this topic between 1982 and 2022 (September). In total, 746 studies from Scopus and Web of Science databases were incorporated and analyzed.

Furthermore, researchers and practicing professionals may use this study's findings to broaden the central aspects of developing studies about the dynamic association among oil prices and assets in financial markets. Additionally, these findings can be incorporated into further research efforts to better understand the linkages among oil prices and financial variables, energy markets, and assets related to sustainable finance. Based on the results, the co-authorship analysis indicates synergies in the field of study analyzed from collaborative networks among researchers.

The cluster analysis helps determine the key theories and methodologies that are at the frontier of knowledge of the research field about the linkages among oil prices and assets in financial markets, with a special focus on the dependence among the variables oil prices, exchange rates, stock prices, energy markets, and assets related to sustainable finance. Methodologies such as wavelet analysis, copula, DCC-GARCH, and volatility spillover were identified as the most used to perform these analyses. This study provides researchers and practitioners with a comprehensive understanding of the status quo and research trends of ontology research of dynamic association among oil prices and assets in financial markets and promotes further studies in this domain. The identification of these relations provides benefits in risk diversification, hedges, speculation, and inflation targeting.

The current systematic and scientometric review offers a comprehensive analysis of research trends, and also allows us to identify that data science models face a great challenge in acquiring a better understanding of the above-mentioned relationships. In this way, we would like to encourage researchers to broaden the scope of research and provide new methodologies for measuring the dynamic co-movements among oil prices and financial assets, energy markets, and assets related to sustainable finance, and thus boost the scientific contributions. Hence, some key points are acknowledged. First, machine learning, deep learning, big data, and artificial intelligence are used to measure the dynamic co-movements among oil prices, financial assets, energy markets, and assets related to sustainable finance. This analysis can be more robust in the findings and provide more precise estimations and forecasting. Second, the study of the energy markets and assets related to sustainable finance and the nexus between oil prices and renewable energies can offer an overview to investors and policy makers keen to understand the dynamics of conditional correlations among, for example, green bonds, CO_2 prices, and oil prices, which can affect diversification strategies and the design of environmental policies. This kind of analysis could be more relevant due to the gradual energy transition proposed by international markets, mainly European and developing markets, and the consequent responses of economies to these types of regulations. Third, this paper intends to encourage researchers to explore implementing this type of analysis using assets from emerging markets, e.g., to analyze how oil prices shocks affect financial markets, especially in emerging economies. Additionally, these kinds of analyses must involve refined techniques that can offer robust results.

2. Chapter 2. Dynamic relationships among green bonds, CO_2 emissions, and oil prices

Green bonds play a pivotal role in the financing of sustainable infrastructure systems. Likewise, CO_2 emissions and oil prices can cause an impact on the green bonds market. In order to better understand this issue, this study analyzes the relationship among green bonds, CO_2 futures' prices, and oil prices using a daily data set that includes 2206 observations corresponding to daily information from January 1, 2014 to June 15, 2022. The Granger Causality Test and the Dynamic Conditional Correlation (DCC-Garch) Model were employed to conduct this analysis. Furthermore, a sensitivity analysis was performed to identify crisis periods concerning the sample period and provide an analysis of DCC-Garch results during extreme market conditions like the COVID-19 pandemic and the Russian invasion of Ukraine. The Granger Causality Test results present a unidirectional causality running from the Green Bond Index to the oil price returns. Also, there is a unidirectional causality running from the Green Bond Index to the CO_2 futures' returns. Additionally, a unidirectional causality runs from the oil price returns to the CO_2 futures' returns. The results for the DCC-Garch indicate a positive dynamic correlation between the Brent oil price return and the CO_2 futures' returns. Finally, the Green Bond Index shows a negative dynamic correlation to the oil return and the CO_2 futures' returns presenting a strong correlation in uncertainty periods.

Keywords: co-movements, dependence, oil price, green bonds, CO_2 emissions, scientometric analysis.

2.1 Introduction

The energy sector is an essential driver of economic growth due to all the activities involved in the economy's aggregate demand, including power generation, industrial use, transportation, and residential use (Sadorsky, 2009). The power generation sector is growing in terms of energy demand and carbon dioxide emissions, and in the context of global warming, this sector needs to be balanced with future economic and environmental needs (Sadorsky, 2009). An analysis of trends of CO_2 emissions and their relation with the oil prices and the green bonds market has been proven to be useful for policy-makers and energy policy analysts. Understanding the primary sources of greenhouse gas emissions and the main instruments for their reduction is essential for their worldwide management and climate change mitigation (Quadrelli & Peterson, 2007).

Green bonds play a significant role in financing sustainable infrastructure systems (SIS). This financial mechanism was introduced by the European Investment Bank (EIB) in 2007 as a novel arrangement in response to the growing environmental crisis. It offers characteristic environmental benefits due to its purpose of financing or refinancing green projects, including low carbon, energy-efficient, and climate-friendly projects (Nguyen et al., 2021). In this context, the green bonds and the energy sector have a close connection given by environmental concerns.

According to the standard microeconomics theory, in a Marshallian consumer demand function, the most important determinants for a consumer good are the price of the good, the consumers' income, and the good's substitute price (Marshall, 1890). Thus, in order to model energy demand, it is necessary to postulate a model that involves the price of energy consumption, income, and the prices of a substitute source of energy (Sadorsky, 2009). According to Omri et al. (2015b), it is broadly accepted that renewable energy is a substitute for crude oil in both consumption and production of other energy sources. Therefore, a negative link between oil prices and renewable energy demand is expected because increases in oil prices would encourage businesses and households to reduce consumption, purchase more energy-efficient products and switch to renewable energy sources (Henriques & Sadorsky, 2008). Nevertheless, according to Azhgaliyeva et al. (2022), if a green bond has value as an environmental asset, then a positive correlation is expected between the green bond and crude oil prices. It is likely that when oil prices rise then the renewable energy investment growth, as there is an inclination to substitute away from crude oil for alternative energy, which should lead to the increase in the issuance of green bonds, particularly in oil-importing economies. In contrast, a positive relationship between oil price and CO_2 emissions is expected due to the direct connection between energy demand and carbon dioxide emissions (Sadorsky, 2009). At this point, green bonds, as one of the most important financial eco-innovation mechanisms, play a relevant role in the financing of SIS, particularly renewable energy projects (Mejia-Escobar et al., 2020; Mejía-Escobar et al., 2021).

Literature review shows that oil prices are related to the real economy and the financial markets/assets either directly or via different channels that include stock markets, exchange rates, and firms' investment spending (Filis et al., 2011; Malik & Rashid, 2017; Melek, 2018;

Reboredo, 2012). Furthermore, the oil prices effects on the economy can be justified because oil is one of the most traded commodities in the global financial markets and a crucial raw material for production, transportation, heating, and energy generation (Cherubini, 2010; Salem, 2017). Also, an increase in oil prices can boost the cost of production and, therefore, decrease firms' profits. Consequently, rising oil prices can bring inflationary pressure, reducing the demand for firms' goods and services (Melek, 2018). Based on these concerns, a set of comprehensive studies have been conducted in order to discuss the consequences of oil price effects on investment in the financial stock markets (Akkoc & Civcir, 2019; Civcir & Akkoç, 2021; Dutta et al., 2018; Lamouchi & Alawi, 2020; B. Lin & Chen, 2019; Omri, ben Mabrouk, et al., 2015; X. Ren et al., 2019; Singhal & Ghosh, 2016). The main findings show that the relationships between oil price and the different markets are time-varying and the presence of volatility spillover from oil price to the stock markets, increasing the co-movements in periods of oil price turmoils. Besides, the results indicate that volatility spillover from oil prices to sectoral indicators varies significantly. These results reflect the necessity of dynamic macroeconomic policies to manage the spillover effects on volatility. The findings are also helpful for investors since they show that by diversifying and hedging their investment across different sectors would reduce their portfolios' risks. (Akkoc & Civcir, 2019; Civcir & Akkoç, 2021).

However, a knowledge gap has been identified despite all the advances in studying the relationships among green bonds with other financial variables such as (i) conventional bonds and commodities (T.-L. Le et al., 2021; Nguyen et al., 2021), (ii) the connectedness with financial markets (X. Liu et al., 2021; Reboredo et al., 2020; Reboredo & Ugolini, 2020; Saeed et al., 2020, 2021), (iii) the relationship with the renewable energy stocks (Tiwari et al., 2021), and (iv) as a hedge for carbon market risk (Jin et al., 2020; X. Ren, Li, yan, et al., 2022). To the best of our knowledge, no study in the current literature has provided an in-depth analysis of the co-movements among the green bonds, CO_2, and oil prices, for example (González-Ruiz et al., 2023) suggest analyzing the dynamics correlations among these three variables. Thus, a deeper analysis of this issue will lead to a better comprehension of the evolution of oil prices, thanks to the implementation of instruments that attempted to use sustainable energies during the studied period. According to Marimoutou and Soury (2015) and Ma et al., (2021), this analysis is relevant because oil is a fundamental component of energy prices and an important source of CO_2 emissions.

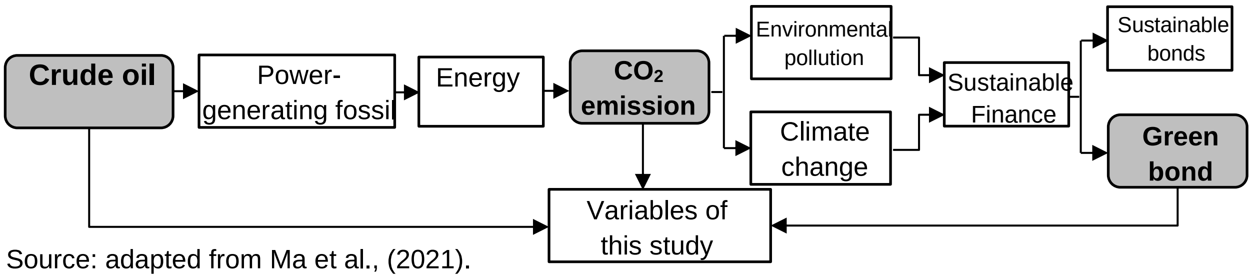
We make three main contributions to the literature. First, we provide an in-depth scientometric analysis in order to have a better understanding of the relationships between crude oil prices, CO_2 futures' prices, and green bonds. Three research trends were identified and point to matters related to (i) the impact of energy consumption, CO2 emissions, oil prices, and climate changes on economic growth; (ii) political and institutional factors driving renewable energy consumption, and (iii) the correlation among different financial assets, Second, we provide new evidence by examining the dynamic relationship among crude oil prices, CO_2 futures' price, and the green bonds using two models namely, the Granger Causality Test and the Dynamic Conditional Correlation Garch (DCC-Garch) – to provide evidence of the evolution of the linkage between these variables. Third, we bring a month-wise analysis of DCC-Garch results during extreme market conditions like the COVID-19 pandemic and the Russian invasion of Ukraine. Thus, this study provides further insights for decision-makers on designing strategies for promoting eco-friendly policies that contribute to structure sustainable investment portfolios.

The paper is organized as follows. Section 2 presents a systematic literature review of the relationships among green bonds, CO_2 emissions, and oil prices through a scientometric analysis. Section 3 presents the data, the descriptive statistics, and the methodologies used. Section 4 analyzes the results and provides an analysis of DCC-Garch results during extreme market conditions like the COVID-19 pandemic and the Russian invasion of Ukraine. Finally, Section 5 presents the concluding remarks, contributions, and further research.

2.2 Literature review

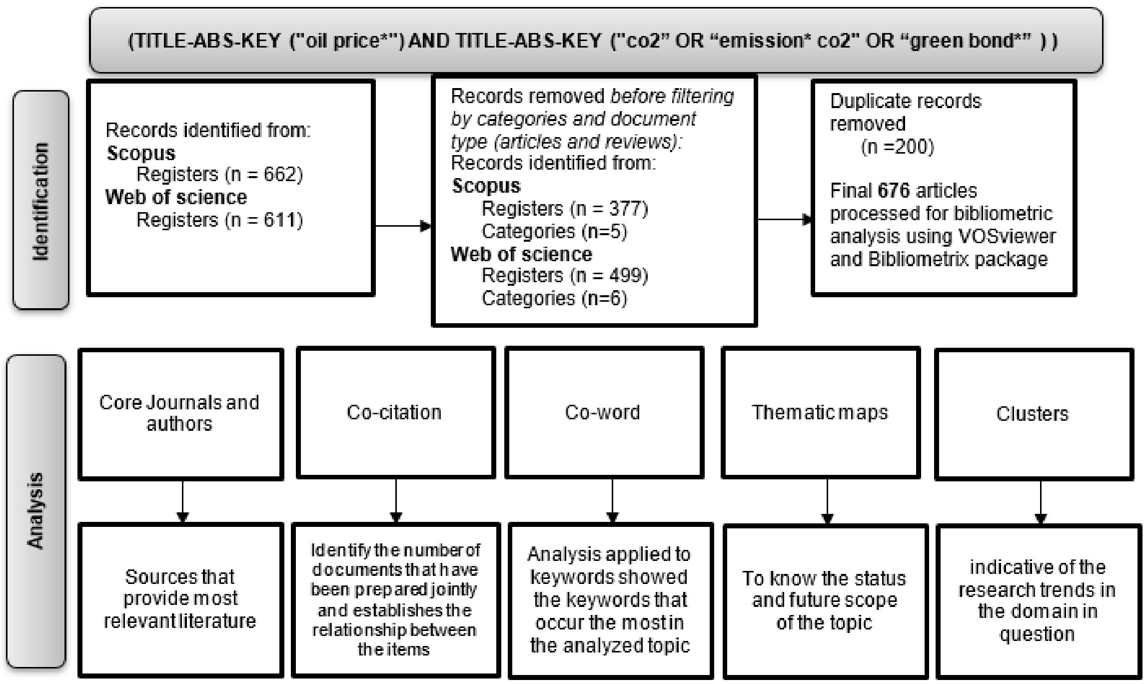
For explaining the connection among green bonds, CO_2 emissions, and oil prices, it is necessary to understand their roles. Oil price is the primary indicator in the energy market, and almost all other energy product prices are influenced by it, including natural gas and coal (Z. Ma et al., 2021). Thus, energy prices are correlated with carbon emissions rights and green bonds because this last financial mechanism represents firms' attention to environmental protection, which promotes the development of a low-carbon economy (Wang and Wang, 2022; González-Ruiz et al., 2023). Figure 2-1 presents the industrial chain connection among crude oil, carbon emission rights, and green bonds.

Figure 2-1: Linkages among crude oil, CO_2 emissions, and green bonds.



Source: adapted from Ma et al., (2021).

Figure 2-2: Literature search strategy



This study undertook a comprehensive and holistic scientometric review of the leading studies about the dynamic relationships among green bonds, CO_2 emissions, and oil prices. Several studies related to sustainability concerns have used this method (Marquez et al., 2021; Mejia-Escobar et al., 2020; Mejía-Escobar et al., 2021). Due to their stronger academic reputations, the research papers reviewed were obtained from the Scopus and Web of Science (WoS) bibliographic databases. The following keywords were used in both: oil price, CO_2, CO_2 emissions, and green bonds. Thus, the search equation used in both databases was: (TITLE-ABS-KEY ("oil price*") AND TITLE-ABS-KEY ("CO2" OR "emission* CO2" OR "green bond*")). After that search, all the research papers were downloaded and indexed into the Mendeley reference manager for further analysis. After removing the duplicates, we used 676 research papers for scientometric analysis using the

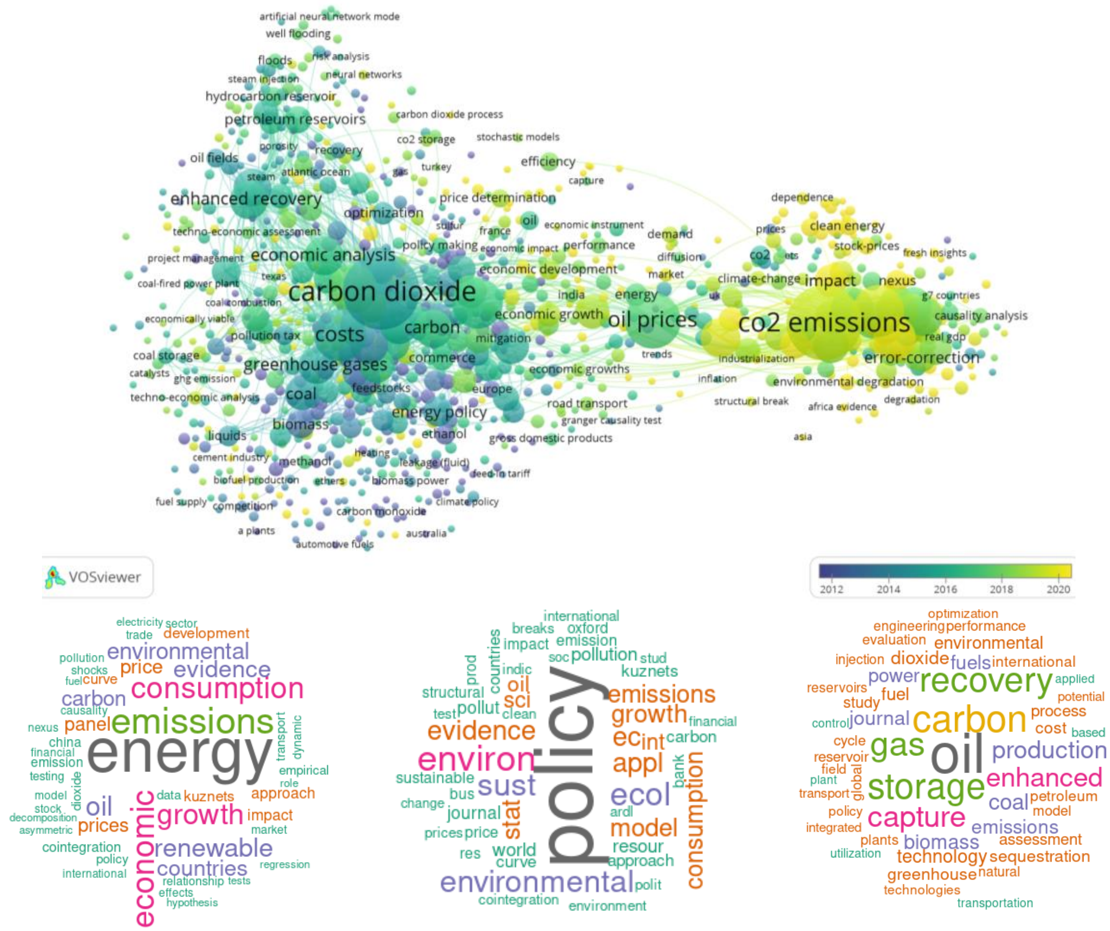
VOSviewer version 1.6.18 (van Eck & Waltman, 2017) and the Bibliometrix package for R (Aria & Cuccurullo, 2017). Figure 2-2 shows the literature search strategy.

Then, structural patterns and research trends were identified by employing illustrative diagrams and maps. In this way, three research trends were detected and examined in the scientific literature. Figure 2-3 presents, on the top, the relationships of the most crucial studies on relationships among green bonds, CO_2 emissions, and oil prices. On the bottom, it shows the three research trends.

The first trend focuses on the effects of factors such as energy consumption, CO_2 emissions, oil prices, and climate changes on economic growth (de Souza et al., 2018; Ftiti, Guesmi, Teulon, et al., 2016; Khan et al., 2021; Naser, 2015). The evidence suggests that energy consumption has a positive long-term impact on economic growth. Thus, energy consumption (i.e., oil or nuclear) has predictive power for economic growth, directly impacting the variation of the real Gross Domestic Product (GDP) in all countries analyzed (Ftiti, Guesmi, Teulon, et al., 2016; Naser, 2015). In this way, in the study conducted by de Souza et al. (2018) for MERCOSUR (for its Spanish acronym of Southern Common Market) countries, they found that energy consumption from renewable sources had a negative impact on CO_2 emissions, while the energy consumption from non-renewable sources had a positive impact. The positive impact of economic development on CO_2 emissions was also observed due to economic activities of all countries reacting to persistent fluctuations in oil prices (de Souza et al., 2018).

In this same line, several studies analyze the links' variations in environmental quality to national economic growth using the Environmental Kuznets Curve (EKC) analysis. The EKC hypothesis proposes an inverted U-shaped relationship between environmental degradation and economic growth; it has been tested in different countries in the last two decades (Akca, 2021; Alshehry & Belloumi, 2017; Balaguer & Cantavella, 2016; Boufateh, 2019; Q. Chen & Taylor, 2020; Erdogan et al., 2020; Moomaw & Unruh, 1997; Moutinho et al., 2020; Saboori et al., 2016). The main variables in the EKC hypothesis are the GDP (Gross Domestic Product) and GDP square; other explanatory variables such as energy, trade openness, urbanization, labor and capital, investment, and foreign direct investment (FDI) were also considered. The results suggest that the EKC model is highly sensitive to omitted variable bias and specific effects in every country (Saboori et al., 2016).

Figure 2-3: Relationships of the most significant studies and research trends of linkages among green bonds, CO_2 emissions, and oil prices.



Trend 1 **Trend 2** **Trend 3**

Source: Authors' own research using VosViewer, Bibliometrix tools, as well as Scopus and WoS databases.

A second trend examines the importance of political and institutional factors driving renewable energy consumption (Adom et al., 2018; Azhgaliyeva et al., 2020; T.-H. Le & Nguyen, 2019; J.-B. Lin & Tsai, 2019; Pata, 2021; Sener et al., 2018; Uzar, 2020). According to Uzar (2020), institutional quality positively affects long-term renewable energy consumption. In this way, the analysis conducted by Le and Nguyen (2019) supports the existing direct relationships at the global level among three agendas (i) the use of energy for economic development, (ii) energy security, and (iii) climate change mitigation. The relations among these three agendas imply that each can be strengthened by referencing the others as integrated themes. However, these topics have been studied as separate themes, ignoring that the business world has become more Interdependent. For this reason, an integrated approach is necessary for progress across the multiple goals for sustainable development, including providing safe, affordable, and uninterrupted energy sources for all (comprising the poor and vulnerable groups) while fighting climate change.

The third trend delves into the correlation among different financial assets, including financial mechanisms for funding renewable and non-renewable energies (T.-H. Le & Nguyen, 2019; Zaghdoudi, 2017). In this way, the empirical evidence suggests that the correlation between green bonds and the other studied markets, such as energy prices, especially oil prices (Azhgaliyeva et al., 2021; Yan et al., 2022), and corporate and treasury bonds (Nguyen et al., 2021; Reboredo, 2018) is positive, and negative with stock markets and exchange rates (Naeem, Mbarki, et al., 2021). The co-movements are especially strong during financial crisis periods due to the volatility in the financial markets (T.-H. Le & Nguyen, 2019; Nguyen et al., 2021). Then, as a result, the diversification benefits consequently dimmish during times of turmoil. Furthermore, market maturity could explain the positive integration between green bonds and other assets (T.-H. Le & Nguyen, 2019; Nguyen et al., 2021). In contrast, Zaghdoudi (2017) examines the causal relationship among the OECD (Organisation for Economic Co-operation and Development) countries' domestic oil prices, renewable energy, carbon dioxide emissions, and economic growth from 1990 to 2015. This study also found strong evidence of a negative and significant long-run relationship among oil prices, renewable energy, and CO_2 emissions. The evolution of production technology directly affects the changes in energy consumption.

The development trends described above generally aim at improving the comprehension of the relationships among green bonds, CO_2 emissions, and oil prices. It is essential to note that the study of the green bonds market has recently increased due to the several world policies that propel more sustainable production. These topics involve several research fields, such as the evolution of technologies and financial markets concerning green project financing and the evolution of strategies for promoting eco-friendly policies. The literature review also shows the absence of studies, including the three variables' analysis. In this context, the simultaneous analysis of the three variables, namely, oil prices, renewable energy, and CO_2 futures' prices allows an understanding of the evolution of the connections among them in time and how the external effects affect their co-movement. Hence, the present study aimed at filling the knowledge gap on the relationship among green bonds, CO_2 futures prices, and oil prices.

2.3 Data and models

2.3.1 The dataset

The dataset contains daily closing prices from January 1, 2014 to June 15, 2022 generating 2206 observations. The variables used in this study are CO_2 emissions, green bond, and brent oil price, as shown in Table 2-1. The data obtained from the variables are organized in series, then they are transformed to log-returns, yielding 2206 daily return observations for each variable (Appendix A). All the variables were gathered from Bloomberg.

Table 2-1: List of variables.

Variable	Ticker	Description
CO_2 futures price	MO1 Comdty	CO_2 futures price, Euros per ton
Green Bond Index	GBEUTREU Index	Bloomberg MSCI Euro Green Bond Index Total Return Index Value Unhedged
Oil Brent price	CO1 Comdty	Generic 1st Crude Oil, Brent

Source: Authors' own research using Bloomberg.

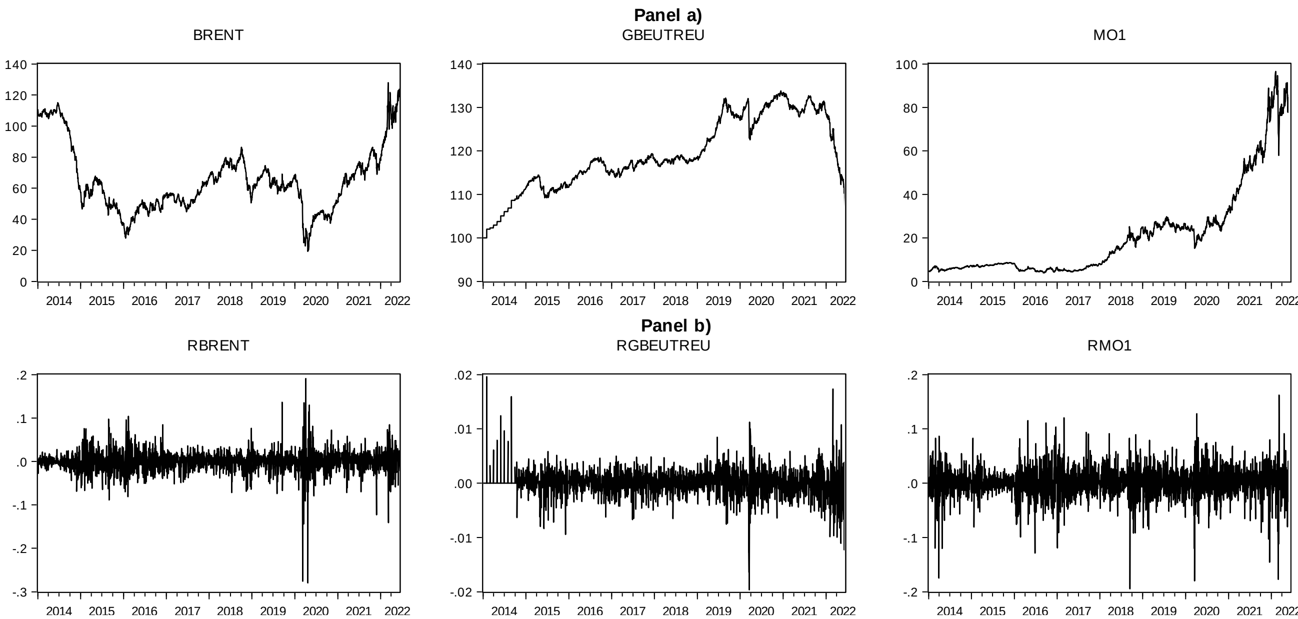
The MO1 Comdty variable is CO_2 futures' price and indicates Euros per emission ton allowance (European Union Allowances -EUA-) in the Intercontinental Exchange Group (ICE) Europe's futures. The EUA are climate credits (or carbon credits) used in the European Union (EU) Emissions Trading System (ETS). EUA futures Contracts, traded on the ICE, are contracts in which the traders are obliged to make or take the delivery of 1,000 emission allowances. Each allowance is an entitlement to emit one ton of carbon dioxide-equivalent gas (Choi et al., 2020). On the other hand, the Bloomberg MSCI Green Bond Index (GBEUTREU Index) is a Euro fixed income benchmark to fund projects with direct environmental benefits. The index includes Euro-denominated fixed-income securities, including treasury, corporate, government-related, and securitized debt. Securities in the index must be rated Investment Grade (Baa3/BBB-/BBB-) with a minimum size of EUR 300m. Bonds are evaluated to ensure they adhere to the established Green Bond Principles and can be categorized as green bonds for their environmental use of proceeds. Additionally, the index offers investors an objective and robust measurement of the market for fixed income securities issued in Euro to fund projects with direct environmental benefits (Bloomberg & MSCI, 2021). On the other hand, the Brent oil price (CO1 Comdty) is included as a fundamental component of energy prices (the energy prices include coal and natural gas). The inclusion of the oil price as a representative energy price is essential because industrial production involves a high fossil fuel consumption. Then, production is an important source of CO_2 emissions, and for this reason, oil prices are determining and driving carbon dioxide prices (Marimoutou & Soury, 2015).

The selected variables are relevant because oil still retains great prominence within the finance world as an essential input for production, a relevant commodity within global financial markets, and a significant source of CO_2 emissions. The considered variables can reflect the recent evolution of the CO_2 emissions and the efforts of green bond markets to contribute toward climate change remediation, conservation of natural resources, biodiversity enhancement or conservation, pollution control, and prevention (Yan et al., 2022).

Figure 2-4 shows the evolution of the daily prices and returns of the variables considered in the analysis. The highest peak was observed when the global pandemic started in March 2020. For oil prices, the main shocks are presented in 2014, when the Fed's taper announcement occurred, which caused the fall of financial asset prices, an increase in price volatility, a decline in trade volumes and market liquidity, as well as a rise in government debt which spreaded between the end of May and August 2014 and denoted a market turbulence. It can also be observed that an oil price crisis surged in 2014.

Furthermore, in 2016, it can be noted that the oil price was affected by the protectionist uncertainty for the emerging Latin American markets, especially Mexico. It was due to strong financial and trade relationships with the rest of the world, particularly the United States. Such uncertainty began with the presidential campaign in the United States when the financial markets reflected the nervousness in every presidential debate (Pham et al., 2018). For example, when investors thought that Mr. Trump would win, the market fell, and when it looked more likely that Mrs. Clinton would win, the markets rose. In 2018, the market moved from an oil shortage in the middle of the year to a crude oversupply at the end of the year, which considerably affected the price, as shown in Figure 2-4. Finally, when the global pandemic produced by coronavirus started in December 2019, the oil price had an important negative impact when world's production presented a significant decrease in the demand for many industrial and technological products. In the first half of 2022, a barrel of oil has presented higher prices due to Russia's invading Ukraine.

Figure 2-4: Daily prices and returns of oil brent price, CO_2 futures price, and green bond index. Panel a) prices and Panel b) returns



Source: Author's own research using data from Bloomberg.

Concerning green bonds, this financial mechanism has been attracting an important degree of interest across investors worldwide as an alternative source to finance low-carbon investments. The market for green bonds has grown sharply, from U.S.$ 3.4 billion in 2012 to US $156 billion in 2017 (Azhgaliyeva et al., 2020). The issuances practically doubled each year after 2016, and the portion of corporate green bonds has been constantly growing, but the green bond market remains smaller than the conventional bond market (Piñeiro-Chousa et al., 2022). In the Latin American and the Caribbean market, from 2014 to 2020, the issuances of green bonds have had an average annual increase of 1.88x (Mejia et al. 2021). It shows an accelerated growth with strong perceptions for investors and issuers to help reach the Sustainable Developments Goals (SDGs). Finally, the price of CO_2 emissions is important because it is related to oil prices. This is one of the leading industrial activities responsible for CO_2 emissions and is also connected to the green bond markets. After all, these markets seek to reduce CO_2 emissions and promote economic activities that are eco-friendly and sustainable in the long term. In Figure 2-4, it can be observed how the CO_2 emissions futures' price had increased too, especially after 2018. In 2018, the EU strengthened the ETS cap in order to deliver the 40% emission reduction target by 2030. In 2019, this reform was effective when the Market Stability Reserve (MSR) started operating; It targets an increasingly reduced volume of authorized permits based on the implementation of a rule-based supply-side control, and whose effects were finally reflected on the prices of CO_2 emissions (Osorio et al., 2021).

Table 2-2 provides the summary statistics of daily returns of the considered series. The daily returns are asymmetric and negatively skewed. It indicates that negative values are predominant in the analyzed period. Hence, this is consistent with leptokurtic and heavy-tailed distortions. In all cases, based on the Jarque-Bera test, the null hypothesis that the distribution is gaussian is rejected. Also, evidence from the Augmented Dickey-Fuller (ADF) testing for the presence of a root unit in the original time series of the prices is not rejected. It indicates that the original series does not have a constant mean or variance consistent with the series in the financial markets. However, the ADF Test points out the stationarity of all return series (Dickey & Fuller, 1979). Conditional heteroscedasticity is significant, as indicated by the results of the ARCH-LM Test, implying the autocorrelation of the analyzed return series.

Table 2-2: Summary statistics of daily returns

Index	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-bera	ADF	ARCH
RMO1	0.00130	0.16204	-0.19444	0.02922	-0.54243	7.77620	2204.988***	-49.47***	30.48***
RGBEUTREU	0.00003	0.01961	-0.01964	0.00245	-0.34554	12.53055	8392.823***	-43.05***	50.99***
RBRENT	0.00003	0.19077	-0.27976	0.02543	-0.97763	20.42174	28249.69***	-46.36***	30.81***

Source: Authors' own research using data from Bloomberg. Notes: This table presents summary statistics of daily returns oil brent price, CO_2 futures price, and green bond index. The January 1, 2014—June 15, 2022 sample yielded 2206 observations. *** indicates the rejection of the null for both normality test (via Jarque-Bera) and unit root test [via Augmented Dickey-Fuller (ADF)]. The ADF test is conducted with an intercept; ARCH-LM, is the heteroscedasticity test up to 18 lags.

On the other hand, pairwise correlations across the returns of the variables considered are presented in Table 2-3. The correlation of oil price return (RBRENT) with the CO_2 futures' returns (RMO1) is positive (19.81%), and with the Green Bond Index (GBEUTREU) is negative (-5.15%). According to Fatica and Panzica (2021), the issuance of a green bond is associated with a reduction in CO_2 emissions. Finally, the correlation between the CO_2 futures' returns and the Green Bond Index return is negative too (-7,44%). It is expected that CO_2 futures' returns, and oil returns have the same behavior against the Green Bond Index because if oil prices rise, then the CO_2 emissions will increase too (Mahmood et al., 2022; Mahmood & Furqan, 2021; Sadorsky, 2009; Zheng et al., 2021). For example, Zheng et al., (2021) argued that oil shocks might significantly influence emissions, and oil supply can also impact carbon allowance prices. Then, the important role of oil supply and prices in determining emissions and carbon allowance prices appear as a clear pathway and policy framework for countries to regulate and control their emissions and the oil market. Furthermore, they reveal the necessity of including their supply of oil and prices to meet their long-term environmental targets. Then, this phenomenon could lead to more green bond issuances. Thus, the green bonds market correlates more with corporate and treasury bond markets and less with stock and energy commodity markets. In a deeper analysis, (Reboredo, 2018) found that green bonds are strongly connected to treasury bonds and corporate bonds in the short- and long-term run and are weakly connected to high-yield corporate bonds, stocks, and energy assets.

Table 2-3: Unconditional correlation of daily returns.

	RMO1	RGBEUTREU	RBRENT
RMO1	1		
RGBEUTREU	-0.0744	1	
RBRENT	0.1981	-0.0515	1

Source: Authors' own research using data from Bloomberg.

2.3.2 The Granger Causality Test

Based on a test, Granger (1969) proposed the notion of causality centered on the asymmetry of the correlation schemes. The test is proposed for a strictly stationary bivariate process $\{(X_t, Y_t)\}$, such that $\{X_t\}$ is a Granger cause of $\{Y_t\}$ if current and past values of X contain extra information on future values of Y that is not contained in current and past Y-values themselves. This definition has key features such as the following.

- X_t and Y_t are stochastic variables.
- The notion of statistical causality, that is, of temporal precedence, is not a substitute for causality in econometric analyses since such statistical causality requires that changes in X_t precede changes in Y_t and that changes in X_t explain or generate Y_t changes.
- The Granger Causality Tests only allow direct causality to be accepted or rejected, but not the existence of indirect causality due to the omission of other variables.

Considering these conditions, Granger (1969) presented the model as follows, with X_t and Y_t as stationary time series with zero mean.

$$X_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t$$

(2.1)

$$Y_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \eta_t$$

Therefore, ε_t and η_t are uncorrelated white noise series. Mathematically, this equation allows for $m \rightarrow\infty$. However, empirically the data horizon is finite for m. Furthermore, the causal relationship in this model could be defined as Y_t, causing X_t given $b_j \neq 0$, or X_t causing Y_t given $c_j \neq 0$.

An approximation to instantaneous causality would be the following.

$$X_t + b_0 Y_t = \sum_{j=1}^{m} a_j X_{t-j} + \sum_{j=1}^{m} b_j Y_{t-j} + \varepsilon_t$$

(2.2)

$$Y_t + c_0 X_t = \sum_{j=1}^{m} c_j X_{t-j} + \sum_{j=1}^{m} d_j Y_{t-j} + \eta_t$$

This methodology test allows to complement the DCC-Garch Model because it determines the existence of a strong short-term correlation among the variables analyzed. In addition, the existence of unidirectional causality in the sense of Granger (1969) allows to conclude the direction in correlation between a pair of assets.

The Granger Causality Test is carried out as a previous step to the execution of the DCC- Garch Model since. If the test accepts the null hypothesis in both cases, Ho: X does not Granger Cause Y and Ho: Y does not Granger Cause X, then there will not be a relationship between the pair of variables analyzed over time; this would make it ineffective to apply the DCC-Garch Model. However, the DCC-Garch Model can be applied directly to rule out the existence of a co-movement between the pair of variables.

Understanding the generated statistical causal relationship among the analyzed variables has been important since this finding gives greater robustness to the estimated conditional dynamic correlation. Thus, identifying which variable causes the other allows greater clarity on the association's structure among the variables analyzed. Several studies have explored the relationship between the oil price and different variables and the impact of such relationships on the economic results (Bayar et al., 2021; Behmiri & Pires Manso, 2012; Pirgaip & Dincergok, 2020; Reboredo, 2018; Troster et al., 2018). They found empirical evidence of causality relationships running from crude oil price to crude oil consumption and GDP and a bidirectional causality relationship between crude oil consumption and GDP, both in the short and long runs. These results indicate that crude oil conservation policies affect the OECD economic growth in the short and long runs in the OECD countries. Therefore, policy-makers should consider that increasing crude oil prices or diminishing crude oil consumption negatively impacts on the economic growth rate (Reboredo, 2018).

On the other hand, Troster et al., (2018) collected evidence on bi-directional causality between changes in renewable energy consumption and economic growth at the lowest tail of the distribution and unidirectional causality from fluctuations in oil prices to economic growth at the extreme quantiles of the distribution. Finally, the same authors found evidence of lower-tail dependence from changes in oil prices to changes in renewable energy consumption. These findings call for government policies aimed at developing renewable energy markets to increase energy efficiency. According to Pirgaip and Dincergok (2020), there is a unidirectional causality running from EPU (Economic Policy Uncertainty) to energy consumption in Japan, from EPU to CO_2 emissions in the USA and Germany; and from EPU to both energy consumption and CO_2 emissions in Canada. In Italy, the causality runs from CO_2 emissions to EPU, but a bidirectional causality exists between EPU and energy consumption. The same authors also explored a unidirectional causality from energy consumption to CO_2 in the USA. Based on the findings, (Pirgaip & Dincergok, 2020) strongly recommend that the G7 countries consider the possible negative effects of EPU on energy conservation policies, which should be implemented to reduce energy consumption and CO_2 emissions, as committed in the recent climate mandate.

Finally, according to Bayar et al., (2021), the causality analysis revealed a unilateral causality from trade globalization to renewable energy in Estonia, Latvia, and Slovenia. Also, they found another causality from renewable energy to trade globalization in Croatia and Lithuania. However, no significant causality between financial globalization and renewable energy was discovered. On the other hand, a unilateral causality from CO_2 emissions to renewable energy in Lithuania and Slovenia was identified. This can be added to the one evidenced by renewable energy to CO_2 emissions in Czechia, Hungary, and Latvia. It is also relevant to mention the reciprocal causality between, renewable energy to CO_2 emissions in Romania and Slovakia, and a unilateral causality from real GDP per capita to renewable energy in Czechia, Romania, and Slovenia observed in the causality analysis.

2.3.3 Dynamic Conditional Correlation Model (DCC-Garch)

There is a set of models designed for time-varying correlation based on historical data. The Dynamic Conditional Correlation Model (DCC-Garch) was introduced by Engle (2002), and more recently, it has been related to the ample literature on multivariate Garch; a series of studies conducted have introduced different methods to estimate conditional correlations (Bali & Engle, 2010; Cappiello et al., 2006; Colacito et al., 2011; de Nard et al., 2022; R. F. Engle et al., 2019; Pakel et al., 2021; Rangel & Engle, 2012). Most of the models implemented by these studies seek to parametrize the covariance matrix of a set of random variables, conditioned to a set of observable state variables that typically include the past realization of the variables of interest (in this case, returns). In this study, The Granger Causality Test has been used to identify causality among the selected variables: green bonds, CO_2 emissions, and oil prices. This test verifies if one variable can predict another variable and if it has a unidirectional or bidirectional character, thus determining the co-movement's direction. Then, the test allows to complement the DCC-Garch Model to conclude if there is a strong correlation between the variables analyzed in the present study.

The test consists of checking if a variable's results are useful to predict another variable, if it has a unidirectional or bidirectional character. Let $r_{i,t}$ denote the return of asset i at time t, and follows the process (for i = 1, . . . , n, t = 1, . . . , T).

$$r_{i,t} = \mu_{i,t} + \sigma_{i,t} z_{i,t} \quad (2.3)$$

where $z_{i,t}$ is a standard normal random variable, $\sigma_{i,t}^2$ and $\mu_{i,t}$ are the conditional variance and mean of the return, respectively. And $\varepsilon_{i,t}$ is the return innovation. Covariances between assets i and j, follow a first order scalar MGARCH (R. Engle, 2002; R. Engle & Kroner, 1995; Tse & Tsui, 2002). Then, the specification of the conditional variance is:

$$\sigma_{i,j,t}^2 = \lambda_{i,j} + \alpha\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta_j\sigma_{i,t-j}^2 \quad (2.4)$$

The DCC-Garch Model is characterized by showing if the number of parameters is independent from the number of the used series. Then, Engle (2002) proposes the following process for the MGARCH estimation:

$$W_t = D_t M_t D_t \quad (2.5)$$

Where M is a matrix of conditional correlations and D is a diagonal matrix with the following form:

$$D_{t}=\begin{bmatrix}\sigma_{1,t}^{2} & 0 & 0\\ 0 & \sigma_{2,t}^{2} & 0\\ 0 & 0 & \sigma_{3,t}^{2}\end{bmatrix} \tag{2.6}$$

The equation of the conditional correlation matrix written in deviations from the unconditional long-run correlation means of standardized errors (ζ_t) is:

$$M_{t}= (1-\alpha-\beta)\bar{R}+\alpha\zeta_{t-1}\zeta_{t-1}^{'}+\beta M_{t-1} \tag{2.7}$$

Where $\bar{R}$ is the long-run average correlation. The matrix M_t is guaranteed to be positive definite as long as the initial parameters α, β, and (1 − α − β) are all positive and if the initial value M1 is positive definite. The principle behind the mean-reverting DCC-Garch is that when returns move in the same direction, either moving up or down, the correlation will rise above its average level and remain there for a while. Gradually, this phenomenon will decay, and correlations will come back to their long-run average. The parameters α and β determine the speed of the adjustment and are called the correlation's persistence parameters. α represents the impact of past shocks on a current conditional correlation, and β captures the impact of the past correlations. If α + β = 0, then the model collapses to one with constant conditional correlation (CCC). When the sum of these two parameters approaches one, the estimated correlations become increasingly dynamic. These two parameters will need to be estimated from the data.

The DCC-Garch has been extensively used to analyze dynamic conditional covariances and correlations across investment instruments (Basher & Sadorsky, 2016; Singhal & Ghosh, 2016; Surya & Wibowo, 2018; Turhan et al., 2014). However, the study conducted by Caporin and McAleer (2013) points out some of the limitations of the DCC-Garch representation for estimating and forecasting time-varying conditional correlations. Among the pointed out issues, there is the lack of a proper discussion on stationarity conditions or asymptotic properties of the estimators in most representations or extensions of DCC-Garch. However, stationarity can be achieved by using returns in the model. As stressed by the study, this criticism does not entirely rule out the possibility of using DCC-Garch as a filter or a diagnostic check that can capture the dynamic conditional correlations. Therefore, the recent criticism does not invalidate this paper's effort to use DCC-Garch to obtain time-varying measures of the interdependence across green bonds, CO_2 emissions, and oil prices. As an illustration, several authors use the DCC methodology to estimate the dynamic relationships between the oil price and different financial assets such as exchange rates, gold, VIX, bonds, and stock markets, among others (Turhan et al., 2014; Basher and Sadorsky, 2016; Singhal and Ghosh, 2016; Surya and Wibowo, 2018).

2.4 Empirical results

2.4.1 Causality among the variables

Before analyzing the DCC-Garch Model, the Granger Causality Test is presented in order to identify the causality among the selected variables with a level of 95% of confidence. As shown in Table 2-4, results indicate a unidirectional causality from Green Bond Index (RGBEUTREU) to oil price returns (RBRENT) due to the rejection of the null hypothesis. This research results suggest that environmental investments affect oil prices. It means that the movements in green bond prices lead to changes in oil prices. In contrast, Lee et al. (2021) found a bi-directional lower-tail causality between crude oil and green bond markets, which indicates a feedback relationship, suggesting that oil prices and green bond prices are interdependent when these markets are in a bearish state (lower quantile).

Table 2-4: Pairwise Granger Causality Tests.
Lags: 2

Null Hypothesis	Obs	F-Statistic	Prob.	Null Hypothesis
RBRENT does not Granger Cause RGBEUTREU	2204	0.89168	0.4101	Not Rejected
RGBEUTREU does not Granger Cause RBRENT		4.02322	0.0180	Rejected
RBRENT does not Granger Cause RMO1	2204	5.75145	0.0032	Rejected
RMO1 does not Granger Cause RBRENT		0.75946	0.4680	Not Rejected
RMO1 does not Granger Cause RGBEUTREU	2204	1.17328	0.3095	Not Rejected
RGBEUTREU does not Granger Cause RMO1		3.67727	0.0254	Rejected

Source: Author's own research using data from Bloomberg.

Also, a unidirectional causality runs from oil price returns (RBRENT) to CO_2 futures' returns (RMO1) as a result of the rejection of the null hypothesis. In this case, there is evidence that oil prices directly impact the future prices of CO_2 emissions. In the same line, Mensah et al. (2019) determined a unilateral cause from oil prices to carbon emissions both in the long and short run. According to the results, a unidirectional causality runs from the Green Bond Index (RGBEUTREU) to the CO_2 futures' returns (RMO1) indicate by the rejection of the null hypothesis. It means that green bonds have a unidirectional connection with the CO_2 futures' returns. Then, if the strong demand for the green bond market occurs, in turn, it will affect the CO_2 permits. This result is supported by Hung (2021). Nevertheless, Hammoudeh et al. (2020) indicate that the Green Bond Index does not cause the CO_2 futures' returns and observed a significant causality from CO_2 futures' returns to green bonds, especially in 2015, when oil prices collapsed.

2.4.2 Dynamic Conditional Correlations among the variables

Table 2-5 shows the DCC-Garch parameters estimates from the pairwise considered, which are significantly different from zero. The estimated parameters α and β in the DCC-Garch Models capture the effects of lagged standardized shocks and lagged conditional correlations. When α increases, the lagged squared residuals (the ARCH terms) play an increasingly important role in estimating the correlation. If β increases, the conditional correlation becomes more persistent.

Table 2-5: Estimated parameters of DCC-Garch models.

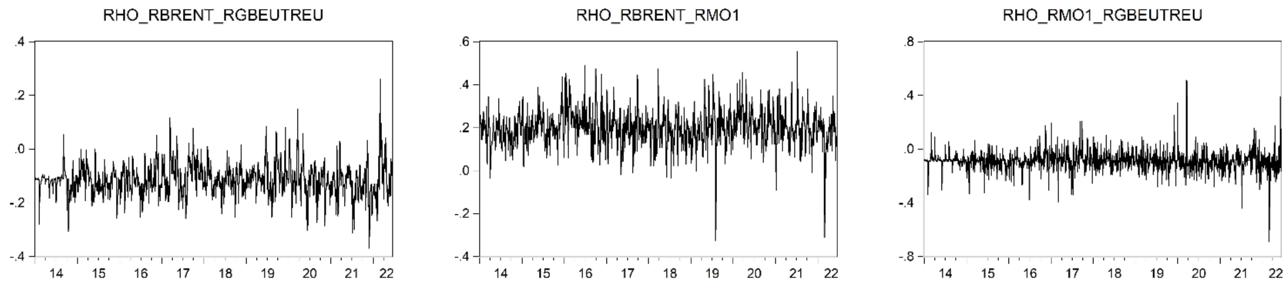
Pair	Alpha (α)	Beta (β)	(α) + (β)
ρ(RBRENT, RMO1)	0.064***	0.654***	0.718
ρ(RBRENT, RGBEUTREU)	0.039***	0.760***	0.799
ρ(RMO1, RGBEUTREU)	0.069***	0.448***	0.518

Source: Authors' own research using data from Bloomberg. Notes: ∗,∗∗, and ∗∗∗ indicate a significance at the 10, 5 and 1% level, respectively.

In most of the DCC-Garch Models' results, the magnitude of β indicates a strong persistence in the dynamic conditional correlation, except for the relationship among the CO_2 futures' returns and the Green Bond Index ρ(RMO1, RGBEUTREU), which present a moderate value of β (0.448). Additionally, the sum of the conditional correlations also exhibited high persistence (α + β), with the average sum of the two coefficients being over 0.678 during the sample period. Then, the estimated correlations become increasingly dynamic. This implies that the analyzed pairs' volatility process is stable and presents a high degree of persistence concerning the past correlations. Parameter β captures the high impact of the past correlations in all the cases. The results showed a low impact of the innovations, measured by α. Then, there is a lower variance in the correlation process.

Figure 2-5 presents a common characteristic of pairwise correlations shown: they reached two peaks. The first peak was during the beginning of the global pandemic in 2019-2020, and the second peak in 2022, which resulted from Russia's invasion to Ukraine. Then, the peaks of the conditional correlations coincided with these two major events that affected almost all the variables in the economies.

Figure 2-5: Dynamic Correlations among oil brent price return, CO_2 futures returns (RMO1), and Green Bond Index (RGBEUTREU).



Source: Authors' own research using data from Bloomberg.

The DCC-Garch Model reveals a time-varying correlation in the range of [−0.33; 0.55] between oil and CO_2 futures' returns, [−0.37; 0.26] between oil and the Green Bond Index, and [−0.69; 0.088] between the Green Bond Index and the CO_2 futures' returns (Figure 2-5 and Table 2-6). The results are consistent with Chevallier (2012), who found a dynamic correlation of [−0.05; 0.05] between oil and the CO_2 futures' prices of the European Climate Exchange (ECX) using data from 2005 to 2008. Additionally, several studies have confirmed the existence of a positive correlation and considerable co-movements between CO_2 emissions and oil prices (Boersen & Scholtens, 2014; Chang et al., 2019; Y. Chen et al., 2019; Koch, 2014; Y. Lee & Yoon, 2020).

The oil price is connected to the demand of green markets because lower oil prices induce oil demand and may alter the demand for socially responsible investment (Broadstock & Cheng, 2019; Sadorsky, 2014). Then a negative correlation is expected between these two variables. In this way, Sadorsky (2014) using weekly data from 1998 to 2012, a dynamic correlation of [−0.37; 0.58] between oil and Socially Responsible Investing (SRI) was found, which refers to investing in companies that score well on environmental, social, and governance (ESG) factors. This variable can be used as a proxy for green markets. In contrast, Syed et al., (2022) employing the Nonlinear Autoregressive Distribution Lag (NARDL) for studying the dynamic linkage between the oil price and green bonds, concluded that oil prices positively influence the green bonds performance. The study found that a 1 percent increase (decrease) in oil prices increases (decreases) the performance of green bonds by 0.05 percent.

To describe the dynamic correlation between the Green Bond Index (RGBEUTREU) and the CO_2 futures' returns (RMO1), it is necessary to keep in mind that investment in green projects such as trading green bonds can effectively mitigate the risks of CO_2 emissions (Naeem, Mbarki, et al., 2021). However, there is a lack of studies that apply dynamic techniques to the relation between these two variables.

Table 2-6 describes the statistics of rho (ρ) coefficients obtained from the DCC-Garch Models. The mean value of the DCC coefficient between the Brent oil price return and the CO_2 futures' returns ρ(RBRENT, RMO1) is positive (19,8%). Furthermore, a negative average DCC-Garch coefficient is shown between the Green Bond Index and the oil price ρ(RBRENT, RGBEUTREU), and the CO_2 futures' returns ρ(RMO1, RGBEUTREU) (-11,5% and -8,8%, respectively). All the DCC rho coefficients present autocorrelation (see ARCH test results), meaning a time dependence structure with its lags. Finally, all rho coefficients are stationary, this implies that correlations found have a constant mean and variance.

Table 2-6: Descriptive statistics of rho (ρ) coefficients obtained from DCC-Garch models

Pair	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-bera	ADF	ARCH
ρ(RBRENT, RMO1)	0.198	0.552	-0.325	0.077	-0.21	6.54	1171.2***	2486.9***	-18.46***
ρ(RBRENT, RGBEUTREU)	-0.115	0.261	-0.370	0.056	0.46	5.93	863.7***	4119.5***	-15.16***
ρ(RMO1, RGBEUTREU)	-0.088	0.513	-0.692	0.070	0.92	17.60	19902.9***	1078.6***	-24.48***

Source: Author's own research using data from Bloomberg. Notes: This table presents summary statistics of daily returns oil brent price, CO_2 futures price, and green bond index. The January 1, 2014—June 15, 2022 sample yielded 2206 observations. *** indicates the rejection of the null for both normality test (via Jarque-Bera) and unit root test [via Augmented Dickey-Fuller (ADF)]. The ADF test is conducted with an intercept; ARCH-LM, is the heteroscedasticity test up to 18 lags.

2.4.3 Sensitivity analysis

In this section, we perform a sensitivity analysis of DCC models considering two identified crisis periods in the sample period to compare the results with the complete sample (Akram & Haider, 2022; Prabheesh et al., 2020; Rai & Garg, 2022). Table 2-7 reports the month-wise coefficient of the dynamic correlation rho (ρ) between oil price returns (RBRENT), the CO_2 futures' returns (RMO1), and the Green Bond Index (RGBEUTREU). This analysis is conducted due to our sample period being ideal for testing the impact of two recent events that induced economic crises and influence the dynamic relationship between the analyzed variables. These events are the COVID-19 pandemic (Panel A) and the Russian invasion of Ukraine (Panel B). In Panel A, we find a solid positive dynamic correlation (0.28) between Brent oil price return and the CO_2 futures' returns ρ(RBRENT, RMO1), especially in March 2020 when the global confinement started. Also, a weak negative dynamic correlation (-0.045) between the Green Bond Index and the oil price ρ(RBRENT, RGBEUTREU). Remarkably, the relationship between CO_2 futures' returns and the Green Bond Index became positive (0.037) in March 2020 ρ(RMO1, RGBEUTREU). The results imply that the uncertainty revolving around the COVID-19 outbreak led to a change in the dynamics between the variables. For instance, the oil demand decreased, and oil prices decline around the world. Further, the global production fall induced the reduction of CO_2 emissions and Green Bond have a small increment of the issuances in 2020 compared to 2019.

Table 2-7: Month-wise DCC-Garch results

Pairs/Time	ρ(RBRENT, RMO1)	ρ(RBRENT, RGBEUTREU)	ρ(RMO1, RGBEUTREU)
Panel A: COVID-19			
January-20	0.21231	-0.08804	-0.07001
February-20	0.29864	-0.12295	-0.10296
March-20	0.28042	-0.04599	0.03745
April-20	0.23782	-0.11430	-0.11155
May-20	0.19720	-0.07983	-0.10051
June-20	0.23108	-0.17117	-0.07870
July-20	0.18393	-0.10065	-0.12284
August-20	0.24349	-0.11337	-0.07244
September-20	0.18970	-0.15574	-0.09765
October-20	0.19658	-0.10723	-0.09595
November-20	0.24697	-0.14450	-0.09766
December-20	0.20592	-0.13270	-0.11251
Panel B: Russian invasion of Ukraine			
January-22	0.22372	-0.16593	-0.09304
February-22	0.16951	-0.13325	-0.11270
March-22	0.04022	0.00522	-0.19210
April-22	0.18745	-0.06192	-0.08072
May-22	0.21730	-0.14930	-0.10828
June-22	0.12983	-0.06950	-0.00481

Source: Authors' own research using data from Bloomberg.

In Panel B, the results caused by the Russian invasion of Ukraine in February and the consequent European energy crisis exacerbated post-COVID-19 inflation impacting the dynamic correlation between the variables considered. The results are opposite to the findings of the global pandemic, especially in March 2022. We find a weak positive dynamic correlation (0.040) between Brent oil price return and the CO_2 futures' returns ρ(RBRENT, RMO1), a lack of correlation (0.005) between the Green Bond Index and the oil price ρ(RBRENT, RGBEUTREU), and finally a solid negative dynamic correlation (-0.192) among the CO_2 futures' returns and the Green Bond Index ρ(RMO1, RGBEUTREU) . The macroeconomic context of rising interest rates, increase in commodity prices including oil prices, and high volatility of the financial markets resulted in a decrease in the green bond issuance and uncertainty in the CO_2 futures' returns (Figure 2-4, Panel a). Our findings are in agreement with Baur (2012), who suggests that a crisis period led to an increased co-movement of returns among financial markets, and Gajurel and Chawla (2022) who argue the majority of the economic sectors experience the contagion effect from the global oil market during the crisis period.

2.5 Concluding remarks and policy implications

This study explores the dynamic relationship among green bonds, CO_2 emissions, and oil prices. Oil is a significant determinant of global economic performance, and its price's dynamics can affect the world's economy in several ways, such as the market assets and the economic production. An increase in the oil prices will raise the cost of production of goods and services, leading to a rise in price levels and high inflation. Concerns about possible increases in price levels will produce uncertainty and negative sentiments in the financial markets, and the expected inflation will lower equity values. In addition, oil prices can set economic trends by driving the gross domestic product's growth (GDP). Hence, there is evidence of a linkage among the three variables analyzed: green bonds, CO_2 emissions, and oil price; it is due to the existing connection among them in industrial production (Figure 2-1), then the three represent the development of the economic activity in the present.

Understanding the interactions and dynamic relationships between green bonds, CO_2 emissions, and oil prices are paramount to ethical investors. This information is essential for gaining superior risk-adjusted returns through properly allocating a sustainable financial portfolio and managing risk (Dutta et al., 2021). The results for the negative co-movements between green bonds with the oil prices and among green bonds with CO_2 futures' price have two major implications. The first is that negative correlations provide diversification opportunities for investors worldwide. The second concerns policy-makers; when oil prices and CO_2 futures' price increase, the Green Bonds Index is expected to decrease. Then green bonds appear as an attractive financial mechanism for environmentally friendly investors; issuers can employ this device to diversify their investor base and improve their environmental, social, and governance (ESG) scores (Dutta et al., 2021; Reboredo & Ugolini, 2020). These results appear as an opportunity for policy-makers to design strategies for promoting eco-friendly policies that contribute to enlarging the supply of green bonds, allowing sustainable investment portfolios to be structured. Finally, the relation between the CO_2 futures' price and the oil price is mostly positive, which is helpful for forecasting the CO_2 futures' price according to the evolution of the oil price in the international markets.

Despite the contributions of the present study, limitations should be acknowledged. First, the daily data are available only for developed markets such as Europe. This is mainly due to the lack of data for dynamic correlation studies among CO_2 emissions and green bond markets to contrast the results obtained in this analysis, for example, data from the emerging markets. Second, the limited literature on green bond markets and their relations with oil prices and CO_2 emissions simultaneously to compare results.

The above findings are relevant to investors and policy-makers keen to understand the dynamics of conditional correlations among green bonds, CO_2 prices, and oil prices, which can affect diversification strategies and the design of environmental policies. In this regard, given that green bonds are becoming an essential financial mechanism for achieving the SDGs, it is also mandatory to gain a better understanding of decision-makers perspectives in designing investment portfolios. Further research could also help to comprehend this issue deeply in this concern. Thus, there is great potential for further research on green bonds and their relationships with other financial assets, particularly those highly related to investment decisions, for example, stocks, which have been little explored. For this, machine learning models could be implemented. These studies could also be extended to Latin American and the Caribbean markets, where research on these issues is scarce. Furthermore, a hedging analysis can be conducted in further research of co-movements, their time-frequency domains, and investment horizons can have implications for dynamic hedging, asset allocation, and utility earnings. Finally, the authors hope that finance will be fully sustainable in the short term. In this scenario, green bond will be a pivotal player.

3. Chapter 3. A wavelet analysis of the dynamic connectedness among oil prices, green bonds, and CO_2 emissions

Wavelet power spectrum (WPS) and wavelet coherence analyses (WCA) are used to examine the co-movements among oil prices, green bonds, and CO_2 emissions on daily data from January 2014 to October 2022. The WPS results show that oil returns exhibit significant volatility at low and medium frequencies, particularly in 2014, 2019-2020, and 2022. Also, the Green Bond Index, presents significant volatility at the end of 2019-2020 and the beginning of 2022 at low, medium, and high frequencies. Additionally, CO_2 futures' returns present high volatility at low and medium frequencies, expressly in 2015-2016, 2018, the end of 2019-2020, and 2022. WCA's empirical findings reveal (i) that oil returns have a negative impact on the Green Bond Index in the medium term. (ii) There is a strong interdependence between oil prices and CO_2 futures' returns in short, medium, and long terms, as inferred from the time–frequency analysis. (ii) There also is evidence of strong short, medium, and long terms co-movements between the green bond Index and CO_2 futures' returns, with the green bond Index leading.

Keywords: Co-movements, dependence, wavelet analysis, oil prices, green bonds, CO_2 emissions, bibliometric analysis.

3.1 Introduction

The inclusion of oil prices in the analysis of the environmental context comes from the substitution and income effect caused by any change in the product price relative to its demand function (Barsky & Kilian, 2004; Hamilton, 1983; Kilian, 2009). The substitution effect occurs when goods get cheaper, and this generates incentives to consume more of the cheaper good and less of the expensive one. On the other hand, the income effect occurs when the price of the good falls and the purchasing power increase, causing a result similar to a rise in income. This theory is called the Slutzky-Hicks Theory (Allen, 1950). In this way, oil price shocks can affect carbon emissions and green bond issuances through changes in fossil fuel consumption. For instance, the sharp decline in oil prices during 2014-2015 increased carbon emissions due to the relatively more expensive clean energy projects (Kassouri et al., 2021, 2022). In this context, a fall in oil prices obstructs carbon mitigation initiatives as green bonds promote them (Kassouri et al., 2022).

The implementation of the European Union Emissions Trading System (EU ETS) in January 2005, EU Allowances (EUAs) became a tradeable asset that could be negotiated in organized spot, futures, and options markets (Reboredo, 2013). Likewise, in January 2014, the International Capital Markets Association (ICMA) published the Green Bond Principles (GBP) to establish the rules for a bond to be labeled green. Since then, investors have at their disposal information to enable them to discern the environmental benefits of their fixed-income investments against alternative investments (Mejía-Escobar et al., 2021; Reboredo, 2018). Thus, green bonds are a well-established sustainable investment instrument that have been gaining popularity among (i) investors, especially environmentally-conscious investors, (ii) companies concerned about climate-related risk exposition and the opportunities of financing their eco-friendly projects, and (iii) governments for the potential influence of green bonds on their climate change policies (Reboredo, 2018).

Numerous studies evidence the relationship between (i) oil prices and green bonds (Azhgaliyeva et al., 2021, 2022; Dutta et al., 2021; C.-C. Lee et al., 2021; Reboredo & Ugolini, 2020; Saeed et al., 2021; Su et al., 2022), (ii) oil prices and CO_2 emissions (Alhodiry et al., 2021; M. Ali et al., 2022; Habib et al., 2021; Maji et al., 2020; Mensah et al., 2019; Mujtaba & Jena, 2021; Sadorsky, 2009; Wen et al., 2017; B. Zhang & Zhou, 2022; Zou, 2018), and (iii) green bonds and CO_2 emissions (Jin et al., 2020; Lichtenberger et al., 2022; Nenonen et al., 2019; Rannou et al., 2021; X. Ren, Li, yan, et al., 2022; Tiwari et al., 2022; X. Wang et al., 2022).

However, a knowledge gap has been identified despite all the advances in studying the previously mentioned relationships with other financial assets; just a few recent studies in the current literature have provided an in-depth analysis of the co-movements among the green bonds, CO_2 emissions, and oil prices simultaneously (H. Li et al., 2022; Marín-Rodríguez, González-Ruiz, & Botero, 2022). These two studies provide an important foundation for our paper. Furthermore, by using wavelets, we contribute to the debate on the dependences among green bonds, CO_2 emissions, and oil prices simultaneously, conducting a time-frequency analysis of the dependence among these three variables. Moreover, we emphasize the economic and policy implications of the results obtained. Additionally, we make a novel extension to the existing literature focusing on clean energy stocks and other financial markets.

For example, Li et al. (2022) found that oil price has a negative effect on the Green Bond Index, and that carbon prices positively influences the Carbon Efficiency Index in the short and medium term. Additionally, the Green Bond Index positively affects carbon prices in the short and medium term and negatively impacts the Carbon Efficiency Index. In addition, carbon price shocks positively affect the Carbon Efficiency Index in the short and medium term. Furthermore, Marín-Rodríguez, González-Ruiz, & Botero (2022) using Granger Causality and DCC-GARCH methodologies, observed a unidirectional causality running from the Green Bond Index to the Brent oil returns and a unidirectional causality running from the Green Bond Index to the CO_2 futures' returns and a unidirectional causality running from the Brent oil returns to the CO_2 futures' returns. Also, their results for DCC-GARCH indicate a positive dynamic correlation between the Brent oil price return and the CO_2 futures' returns and a negative dynamic correlation between the Green Bond Index concerning the oil return and the CO_2 futures' returns, presenting a solid correlation in uncertainty periods. Thus, a deeper analysis of this concern will lead to a better comprehension of the evolution and co-movements of these three variables in a global decarbonization scenario.

This research is aimed at quantifying such co-movements identifying their effects on different time periods and how this relationship varies according to the economic conditions. Thus, this paper makes two substantial contributions to the existing body of knowledge and practice. First, this study is the first to incorporate a scientometric analysis of dynamic co-movements among oil prices, green bonds, and CO_2 emissions with particular emphasis on measuring different time period relationships, limiting the search equation to the existence of co-movements, contagion, or dependence among the variables. Second, it provides new evidence by examining the dynamic relationship among crude oil prices, CO_2 futures' price, and green bonds using a wavelet coherence approach to determine the effects of oil price shocks on CO_2 emissions and green bonds issuances over different time frequencies: short, middle, and long-term. In addition, this study analyzes whether the correlation changes over different scales in the period studied, 2014-2022. Thus, this study's outcomes can help researchers, managers, policymakers, and decision-makers to understand the importance of the oil price shocks on the design of assets and policies that tend to improve sustainability practices.

The paper's outline is as follows: Section 2 studies the background and bibliometric analysis of asset market linkages among oil prices, green bonds, and CO_2 emissions. Section 3 presents the data, the descriptive statistics, and the methodologies used.

Section 4 analyzes the results. Section 5 discusses the empirical results. Finally, in Section 6, some concluding remarks are offered.

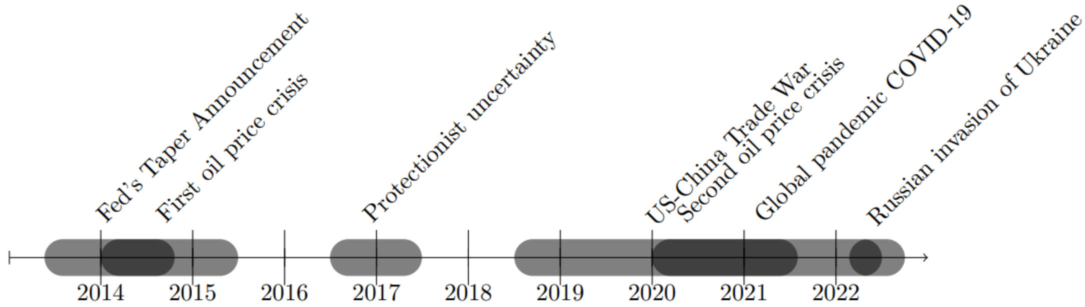
3.2 Context of the analysis and literature review

3.2.1 Context of the analysis

For the selected analysis period, 2014-2022, some different exogenous shocks or crises could have caused rupture or change among the linear relationships of financial assets considered in this study. As a starting point, the financial shocks definition by Beirne & Gieck (2014) will be used. This definition states that they are turbulences in asset markets in advanced and emerging economies that affect other international financial markets. Figure 3-1 presents the timeline of the main common financial shocks. The first event is the Federal Reserve's Rate reduction announcement (known as the FED's Taper Announcement), which caused a fall in the prices of financial assets, an increase in volatility, and a decrease in trade volumes and market liquidity, as well as a rise in a government bond, spreads between the end of May and August 2014 at the height of the market turmoil. Later, the first oil price crisis emerged in 2014 and then in 2016. Subsequently, focusing the analysis on a specific region such as Latin America, several events in the region were affected by protectionist uncertainty in its emerging markets, especially Mexico, due to its strong financial and commercial links with the rest of the world, particularly with the United States. Such uncertainty started with the presidential campaign in the United States when the financial markets reflected the tension during each presidential debate. For example, when investors thought the then-candidate Trump would win, the market would drop; and when candidate Clinton seemed most likely to win, markets rose. This was especially reflected in the fluctuation of the financial markets.

In addition, from that scheme, other events have caused imbalances in financial assets, not only in Latin America but also globally, such as the trade war between China and the United States that began in March 2018 after Donald Trump announced the tariff imposition of 50,000 million dollars on Chinese products. In response to those actions, the government of the People's Republic of China applied tariffs on numerous American products.

Figure 3-1: Timeline of principal common financial shocks, 2014-2022.



Source: Author's own research.

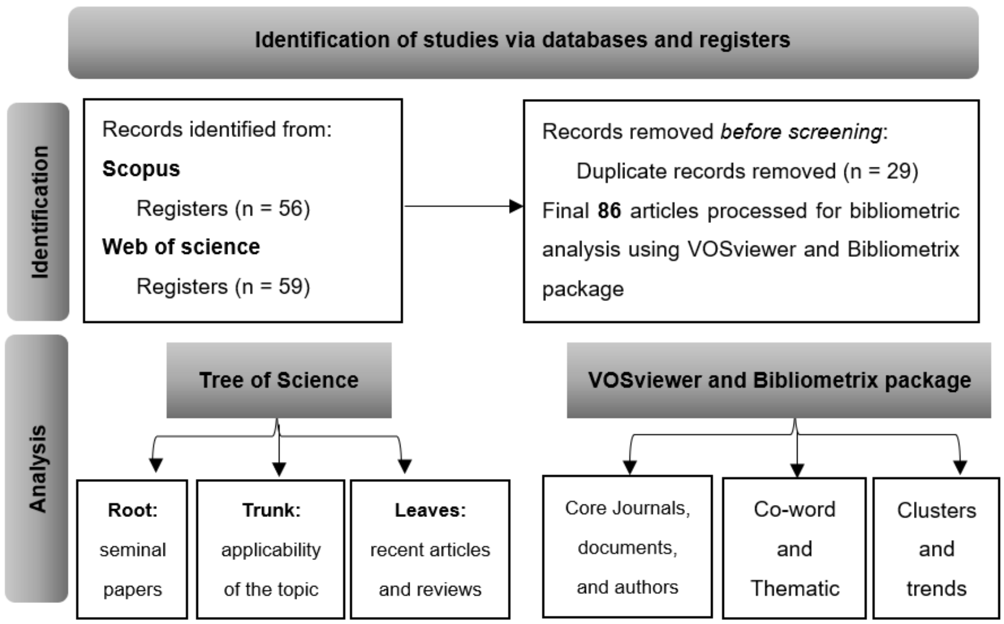
A dispute, in which the World Trade Organization (WTO) had to intervene to reduce tensions rose. Afterward, the global crisis caused by the COVID-19 virus pandemic (an acronym for coronavirus disease, 2019) occurred. It originated in China in December 2019. After it spread to different countries, on March 11, 2020, it was declared a global pandemic by the World Health Organization (WHO). The virus's expansion has generated economic and social uncertainty, which has influenced the global financial and economic markets, generating losses. Those are difficult to quantify even today given that the pandemic has not yet been overcome. Additionally, it is necessary to mention that during this global pandemic, there has been a second crisis in oil prices; The member countries of OPEC (Organization of Petroleum Exporting Countries) have decided to cut production due to the sharp drop in crude oil prices, the decline in demand and the substantial volatility. Finally, the recent Russian invasion of Ukraine on February 24, 2022, is bringing consequences in a range of areas, mainly: (i) humanitarian crisis, (ii) food security crisis, and (iii) energy volatility crisis.

3.2.2 Literature review

This research includes a scientometric review of the leading studies about the dynamic relationships among oil prices, green bonds, and CO_2 emissions. The documents reviewed were obtained from the Scopus and Web of Science (WoS) bibliographic databases. The research equation was: (TITLE-ABS-KEY ("oil prices*" OR "oil-price*" OR "crude oil" OR "crude-oil") AND TITLE-ABS-KEY (CO2 OR "CO2 emission*" OR "carbon dioxide emission*" OR "carbon emission*" OR "emission* CO2" OR "green bond*") AND TITLE-ABS-KEY ("contagion" OR "interdependence*" OR "comovement*" OR "co-movement*" OR "correlation*")). All the research documents identified were downloaded and ed into the

Mendeley Reference Manager for the scientometric analysis. After removing 29 duplicates, we utilized 86 research documents for the scientometric analysis using three tools: (i) the tree of science Robledo et al. (2014), (ii) the VOSviewer version 1.6.18 van Eck & Waltman (2017), and (iii) the Bibliometrix package for R Aria & Cuccurullo (2017). Figure 3-2 shows the literature search strategy.

Figure 3-2: Literature search strategy.



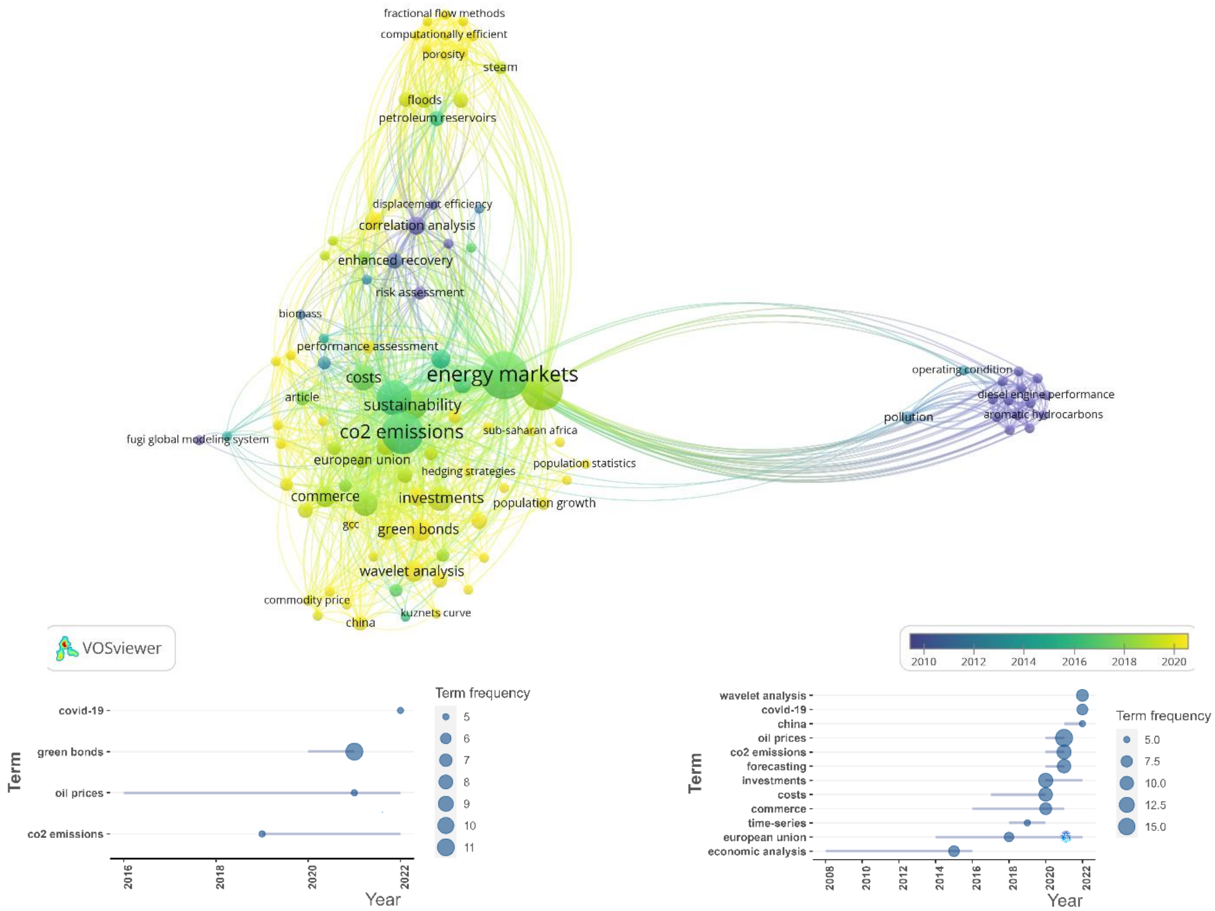
As indicated by (Robledo et al., 2014), the studies found at the root of the tree of science include seminal articles from the original ones about the dynamic associations among oil prices, green bonds, and CO_2 emissions. For example, studies conducted by (Henriques & Sadorsky, 2008; Kumar et al., 2012; Reboredo, 2015; Reboredo et al., 2017; Sadorsky, 2012) were found in the root, and those papers are the identified seminal studies about the linkages among oil prices and assets related to sustainable finance, such as renewable energy or clean energy stock prices. (Kumar et al., 2012; Sadorsky, 2012) analyze the correlations between clean energy stock prices and oil prices. The findings suggest, for daily data from 2001 to 2010, that stock prices of clean energy companies correlate more highly with technology stock prices than oil prices (Sadorsky, 2012). Additionally, based on the weekly observations for the period 2005-2008, (Kumar et al., 2012) found that past movements in oil prices explain the indexes of clean energy stocks, stock prices of high technology firms, and interest rates.

Conversely, (Robledo et al., 2014) argue that documents in the trunk mainly include the first authors who discovered the applicability and have become references for dynamic associations between oil prices and the financial markets analyzed. Here, documents that study the relationship among energy markets and assets related to sustainable finance can be found, and those used the methodologies of Dynamic Conditional Correlation analysis (DCC-GARCH) or volatility linkages (Dutta et al., 2018; B. Lin & Chen, 2019; Marín-Rodríguez, González-Ruiz, & Botero, 2022a; Reboredo, 2018); and wavelet analysis (Kassouri et al., 2022; Maji et al., 2020). According to Dutta et al. (2018), the results, using daily data from 2009 to 2017, indicate a volatility connection between the emissions and the European Clean Energy Price Indexes. However, this result does not hold for the United States market, suggesting that emissions' return and volatility shocks are country or region-specific. Lin & Chen (2019), using a daily dataset from 2013 to 2017, found that: (i) There are significant time-varying correlations and a long-run persistence between the Beijing Carbon Emissions Trading (CET) market, the coal market, the stock market of New Energy Companies (NEC), and the coal market; (ii) the new energy stock market has a higher volatility persistence. Additionally, (ii) there is a bi-directional spillover effect between the coal market and the stock market of New Energy Companies.

Finally, the documents in the leaves, according to Robledo et al. (2014), are recent articles and reviews that should condense the analysis of dynamic relationships among oil prices, green bonds, and CO_2 emissions. In the literature review, Marín-Rodríguez, González-Ruiz, & Botero Botero (2022) can be outlined. In the new trends, in the leaves, there are several methodologies identified which have studied the dynamic relationships among energy markets and assets related to sustainable finance, for example, using Time-Varying Parameter Vector Auto Regression (TVP-VAR) (H. Li et al., 2022), wavelet analysis (Bouoiyour et al., 2023; Kassouri et al., 2022; Luo et al., 2022; A. I. Maghyereh et al., 2019; Shah et al., 2022; Xuefeng et al., 2022), DCC-GARCH and its extensions (Dutta et al., 2021; Marín-Rodríguez, González-Ruiz, & Botero, 2022), Copula functions (Elie et al., 2019; Naeem, Bouri, et al., 2021; Wen et al., 2017), time-varying conditional analysis comprising hedging effectiveness and optimal hedge ratios (Gustafsson et al., 2022), and quantile analysis (X. Ren, Dou, et al., 2022; X. Ren, Li, yan, et al., 2022; Saeed et al., 2021; B. Zhang & Zhou, 2022).

On the other hand, when exploring the existing literature about the dynamic relationship among oil prices, green bonds, and CO_2 emissions using the VOSviewer, the research pointed out that the most used keywords for this type of analysis are: 1) energy markets, 2) oil prices, 3) CO_2 emissions, and 4) economic analysis. The results of the analyses are presented in figure 3-3.

Figure 3-3: Main keyword trends identified in the research topic are dynamic linkages among oil prices, green bonds, and CO_2 emissions.



(a) Author's keywords trend topics (b) Keywords plus trend topics

Source: Authors' research using VOSviewer, Bibliometrix tools, Scopus and WoS databases.

Furthermore, during the revision through the Bibliometrix package for R applying on author keyword analysis, which offers information about research trends from the researchers' points of view (Garfield, 1970), the results indicate that the most prominent research areas are COVID-19 (2022), green bonds (2020-2021), oil prices (2016-2022), and CO_2 emissions (2019-2022). On the other hand, implementing the analysis on the keywords plus, which are terms extracted from titles or abstracts Aria & Cuccurullo, (2017), the findings reveal that the leading research areas are wavelet analysis and COVID-19 (2022), China (2020-2022), oil prices, CO_2 emissions, forecasting (2019-2021), and investments (2020-2022).

Thus, the relationships among oil prices, green bonds, and CO_2 emissions can be classified into these two major trends provided by (i) the authors' keywords and (ii) keywords plus. The first trend (figure 3-3, panel a) delves into the bonds among these three variables, including the effects of the COVID-19 disease (H. Li et al., 2022; Marín-Rodríguez, González-Ruiz, & Botero, 2022). In this trend the keywords COVID-19, green bonds, oil prices, and CO_2 emissions are precisely leading the trend topics. This result is according to the studies in the leaves of the Tree of Science. Additionally, in this first trend, the documents that study the impacts of the COVID-19 in the green bonds markets can be included (Liu, 2022; Naeem, Mbarki, et al., 2021; Rao et al., 2022; Tiwari et al., 2021, 2022), as well as, CO_2 emissions (Agboola et al., 2021; Balsalobre-Lorente et al., 2020; Dong et al., 2022; Shah et al., 2022; Tiwari et al., 2022), and oil prices (Alshdadi et al., 2022; Ghorbali et al., 2022; Habib et al., 2021; Ozturk & Cavdar, 2021; Ren et al., 2021; Xuefeng et al., 2022). The findings suggest that the COVID-19 pandemic shock caused huge fluctuations and negative returns in green bonds markets (Liu, 2022). Furthermore, the contraction of the economic growth since the beginning of the COVID-19 pandemic produced a reduction in CO_2 emissions (Agboola et al., 2021). Finally, the results also indicate that the COVID-19 impacted negatively crude oil prices which contributed to the reduction of CO_2 emissions during the pandemic period (Habib et al., 2021).

The second trend (figure 3-3, panel b) analyzes the interlinkages between oil prices and CO_2 emissions. For example, (Ali et al., 2022; Alkathery & Chaudhuri, 2021; Apergis & Payne, 2015; Royal et al., 2022; Sadorsky, 2009; Zaghdoudi, 2017) analyze the co-movements among oil prices, CO_2 emissions, and renewable energy. The findings suggest that renewable energy improves environmental quality in both, the short and long run; an increase in oil prices causes a decrease in CO_2 emissions and has an important effect on economic growth. Additionally, other documents within this trend study the effects of oil price shocks on CO_2 emissions (Bassey, 2015; Habib et al., 2021; Husaini et al., 2021; Maji et al., 2020; X. Ren, Li, Qi, et al., 2022; Wei et al., 2022). Their results indicate that there is a negative relationship between oil price shocks and CO2 emissions; higher oil prices can mitigate CO_2 emissions while lower oil prices can increase sectoral CO_2 emissions. Besides, COVID-19 affects crude oil prices, the major contributor to the reduction of CO_2 emissions during the pandemic period. In this trend the keywords COVID-19, wavelets, China, oil prices, CO_2 emissions, and forecasting are the foremost trend topics.

Finally, based on the scientometric analysis of the main studies on the dynamic co-movements among oil prices, CO_2 emissions, and green bonds conducted by Marín-Rodríguez, González-Ruiz, & Botero Botero (2022) on the dynamic co-movements among oil prices and financial markets (including energy markets and assets related to sustainable finance), the findings indicate that the most promising areas for further research in this field are represented by co-movement, copula, wavelet, dynamic correlation, and volatility analysis. Furthermore, the authors indicate that energy markets and assets related to sustainable finance emerge as crucial trends in exploring dynamic co-movements of oil prices. Additionally, as we mentioned before, Marín-Rodríguez, González-Ruiz, & Botero (2022) make a previous application to the analysis on the dynamic co-movements among oil prices, CO_2 emissions, and green bonds using Granger causality and DCC-GARCH methodologies. Thus, in line with these two documents, and the results of the present literature review this study attempts to make a deeper analysis considering a time-frequency analysis (using wavelets methodology) that searches for the connection among the three variables studied in the short, medium, and long term.

3.3 Methodology

3.3.1 The dataset

The dataset consists of daily closing prices of Brent oil prices, green bonds, and CO_2 emissions (Table 3-1). Our sampling period spans from January 1, 2014, to October 3, 2022, including 2290 daily observations (Appendix A). The starting date of the sample is determined by the availability of the Green Bond Index data. All data were gathered from Bloomberg. Futures' prices of CO_2 emissions (MO1 Comdty), according to Reboredo (2013) and Rittler (2012) were used. They indicate that the futures market leads the price training process by first, locating information and then transferring it to the spot market. Furthermore, the Bloomberg MSCI Green Bond Index (GBEUTREU Index) is a Euro fixed-income benchmark to fund projects with direct environmental benefits. This index incorporates Euro-denominated fixed-income securities, such as treasury, corporate, government-related, and securitized debt. Additionally, the index reflects the performance of Euro-denominated fixed-income securities, including treasury, corporate, government-related, and securitized debt. Furthermore, the Brent oil price (CO1 Comdty) is included as a fundamental component of energy prices.

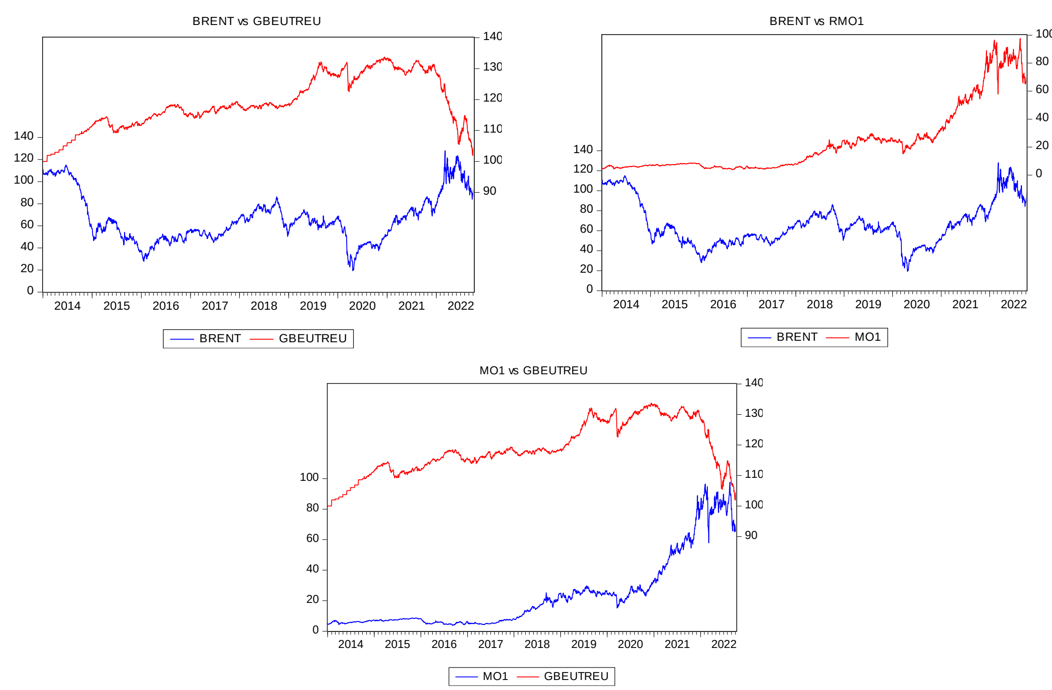
Table 3-1:List of variables.

Variable	Ticker	Description
Oil Brent price	CO1 Comdty	Generic 1st Crude Oil, Brent
Green Bond Index	GBEUTREU Index	Bloomberg MSCI Euro Green Bond Index Total Return Index Value Unhedged
CO_2 futures price	MO1 Comdty	CO_2 futures price, Euros per ton

Source: Authors' own research using Bloomberg.

Figure 3-4 illustrates the temporal dynamics of Brent oil prices, green bonds, and CO_2 emissions by pairs, evidencing that oil prices positively depend on CO_2 futures prices (MO1 Comdty). Still, the dependence is negative with the Green Bond Index (GBEUTREU Index). Furthermore, in recent times the co-movements are increasing between the Green Bond Index (GBEUTREU Index) and CO_2 futures prices (MO1 Comdty), indicating clear graphical evidence of dependence, particularly in 2022.

Figure 3-4: Daily prices and returns of Brent oil prices (RBRENT), Green Bond Index (RGBEUTREU), and CO_2 futures' returns (RMO1). Panel a) prices and Panel b) returns.



Source: Author's own research using data from Bloomberg.

Table 3-2:Summary statistics of daily returns

Index	Mean	Max	Min	Std. Dev.	Skew.	Kurt.	JB	ADF	LBQ (25)	LBQ2 (25)
RBRENT	-0,000063	0,1908	-0,2798	0,0256	-0,982	19,46	26198,4*	-47,16*	48,36 [0,003]	836,81 [0]
RGBEUTREU	0,000004	0,0196	-0,0196	0,0027	-0,164	11,13	6315,4*	-44,18*	61,73 [0]	1655,0 [0]
RMO1	0,001145	0,162	-0,1944	0,0292	-0,527	7,61	2133,5*	-50,34*	38,42 [0,042]	306,21 [0]

Source: Authors' own research using data from Bloomberg. Notes: This table presents summary statistics of daily returns Brent oil prices (RBRENT), Green Bond Index (RGBEUTREU), and CO2 futures' returns (RMO1). The January 1, 2014—October 3, 2022, sample yielded 2290 observations. (*) indicates the rejection of the null hypothesis at the 5% level for both the normality test (via Jarque-Bera) and unit root test [via Augmented Dickey-Fuller (ADF)], the ADF test is conducted with an intercept. LBQ (25) and LBQ2 (25) denote the Ljung–Box Q-statistics for serial correlation in the returns and squared returns series, respectively, computed using 25 lags, with p values reported in square brackets.

Table 3-2 depicts descriptive statistics of daily returns of the considered series computed as the first difference of the natural log of the prices or indexes. The average daily returns are close to zero for all series. The standard deviations reveal that green bonds are less volatile than Brent oil prices and CO_2 futures' prices. All daily returns are negatively biased and exhibit high values for the Kurtosis statistics consistent with heavy-tailed distortions. The Jarque–Bera (JB) test strongly rejects the normality of the unconditional distribution of the return series and the non-stationarity tests [via Augmented Dickey-Fuller (ADF)] (Dickey & Fuller, 1979) evidence that all return series are stationary. Finally, the Ljung–Box Q-statistics (LBQ) indicate the presence of a serial correlation in both, the return series, and the squared return series; it is consistent with the existence of conditional heteroskedasticity effects.

3.3.2 Wavelet analysis

The wavelets methodology is one of the mathematical applications that has recently been applied to modeling in several fields, including economics and finance. It allows to analysis of the time series frequency and time domain simultaneously. This methodology is based on the Fourier Analysis, which focuses on studying frequency domain signals. In this way, wavelets are functions that oscillate as a wave and present fades; that is, they decay. Due to these particularities, this methodology is considered an ideal filter that allows the fragmenting of a signal into different levels of a resolution, capturing large and small particularities of the analyzed series. This is known as multi-resolution decomposition using wavelets, which facilitates the decomposition of the original signal into different levels of resolution where each level will necessarily be associated with a specific time scale. The existence of non-stationary phenomena, that is, those presenting variations over time, and which do not have a constant mean and/or variance in various disciplines such as geophysics, medicine, statistics, economics, and finance, among others, has expanded the use of wavelets to be ideal for the treatment of this type of series.

Ftiti, Guesmi, & Abid (2016) indicate that among their advantages, the following stand out: (i) wavelets are a process that breaks down data into different frequency components. This decomposition of different scales facilitates to distinguish of seasonality, structural changes, volatility clusters, and the identification of the local and global dynamic properties of the variables; (ii) Wavelets provide a better alternative for exploring the interconnection between oil and stock markets, as they do not impose parametric constraints on stock market dynamics and oil price fluctuations and (iii) The wavelet process adapts to different characteristics of the time series in general (such as the stock market and oil price series), where the variance is variable over time, and the covariance matrix presents possible structural breaks. This feature helps discriminate between interdependence (long-term co-movement) and contagion (short-term co-movement) in the relationship between oil and financial markets that will be the subject of application in this study. However, (Dibal et al., 2018) identify weaknesses in the methodology such as its excessive redundancy, its computational intensity and the fact that that an original signal cannot be perfectly reconstructed from the coefficients estimated by the process.

This research studies the co-movement among oil prices, green bonds, and CO_2 emissions leading to know the linkage across different horizons (i.e., short-medium-, and long-term). The wavelet coherency approach by Grinsted et al. (2004) offers this possibility by decomposing the economic relationship into time-frequency components. Furthermore, the wavelet coherency can be applied to bivariate and multivariate contexts, where patterns of covariation and causal relationships among variables across different scales are examined over time (W. M. A. Ahmed, 2022). This methodology is similar to the Pearson Bivariate Correlation Coefficient. It measures the degree of co-movement in the time-frequency (location–scale) domain between a pair of time series variables x(t) and y(t)(S. Singh et al., 2022).

- <u>The Continuous Wavelet Transform (CWT)</u>

Thus, the wavelet technique (i) decomposes the return series into time-scale components, and (ii) represents the variability and structure of the stochastic processes on a scale-by-scale basis. The wavelet function is a small wave and can be manipulated (stretched or squeezed over time) to extract the frequency components from a complex signal (Bouri et al., 2020).

The mother wavelet is used to produce small waves. It is expressed as a function of time and scale s as:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \tag{3.1}$$

where τ, s, and $\frac{1}{\sqrt{s}}$ represent the time position (translation parameter), scale (dilation parameter related to frequency) and normalization factor, respectively. The normalization factor ensures that the transformation remains comparable across scales and over time.

The literature provides various wavelets for the time series decomposition depending on the research topic. To examine the wavelet coherence among oil prices, green bonds, and CO_2 emissions, the Morlet Wavelet is used (Morlet et al., 1982). This wavelet provides the best balance between time and frequency localization (Addison, 2017). Grinsted et al. (2004) show that the Fourier period for the Morlet wavelet is almost equal to the scale used:

$$\psi^M(t) = \frac{1}{\pi^{1/4}}e^{i\omega_0 t}e^{-t^2/2} \tag{3.2}$$

where ω_0 indicates the central wavelet frequency. Like Bouri et al. (2020), this research used $\omega_0 = 6$, as the Morlet wavelet; this central frequency provides good localization between time and frequency.

- <u>Wavelet power spectrum</u>

The wavelet analysis can be performed using either the continuous wavelet transforms (CWT), or the discrete wavelet transform (DWT). The CWT has several advantages over the DWT. For example, the CWT provides independence to select wavelets according to the length of data, and the redundancy in the CWT makes the interpretation and discovery of patterns or hidden information easier (Aguiar-Conraria & Soares, 2011). A continuous wavelet transform W_x of a discrete-time series ($x(t)$, t = 0,1,…,n) with respect to $\psi(t)$can be represented as:

$$W_x(\tau, s) = \int_{-\infty}^{+\infty} x(t)\,\psi^*_{\tau,s}(t)dt = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} x(t)\,\psi^*\left(\frac{t-\tau}{s}\right)dt \tag{3.3}$$

where * denotes the complex conjugate. Notably, the wavelet transform preserves the energy of a time series that can be used to analyze the power spectra. Accordingly, the variance is given by:

$$\|x\|^2 = \frac{1}{C_\psi}\int_0^\infty \left[\int_{-\infty}^{+\infty} |W_x(\tau,s)^2| d\tau\right] \frac{ds}{s^2} \quad (3.4)$$

To obtain information about the time series behavior, the wavelet power spectrum (WPS) was used in the present paper,

$$WPS_x(\tau,s) = |W_x(\tau,s)|^2 \quad (3.5)$$

(Hudgins et al., 1993; Torrence & Compo, 1998) define the cross-wavelet power | $W_{xy}(\tau,s)$ | of two time series x(t) and y(t) with the continuous transforms $W_x(\tau,s)$ and $W_y(\tau,s)$ as:

$$W_{xy}(\tau,s) = W_x(\tau,s).W_y^*(\tau,s) \quad (3.6)$$

- Wavelet coherence

The cross-wavelet power shows the areas of high common power between two time series in the time-frequency space. The wavelet squared coherence between the two times series is given by:

$$R_{xy}^2(\tau,s) = \frac{\left|S\left(s^{-1}W_{xy}(\tau,s)\right)\right|^2}{S(s^{-1}|W_x(\tau,s)|^2).S\left(s^{-1}\left|W_y(\tau,s)\right|^2\right)} \quad (3.7)$$

where $R_{xy}^2(\tau,s)$ represent the wavelet squared coherency between x(t) and y(t), in other words $R_{xy}^2(\tau,s)$ is a direct measure of the contemporaneous correlations between x(t) and y(t) at each point in time and for each frequency. $S(.)$ is a smoothing parameter in scale and time. The value of the wavelet squared coherence $R_{xy}^2(\tau,s)$ ranges between zero (no co-movement) and one (high co-movement) can be seen as a scale-specific squared correlation between series. In addition, the wavelet coherence framework allows studying the lead-lag relationship between series while avoiding the squared coherence's inability to distinguish between the positive and negative relationship between series. (Torrence & Webster, 1999) and (Bloomfield, 2013) show that the phase difference depicting the phase relationship between x(t) and y(t) is given by:

$$\phi xy\tau,s=tan{-}1\Im Wxy(\tau,s)\Re Wxy(\tau,s),\phi x,y\in-\pi,\pi \quad (3.8)$$

where the parameters $\Im$ and $\Re$ give the imaginary and real parts of the smooth power spectrum, respectively. A zero-degree phase difference reveals the synchronization of x(t) with y(t) at a particular time-frequency. On the wavelet coherence plots, $\phi_{xy}(\tau,s)$ is symbolized as black rightward, leftward, upward, and downward arrow signs within areas of statistical significance. When the arrow points to the right (left) suggests that x(t) and y(t) are in phase (out of phase); it means that x(t) and y(t) are positively (negatively) associated, with negligible or no time lag. If the arrow points upwards, the first series leads the other by π/2 (the actual period is based on the specific frequency/scale of the wavelet coherence chart), and the opposite for a downward-pointing arrow. Additionally, for the interpretation of the arrows, following Kirikkaleli & Güngör (2021) arrows pointing up, right-up, or left-down denote that the second variable causes the first variable, while arrows pointing down, right-down, or left-up indicate that the first variable causes the second variable.

The wavelet coherence results are standardly shown on a chart with time and scale (or frequency) on the respective axes and the coherences are represented by a color scale. The color spectrum shows the intensity of the association (co-movement) between the pair of the analyzed series. The warmer colors (red) indicate significant co-movements, while colder colors (blues) signify weak co-movements between the series. In regions beyond the black line cone or the cone of influence, the estimates of wavelet coefficients are statistically insignificant at 5% significance and are not considered.

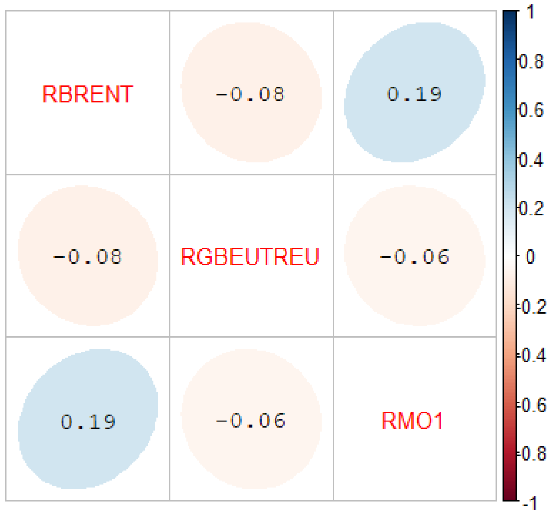
3.4 Application and results

3.4.1 Unconditional correlation analysis

Pairwise correlations across the returns of the variables considered are presented in Figure 3-5. The correlation of oil price return (RBRENT) with the CO_2 futures' returns (RMO1) is positive (19%), and the Green Bond Index (GBEUTREU) is negative (-6%). Additionally, the correlation between the CO_2 futures' returns (RMO1) and the Green Bond Index return (GBEUTREU) is negative too (-8%).

According to the existing literature, it is expected that oil prices and CO_2 emissions have a positive relationship, and their co-movement against the Green Bond Index is in the same sense because an increase in oil prices tends to increase CO_2 emissions. (Mahmood et al., 2022; Mahmood & Furqan, 2021; Sadorsky, 2009; Zheng et al., 2021). Additionally, increasing green bond issuances tends to reduce CO_2 emissions (al Mamun et al., 2022; Fatica & Panzica, 2021). For example, the study conducted by (al Mamun et al., 2022) shows that green finance significantly reduces carbon emissions in the short and long run by supporting waste and pollution control and improving energy efficiency.

Figure 3-5: Unconditional correlation for Brent oil returns (RBRENT), Green Bond Index (RGBEUTREU), and CO_2 futures' returns (RMO1).



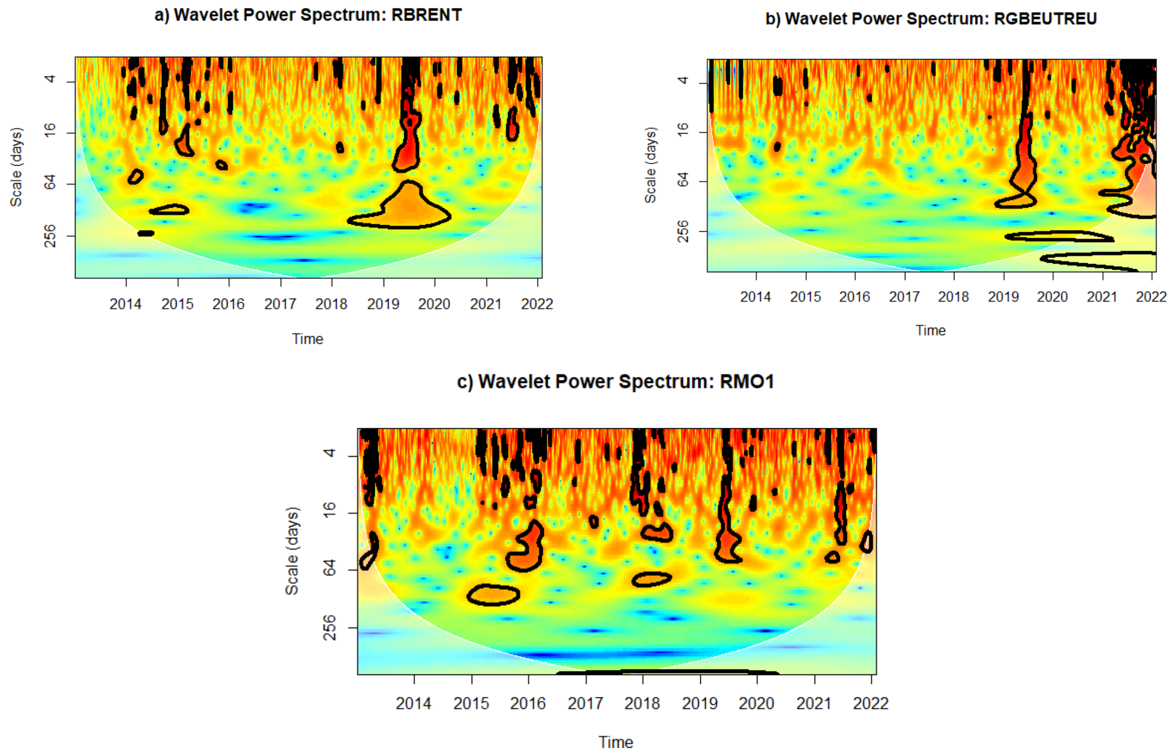
Source: Authors' own research using data from Bloomberg.

3.4.2 Wavelet power spectrum

Figure 3-6 presents the wavelet power spectrum for the Brent oil returns (RBRENT), Green Bond Index (RGBEUTREU), and CO2 futures' returns (RMO1) variables, respectively. The Brent oil returns (RBRENT), Figure 3-6 (panel a), appear to show significant volatility at low and medium frequencies, particularly in 2014, the end of 2019-2020, and 2022. This phenomenon is according to the high volatility observed in these periods due to the FED's Taper Announcement and the first oil prices crisis in 2014, the global COVID-19 pandemic at the end of 2019-2020, and the Russian invasion of Ukraine in February 2022.

The Green Bond Index (RGBEUTREU) behavior, Figure 3-6 (panel b), exhibits significant volatility at the end of 2019-2020 and the beginning of 2022 at low, medium, and high frequencies, which is consistent with the two last events identified previously. For example, in 2019-2020, the issuances of green bonds were extended worldwide. However, in February 2022, the Russian invasion of Ukraine and the subsequent European energy crisis exacerbated post-COVID-19 inflation and impacted the bond market dynamics by increasing interest rates. As a result, high volatility resulted in decreased bond issuance. It is important to note that the Green Bond Principles (GBP) were launched in 2014, its first update occurred in 2015, and the development of this market is constantly changing.

Figure 3-6: Wavelet power spectrum for Brent oil returns (RBRENT), Green Bond Index (RGBEUTREU), and CO2 futures' returns (RMO1).



Source: Authors' own research using data from Bloomberg.

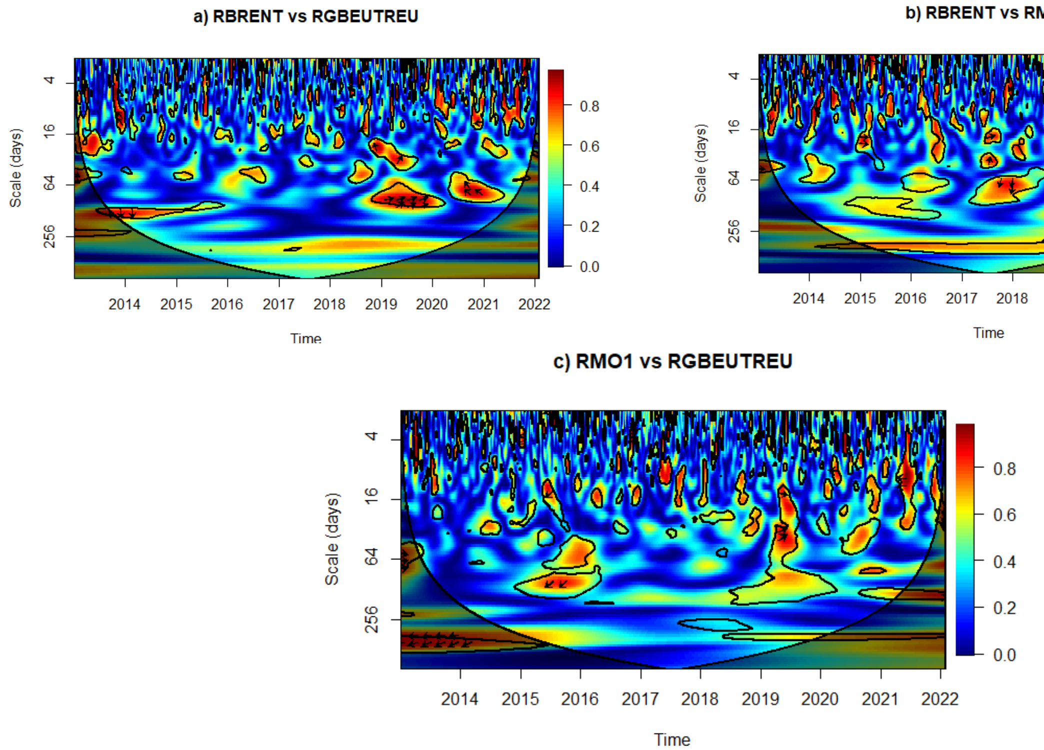
Finally, CO_2 futures' returns (RMO1), Figure 3-6 (panel c), present high volatility at low and medium frequencies, particularly in 2015-2016, 2018, the end of 2019-2020, and 2022.

3.4.3 Wavelet coherence approach

The wavelet coherence approach is applied to capture the causal relationship between the Brent oil returns (RBRENT), the Green Bond Index (RGBEUTREU), and the CO2 futures' returns (RMO1). Figure 3-7 presents the results from the wavelet coherence. It captures the co-movement of these three variables in the time-frequency space.

Figure 3-7 and its table depict the wavelet coherence and phase difference and principal results between each pair of times series considered. In the figure, the horizontal axis (x-axis) represents the research period in days, while the vertical axis (y-axis) represents the frequency domain.

Figure 3-7: Wavelet coherence among Brent oil returns (RBRENT), CO_2 futures' returns (RMO1), and Green Bond Index (RGBEUTREU).



Causality/Period	2014	2015-2016	2018	2019-2020	2021	2022
RBRENT significantly caused RGBEUTREU	Negative MT				Negative MT	
RGBEUTREU significantly caused RBRENT				Positive MT, LT		
RBRENT significantly caused RMO1			Positive ST, MT	Negative MT		Positive LT
RMO1 significantly caused RBRENT	Negative ST			Positive MT	Negative MT	
RMO1 significantly caused GBEUTREU						Negative MT
RGBEUTREU significantly caused RMO1	Positive, MT Negative, LT	Negative ST, MT, LT		Positive MT	Negative ST	

Source: Authors' own research using data from Bloomberg. Note: The value of squared wavelet coherence is depicted in color and the value of relative phase by arrows. The color code for the coherence ranges from blue (low coherence - close to zero) to red (high coherence - close to one). The area affected by edge effects is the semi-transparent region at the left and right boundary separated by the black U-shaped curve, which is the cone of influence (CoI). The thick black contours within CoI are the regions of significant coherence (at 5% level). The direction of the arrows reveals the phase relationship between each moment pair of times series returns in the time-frequency space. Notes: ST: short-term, MT: medium-term, LT: long-term.

This study considered five frequency cycles: 1–4, 4–16, 16–64, 64–256, and 256-512 daily bands. The shortest band, which considers 2-4 days, denotes the highest frequency band, and the most extended band includes 256-512 days the lowest frequency band. For a better comprehension of the results, they include in the short-term (ST), the signals between the 2-4 days and 4-16 bands; medium-term (MT), the signals between the 16-64 days and 64-256 bands; and long-term (LT) the signals in 256-512 days band (see figure 3-7 and its table). Located on the right-hand side of each plot, there is the color gradient code of power, where dark blue indicates low power (close to cero), and dark red implies high power (close to one).

Figure 3-7a shows that wavelet coherence between the Brent oil returns (RBRENT) and the Green Bond Index (RGBEUTREU) from scales 64 to 256 days, down arrows are obtained in 2014, indicating that in the medium-term, the Brent oil returns (RBRENT) significantly affected the Green Bond Index (RGBEUTREU) negatively. However, the direction of the causality changes between 2019-2020 at different frequencies (16-64 and 64-256 days, medium-term and long-term, respectively), since the arrows mostly point right-up, implying a positive relationship and that the Green Bond Index (RGBEUTREU) is an important predictor of the Brent oil returns (RBRENT) in the medium-term and long term for the period between 2019-2020. Finally, in 2021, the Brent oil returns (RBRENT) significantly affected the Green Bond Index (RGBEUTREU) for scales 16-64, and the arrows mostly point left-up, indicating a negative relationship in the medium-term. The summary of the results in the table supports a bi-directional causality relationship between the Brent oil returns (RBRENT) and the Green Bond Index (RGBEUTREU).

Additionally, Figure 3-7b depicts that wavelet coherence between the Brent oil returns (RBRENT) and CO_2 futures' returns (RMO1) presents, from scales 4 to 16 days, arrows that point down and left-down in 2014, indicating that in the short term, the CO_2 futures' returns (RMO1) affected Brent oil returns (RBRENT) significantly with a negative relationship. In 2018, Figure 3-7b indicates that from scales 4-16 and 64-256, the arrows point right, implying that in the short-term and medium-term, Brent oil returns (RBRENT) influenced the CO_2 futures' returns (RMO1) with a positive relationship. From 2019 to 2020, Figure 3-7b shows a change in the direction of the causality for the frequencies 16-64, indicating that in the medium-term CO_2 futures' returns (RMO1) significantly influenced the Brent oil prices (RBRENT) with a positive relationship. However, for the period between 2019-2020, left-up arrows are obtained for a scale of 16-64, indicating that in the medium-term, the Brent oil returns (RBRENT) significantly affected the CO_2 futures' returns (RMO1) with a negative relationship. Additionally, for the frequency 64-256 days in the period 2021, the presence of left-down arrows, indicating that in the medium-term CO_2 futures' returns (RMO1) significantly caused the Brent oil prices (RBRENT) with a negative relationship. Finally, scales 256-512 days, the arrows point right-down, indicating that in the long-term, Brent oil returns (RBRENT) significantly caused the CO_2 futures' returns (RMO1) with a positive relationship. The summary of the findings in the table validates a bi-directional causality relationship between the Brent oil returns (RBRENT) and CO_2 futures' returns (RMO1).

Finally, Figure 3-7cpresents the wavelet coherence between CO_2 futures' returns (RMO1) and Green Bond Index (RGBEUTREU). In 2014, from scales 64 to 256 days, arrows pointed right, denoting that the Green Bond Index (RGBEUTREU) and CO_2 futures' returns (RMO1) have a positive relationship in the medium-term. But, in 2014, from scales 256-512, arrows point left-down, which indicates that the Green Bond Index (RGBEUTREU) affects the CO_2 futures' returns (RMO1) in the long-term having a negative relationship. In 2015-2016 arrows point left-down at different frequencies (4-16, 16-64, and 64-256 days), denoting that the Green Bond Index (RGBEUTREU) causes the CO_2 futures' returns (RMO1) for 2015-2016 in short-term, medium-term, and long-term with a negative relationship. For the period 2019-2020, for the frequency 16-64 days, arrows point right-up, indicating that the Green Bond Index (RGBEUTREU) causes CO_2 futures' returns (RMO1) in the medium-term with a positive relationship. In 2021, for a scale of 4-16, the arrows pointed left-down, denoting that the Green Bond Index (RGBEUTREU) causes the short-term CO_2 futures' returns (RMO1) with a negative relationship. Finally, in 2022 the direction of the causality changes and for the frequency 16-64 days the arrows pointing down indicate that the CO_2 futures' returns (RMO1) variable affects the Green Bond Index (RGBEUTREU) in the medium-term with a negative relationship. The summary of the results in the table supports a unidirectional causality relationship from the Green Bond Index (RGBEUTREU) to CO_2 futures' returns (RMO1), with an exception in 2022 when the direction of the causality changes.

3.5 Discussion

The findings from the wavelet power spectrum reveal that (i) there was significant volatility in the Brent oil returns at low and medium frequencies, particularly in 2014, the end of 2019-2020, and 2022 at low and medium frequencies; (ii) the Green Bond Index exhibit significant volatility at the end of 2019-2020 and at the beginning of 2022 at low, medium, and high frequencies; and (iii) the CO_2 futures' returns present high volatility at low and medium frequencies, specifically in 2015-2016, 2018, the end of 2019-2020, and 2022. This phenomenon is according to the high volatility observed in these periods due to the FED's Taper Announcement and the first oil prices crisis in 2014, the global COVID-19 pandemic at the end of 2019-2020, and the Russian invasion of Ukraine in February 2022. These results are in line with (Jin et al. (2020), who argues that carbon emissions and energy markets (including oil prices) are due to the similar nature of the markets. We can include the green bond issuances for their relationship with these two markets, which is increasing due to the transition of energy to a decarbonized economy. Thus, the three considered markets are sensitive to the same macroeconomic variables, such as climate change, market conditions, and geopolitical situations, such as those reported in recent empirical facts.

Additionally, wavelet coherence results indicate that (i) the Brent oil returns have a negative impact on the Green Bond Index in the medium term for 2015 and 2021, respectively. Still, the Green Bond Index positively impacts the Brent oil returns at the period 2019-2020 in the medium-term and long-term, which indicates a feedback relationship, suggesting that oil prices and green bond prices are interdependent when these markets are in a bearish state. This result is in line with (Lee et al., 2021). Also, the wavelet coherence analysis indicates a negative relationship between oil prices and CO_2 futures' returns in 2019-2020. However, the relationship becomes positive during 2018 (short-term and medium-term) and 2022 (long-term). This paper's findings support (H. Li et al., 2022), since oil price has a negative effect on the Green Bond Index and carbon price due to higher oil prices may lead to higher consumption of non-fossil energy, and then, reducing the demand and willingness of companies to raise green financing. This research findings are also in line with (Mensah et al., 2019) which provide evidence of causality that runs from the oil returns to the CO2 futures' returns. For example, (Mensah et al., 2019) determined a unilateral effect from oil prices to carbon emissions both, in the long and short run. In contrast, (Marín-Rodríguez, González-Ruiz, & Botero, 2022) found a unidirectional causality running from the Green Bond Index to the Brent oil returns, a unidirectional causality running from the Green Bond Index to the CO_2 futures' returns, and a unidirectional causality running from the Brent oil returns to the CO_2 futures' returns.

(ii) The wavelet coherence analysis results also show that there is a causal relationship between CO_2 futures' returns and oil prices, which was negative in 2014 (short-term) and

2021 (medium-term); however, this relationship becomes positive in 2019-2020 (medium-term). This paper's finding is in line with Li et al. (2022), who showed that carbon emissions trading is negatively affected by oil price shocks and the impact is negative in both the short and medium term. A possible explanation for this is that an increase in oil prices may lead to a rise in the use of low-carbon energy and then diminish firms' demand for carbon credits.

(iii) Finally, other results from wavelet coherence suggest that the Green Bonds Index negatively affects the CO_2 futures' returns in the medium-term in 2022. Additionally, the Green Bond Index significantly affected CO_2 futures' returns positively (2014 and 2019-2020) and negatively (2015-2016 and 2021) in the short-term, medium-term, and long-term. In contrast, Li et al. (2022) using time-varying impulse response analysis found that carbon emission trading price is mainly positively affected by the impact of the Green Bond Index in the short and medium-term and tends to 0 in the long term.

The findings in this study extend several implications for researchers, managers, policymakers, and decision-makers. Thus, (i) The negative relationship between oil prices and green bonds causes the financial markets to generate incentives to raise green financing in the context of higher oil prices. Additionally, the positive linkage between oil prices and CO_2 emissions generates that policy decisions on the transition of energy to a decarbonized economy should consider the incentives for generating green bond issuances, which are an essential instrument for the transition to a climate-resilient economy. These results are in line with Jin et al. (2020).

Our findings are also relevant in the contribution for formulating green finance policies and supporting renewable investments. This is due to the negative relation founded between green bonds and CO_2 emissions. This topic acquires a particular interest in emerging countries where more outstanding efforts are required to expand the offer of these eco-friendly instruments. The preceding is because for example in Latin American and the Caribbean markets there is a strong demand for this type of instrument by investors in the local markets. Additionally, the support from policymakers towards the generation of energy transition policies could facilitate and encourage the generation of renewable energies procuring the criteria of climate bond initiatives.

The findings are also according to Jin et al. (2020), who suggests that investors in green bond markets are sensitive to fluctuations in energy and carbon markets because the carbon market can reflect climate change, uncertainty in green public policies, and changes in geopolitical situations. Additionally, we can admit that the search for sustainable investments promoted for the climate change risk has increased the popularity of green bonds, contributing to the enhanced correlation among the green bond market, oil prices, and the carbon market. This phenomenon can explain that during the outbreak of COVID-19 and the recent Russian invasion of Ukraine in February 2022, a greater percentage of co-movement among green bonds, were driven by linkage connections among the markets, Tiwari et al. (2022).

Finally, for market players and decision-makers, our results can help to improve portfolio composition since we present the diversification potential of green bonds to CO_2 emissions and oil prices. Furthermore, based on the principal findings, several co-movements patterns in different frequency bands suggest that investors should determine the corresponding risk prevention strategies based on their investment time horizons. The above results can assist investors in making portfolio selection decisions within Brent oil price, green bond markets, and carbon markets, as well as scale-conscious (or investment horizons-conscious) traders making trading decisions, as (Omane-Adjepong et al., 2019; Qureshi et al., 2020) mentioned.

3.6 Conclusions

The present study explores the time-dependency among the Brent oil returns, the Green Bond Index, and the CO_2 futures' returns using the wavelet power spectrum and wavelet coherence for measuring the co-movements and causality test over the period 2014 to 2022 over different time frequencies: short, middle, and long term. The use of the wavelet approach permits the present research to (i) capture the volatility periods of the Brent oil returns, the Green Bond Index, and the CO_2 futures' returns; and (ii) to study the short-term, medium-term, and long-term causal relationships among the Brent oil returns, the Green Bond Index, and the CO_2 futures' returns since the approach combines both time and frequency domain causalities.

Understanding the co-movements among the Brent oil returns, the Green Bond Index, and the CO_2 futures' returns are essential in assessing macroeconomic performance in the global decarbonization scenario. These three instruments are fundamental in implementing Sustainable Development Goals (SDGs) and the three traditional pillars of sustainable development based on the environmental, social, and economic domains. The SDGs represent the efforts to guide humanity toward long-term prosperity and the variables used in this study are essential in the analysis of the global goals about affordable and clean energy, sustainable cities and communities, responsible consumption and production, and climate action. However, their implementation represents significant challenges due to the tensions and trade-offs among the three pillars of sustainability (Giuliodori et al., 2022). In this context, knowing the relationships among these variables can help researchers, managers, policymakers, and decision-makers to understand the importance of the oil price shocks on the design of assets and policies that tend to improve sustainability practices. For example, Rodriguez-Fernandez (2016) found a positive bidirectional relationship between Corporate Social Responsibility and Financial Performance, originating a positive feedback virtuous circle in Spanish-listed companies.

On the other hand, based on Kirikkaleli & Güngör (2021), climate change risk and its direct and indirect impacts on the price formation of energy markets and assets related to sustainable finance seem to be one of the main areas of further research due to the pressures of climate change over the production technologies, investment practices, and regulations. In this point, green bonds have a pivotal role in being an essential instrument for financing energy transition reinforcing the importance it should have for policymakers to improve the legal framework relating to their issuance. Thus, there is great potential for further research on exploring the relationships among the Brent oil returns, the Green Bond Index, and the CO_2 futures' returns, for example, using artificial intelligence techniques such as machine learning models that have been used for predicting the direction of markets. In particular, deep learning strategies that use neural networks can be helpful for measuring the co-movements among the variables considered; for example, Deep Neural Networks (DNNS); Convolutional Neural Networks (CNN); Autoencoders; and Recurrent Neural Networks (RNN) like Long Short-Term Memory (LSTM), Bidirectional LSTM (BiLSTM), stacked LSTM (SLSTM) or Gated Recurrent Unit (GRU) networks. These studies could also be extended to Latin American and the Caribbean markets, where the lack of data makes this kind of research scarce.

Although this study enlarges the discussion around the dynamic association among oil prices, green bonds, and CO_2 emissions and addresses the diversification potential of green bonds to CO_2 emissions prices and oil prices in different frequency bands, a possible limitation of our study can be related to the data time-frequency. For example, some investors in energy markets and sustainable assets can prefer to make decisions over longer investment horizons, which is in line with (Saeed et al., 2021). Therefore, future research can address this limitation by using lower frequency data (i.e., weekly or monthly data) and considering the heterogeneity of investors over different investment horizons.

4. Chapter 4. Analyzing dynamic co-movements among oil prices, green bonds, and CO2 emissions using the fuzzy logistic autoencoder model

The Fuzzy Logistic Autoencoder (FLAE) model was used to examine the co-movements among oil prices, green bonds, and CO_2 emissions on daily data from January 2014 to October 2022. The results indicate that in the short and medium-term, the Green Bond Index (GB-V) influenced the CO_2 futures' returns (CO2-E), and the Brent oil returns (BB-P) with a negative relationship (category - High). Additionally, the BB-P and the CO2-E returns series are also important to forecast the BB-P and the CO2-E returns in the short and medium-term but in a smaller proportion. Finally, in the case of the Green Bond Index (GB-V) return series forecasts (category - Positive High), their own lags ordered from zero to 251 are included, which indicates that the series is mainly random as it is highly dependent on impacts close to zero, but the BB-P, and the CO2-E returns have a negative but smaller impact on its forecast. This study represents a breakthrough in explaining the relationship among these variables.

Keywords: dependence, oil price, green bonds, CO_2 emissions, deep learning, autoencoders, sustainable finance, machine learning.

4.1. Introduction

Green bonds play a pivotal role in the global transition to a low-carbon economy (Mejía-Escobar et al., 2021). Therefore, understanding the co-movements among green bonds and financial markets would provide vital information for investors, policy-makers, and energy policy analysts due to the significant impact caused by climate change on government policies and climate-related risk for companies (J. D. González-Ruiz et al., 2023; Marín-Rodríguez, González-Ruiz, & Botero, 2022; Reboredo, 2018). According to Li et al. (2022) oil price shocks have an impact on the green bond and the carbon emissions markets. Furthermore, the three considered markets are sensitive to the same macroeconomic variables, such as climate change, market conditions, and geopolitical situations (Marín-Rodríguez et al., 2023; Tiwari et al., 2022).

Several studies have focused on modeling and forecasting patterns of the financial time series during the last several decades. The techniques for predicting the time-series data of financial markets (such as indexes, stocks, and foreign exchange, among others) include conventional models like the Auto-Regressive (AR), Auto-Regressive Moving Average (ARMA), Auto-Regressive Integrated Moving Average (ARIMA), or the Auto-Regressive Integrated Moving Average with exogenous variables (ARIMAX) models. Furthermore, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models (including a large family of conditional heteroskedasticity models) are also extensively used. Nevertheless, in recent times, the use of machine learning (ML) models for predicting within financial fields have stood out. These procedures include Support Vector Machines (SVM), Random Forests (RF), and Deep Learning models such as (i) Deep Neural Networks (DNNS); (ii) Convolutional Neural Networks (CNNs); (iii) Recurrent Neural Networks (RNNs) like Long Short-Term Memory (LSTM) network models, Bidirectional LSTM (BiLSTM), stacked LSTM (SLSTM) or Gated Recurrent Unit (GRU) networks, and (iv) autoencoders (AE); their variants seek dependence on future trends of financial assets and historical data, including the analysis with other variables. However, ML models are meant to produce the most accurate predictions (S. Ahmed et al., 2022).

On the other hand, to measure the dynamic co-movement between a pair of variables, methodologies such as the wavelet analysis, copula, DCC-GARCH, and volatility spillover were identified as the most used to perform these analyses, Marín-Rodríguez et al. (2022a). However, it has been found in the literature that no studies use ML techniques for modeling such dynamic co-movements. This constitutes an essential gap in the existing literature. ML models are used mainly for the following main tasks: description, prediction, and causal inference (Hernán et al., 2019; Jiang et al., 2020), as is explained below. (i) Description, when the algorithm is trained to assign an input to a specific category. This category includes data clustering. Then, the algorithm tries to group the samples with similar features and cluster the information. Also, it is trained for anomaly detection with the purpose of finding anomalies in data. (ii) Prediction, by using data to map some inputs' features to other features of the outputs. The analytics employed for prediction range from elementary calculations (a correlation coefficient or a risk difference) to sophisticated pattern recognition methods and supervised learning models that can be used as classifiers (random forests, neural networks) or predict the joint distribution of multiple variables

(Hernán et al., 2019). Finally, (iii) causal inference involves estimating effects by comparing the outputs among what is exposed with the counterfactual outputs if they had not been exposed instead to a given event (Jiang et al., 2020).

The analytics employed for causal inference range from elementary calculations, which include regression trees and random forests, to complex implementations, such as the Targeted Maximum Likelihood Estimation (TMLE), which has robustness features (Hernán et al., 2019; Jiang et al., 2020). Then, due to the nature of the dynamic relationships calculations carried out in this study, the most endorsed models that appear in Deep Learning (DL) for our purpose are those related to forecasting features; in them, Recurrent Neural Networks (RNNs) and Autoencoders (AE) are the most used compared with the other models. Nevertheless, the advantage of AE (and their variants) compared to RNNs (and their variants) is that RNNs are challenging to interpret, opaque, and hence considered to be black box models, while AE keeps high interpretability (Shankaranarayana & Runje, 2019). Then, AE allows for designing a neural network architecture, like imposing a bottleneck in the network forces. Moreover, the compressed knowledge representation of the original input shows an explicit mathematical representation of the existing relationship among the considered variables. For this reason, this research used AE as a more pertinent model to capture long-term relationships in the time-series data being efficiently examined while keeping high interpretability, for example, using an encoder–decoder transformation (Reza et al., 2022).

Historically, AE were used as a pre-training for Artificial Neural Networks (ANNs) (Schmidhuber, 2015). Currently, they are used for dimension reduction, feature variation, watermark removal, or image denoising. Then, according to Vieira (2015), an autoencoder (AE) is a neural network composed of two parts, namely, an encoder and a decoder. The encoder compresses the input data by reducing its dimensionality and transforming it into a latent space with a specified number of dimensions. The decoder attempts to reconstruct the original input data from the latent space. The AE is a dimensionality reduction method implemented using ANNs. It aims to learn a compressed representation of input data by minimizing its reconstruction error (W. Wang et al., 2014).

The imposed AE's architecture will be fed from the existing correlations among the input's characteristics (oil prices, green bonds, and CO_2 emissions) that the structure can be learned and consequently weighted when the input is forced through the network's bottleneck. On the other hand, a fuzzy logistic model is a type of statistical model that combines elements of both fuzzy logic and logistic regression. Fuzzy logic is a type of mathematical logic that deals with reasoning about uncertain or vague concepts. In contrast, logistic regression is a statistical method used for predicting binary outcomes (e.g., success/failure, yes/no) based on a set of independent variables. In a fuzzy logistic model, the independent variables may be fuzzy or uncertain, and the model uses fuzzy logic to make predictions about the binary outcome. This approach can be useful in situations where the data is imprecise or there is a lot of uncertainty in the independent variables.

In the context of this research, a fuzzy logistic (FL) model can be used to help measure co-movements among the different financial variables studied. This feature is because fuzzy logic can be used to identify patterns and relationships among the different financial variables analyzed that may not be immediately obvious using traditional methods. It can also be used to develop predictive models considering the uncertainty and imprecision inherent in financial data. Thus, fuzzy logic can be used to create a financial model that incorporates multiple variables and their relationship among them; then it can be used to predict the behavior of those variables in the future. The co-movements among different financial variables can be measured by calculating the correlation coefficients, and fuzzy logic can be used to establish a non-linear relationship among the variables.

Additionally, FL models can be used to model the uncertain and vague dependencies among the extracted latent factors (Abdelmaksoud et al., 2022). By combining the two methods, we can use the autoencoder to extract latent factors that capture the underlying co-movements among assets and then use the FL model to model the uncertain dependencies among these factors. This approach can be useful when the financial data is noisy or there is much uncertainty in asset dependencies (Kuzmanovic et al., 2021). Then, as a complement of autoencoders (AE), the FL model known as the Fuzzy Logistic Autoencoder (FLAE) model is made up of powerful techniques that can be used to shape the relationship among variables and to make predictions about market's future movements. These models can help to identify patterns and relationships within the data, make market predictions, and detect anomalies in the data.

This research proposes a co-movement methodology analysis that includes short-, medium, and long-term time series using an FLAE model and data from oil prices, green bonds, CO_2 emissions. Thus, this paper makes three substantial contributions to the existing body of knowledge and practice. First, this study is the first to integrate a scientometric analysis of dynamic co-movements among oil prices, green bonds, and CO_2 emissions, limiting the analysis to machine learning models measuring the co-movements, contagion, or dependence among the variables. Second, it provides new evidence by examining the dynamic relationship among crude oil prices, CO_2 futures' prices, and green bonds using an FLAE model to determine the relationships among these variables over different time frequencies. Third, this study's outcomes would provide valuable information for researchers, managers, policy-makers, and decision-makers to make informed decisions on investments and policies related to the co-movements among oil prices, green bonds, and CO_2 emissions.

The paper's outline is as follows: Section 2 studies the machine learning architectures to model the market linkages among oil prices, green bonds, and CO_2 emissions employing a scientometric methodology. Section 3 presents the data, the descriptive statistics, and the models used. Section 4 analyzes and discusses the empirical results. Finally, some concluding remarks are indicated.

4.2. Literature Review

The systematic literature review included in this study used documents from the Scopus and Web of Science (WoS) bibliographic databases. For compiling the main documents on the dynamic co-movements among oil prices, green bonds, and CO_2 emissions using machine learning, deep learning or autoencoders for the analyses, the research equation used was: (TITLE-ABS-KEY (autoencoder* OR "machine learning") AND TITLE-ABS-KEY ("financial market*" OR "Oil price*" OR "oil-price" OR "Green bond*" OR "Sustainability" OR co2 OR "CO2 emission*" OR "carbon dioxide emission*" OR "carbon emission*" OR "emission* CO2") AND TITLE-ABS-KEY ("Deep learning" OR "Neural Network") AND TITLE-ABS-KEY (correlation OR "dynamic correlation" OR "co-movement*" OR comovement*)). It is necessary to mention that the only document that includes all the parameters in the equation is the one developed by Marín-Rodríguez et al. (2022a), which is a literature review itself. All the research documents identified were downloaded and added to the Mendeley Reference Manager for the scientometric analysis. After removing 60 duplicates, 181 research documents were used for the scientometric analysis using the Bibliometrix package for R (Aria & Cuccurullo, 2017). Figure 4-1 shows the literature search strategy.

Figure 4-1: Literature search strategy.

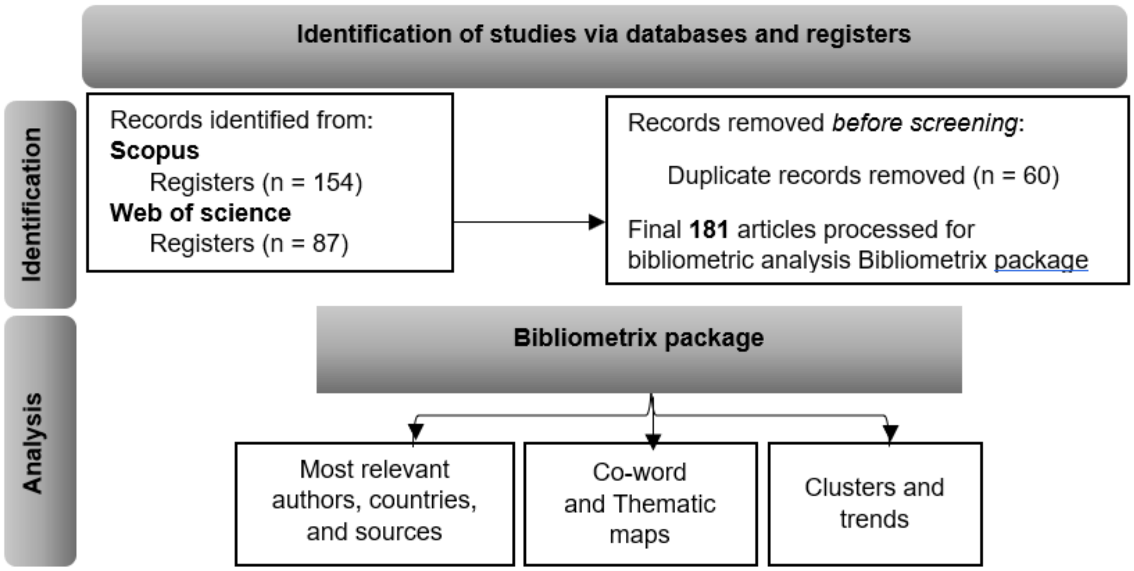
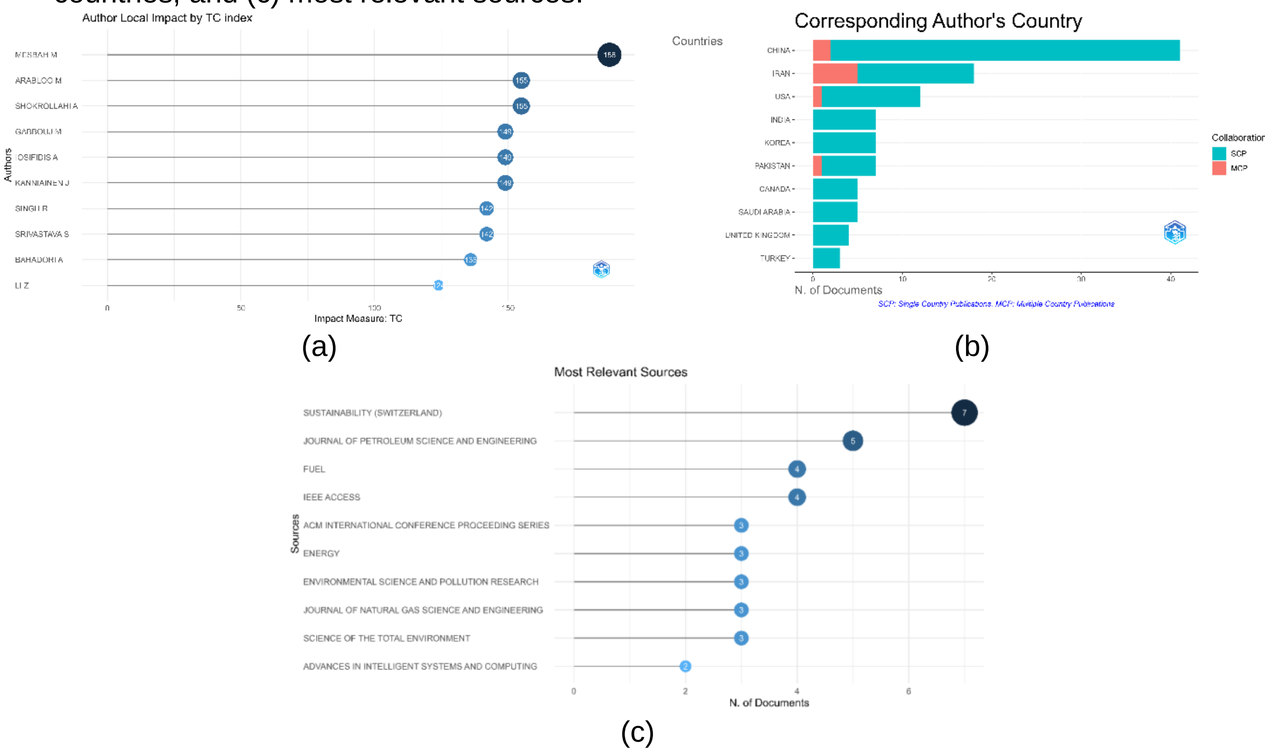


Figure 4-2 presents the most cited authors, corresponding author's countries, and most relevant sources. Figure 4-2a illustrates the top five most relevant authors based on the total citations (TC) about the dynamic co-movements among oil prices, green bonds, and CO2 emissions using machine learning or autoencoders for the analyses are (i) Mesbah, (ii) Arabloo, (iii) Shokrollahi (iv) Gabbouj, and (v) Iosifidis. Figure 4-2b presents the world's leading countries in the analyzed topic. China is the most productive country generating documents on this topic, with a total of 39 publications. In second place, there is Iran (13); in third place, there is the United States (11) followed by India and Korea with seven documents, respectively. Finally, Figure 4-2c shows the essential sources for this topic: Sustainability (7), Journal of Petroleum Sciences and Engineering (5), Fuel (4), and IEEE Access (4).

A thematic map is presented to study the clusters and trends in the research topic. It divides the subject of analysis into four topic quadrants based on the density and centrality of the issues (figure 4-3). Six major keyword clusters were identified in this analysis, but according to (Chansanam & Li, 2022), due to their high density and centrality, the themes that should be examined and studied more profoundly are in the upper-right quadrant. Then, the most promising areas for further research in analyzing dynamic co-movements among oil prices, green bonds, and CO_2 emissions (using machine learning or autoencoders for the analyses) are represented by two principal clusters that include the following keywords: (i) machine learning, neural networks, and carbon dioxide; and (ii) sustainability, regression analysis, and backpropagation.

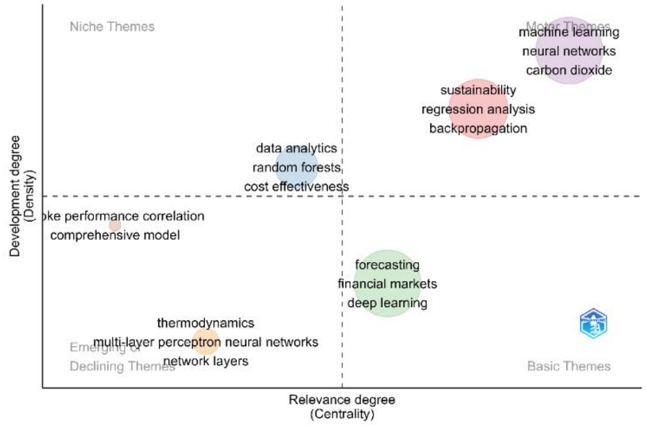
Figure 4-2: Analysis of the documents. (a) Most cited authors, (b) corresponding author's countries, and (c) most relevant sources.



Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

Figure 4-3 also shows a basic topic with high relevance, including the keywords: forecasting, financial markets, and deep learning. Concerning this topic, several documents have been written in recent years, among them (Bhavsar et al., 2023; Hansun et al., 2022; Manjunath & Halasuru Manjunath, 2023; C. Wang et al., 2022; Wu et al., 2022; Yun et al., 2023). For example, (Bhavsar et al., 2023), using the dataset of Infosys (BSE- Bombay Stock Exchange) stock closing prices from Yahoo Finance and news from Google News as sentimental data, compare various deep learning (DL) models like Long short-term memory (LSTM) and convolutional neural networks (CNN) for predicting stock price. The results show a weak correlation between sentimental data and the stock price. Furthermore, (Hansun et al., 2022) propose simple three layers of Bidirectional long short-term memory (Bi-LSTM) networks for Forex forecasting. The experimental results among the four used merged modes show that the concatenation mode (as the default merge mode in Bi-LSTM networks) is the least preferred mode for Forex forecasting.

Figure 4-3: Thematic map.



Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

Table 4-1 presents the 10 most globally cited documents in the time series research using fuzzy techniques among machine learning, deep learning or autoencoders models for the analyses, with a total citation ranging from 52 to 142. Khosravi et al. (2018), Li et al. (2017), Singh and Srivastava (2017), Tatar et al. (2013), and Zhang et al. (2019) have the most citations worldwide with 142, 119, 118, 93, and 82 citations, respectively.

Table 4-1: Top 10 cited documents in the search for dynamic co-movements among oil prices, green bonds, and CO_2 emissions using machine learning or autoencoders for the analyses.

#	Author	Source	Total Citations	TC per Year	Normalized TC
1	Singh and Srivastava (2017)	Multimedia Tools and Applications	142	23.67	2.59
2	Tatar et al. (2013)	Journal of Natural Gas Science and Engineering	119	11.9	1
3	Li et al. (2017)	Catalysis Today	118	19.67	2.15
4	Khosravi et al. (2018)	Geoderma	93	18.6	2.94
5	Zhang et al. (2019)	IEEE Transactions on Signal Processing	82	20.5	3.51
6	Tsantekidis et al. (2017)	2017 25th European Signal Processing Conference (EUSIPCO)	77	12.83	1.4
7	Cheng et al. (2017)	Journal of Imaging	65	10.83	1.18
8	Mesbah et al. (2018)	Journal of CO2 Utilization	58	11.6	1.83
9	Nandy et al. (2019)	ACS Catalysis	53	13.25	2.27
10	Mohan et al. (2019)	2019 IEEE Fifth International Conference on Big Data Computing Service and Applications (BigDataService)	52	13	2.23

Source: Authors' own research using the Bibliometrix tool, as well as Scopus and WoS databases.

The ten most cited articles mainly focus their analysis on two aspects: (i) to model chemical processes and predict them (ii) to model and forecast in financial markets. Therefore, this paper will focus on the documents regarding financial markets. In this way, Mohan et al. (2019) and Singh and Srivastava (2017) indicated that the central point is to predict stock prices using deep learning. Likewise, Tsantekidis et al. (2017) and Zhang et al. (2019) proposed deep learning (DL) models based on recurrent neural networks to capture longer time dependencies which can be used for predicting future price movements from large-scale high-frequency time-series data on Limit Order Books.

Finally, within the reviews involving the inclusion of machine learning models, which include deep learning, for the treatment of time series, several studies have had interesting findings. For example, Cavalcante et al. (2016) provide an overview of several primary studies published from 2009 to 2015 that discuss using various computational intelligence techniques in various financial applications. The review covers techniques for preprocessing and grouping financial data, predicting future market movements, and mining financial text information, among others. On the other hand, Fawaz et al. (2019) present a state-of-the-art performance of deep learning models for Time Series Classification (TSC) by presenting an empirical study of Deep Neural Networks (DNNs) architectures for TSC, including Multi-Layer Perceptron (MLP), Convolutional Neural Networks (CNNs) and Echo State Network (ESN). Additionally, Marín-Rodríguez et al. (2022a), studying the methodologies for measuring the co-movements among financial assets, found a research gap in analyzing employing machine learning, deep learning, big data, and artificial intelligence for measuring dynamic co-movements among oil prices and assets in financial and energy markets, especially in emerging countries.

4.3. Methodology

4.3.1. Data

In this study, three daily closing prices of variables were used. They were obtained from Bloomberg: CO_2 emissions, green bonds, and Brent oil prices (table 4-2). This paper's sample is from 1 January 2014 to 3 October 2022, where the starting point represents the day Green Bond Index become available, including 2290 daily observations (Appendix A). According to Reboredo (2013) and Rittler (2012), futures' prices of CO_2 emissions ($CO2-E$) were used because the futures market price has a better quality since it leads the price discovery process by embodying information first and then transferring it to the spot market. Furthermore, the Bloomberg MSCI Green Bond Index ($GB - V$) included in the analysis is a Euro fixed-income benchmark, which includes bonds in line with the Green Bond Principles, can be categorized as green bonds for their environmental use of proceeds. Finally, the Brent oil price ($BB - P$) is included as a fundamental energy price; it is essential because industrial production involves high fossil fuel consumption.

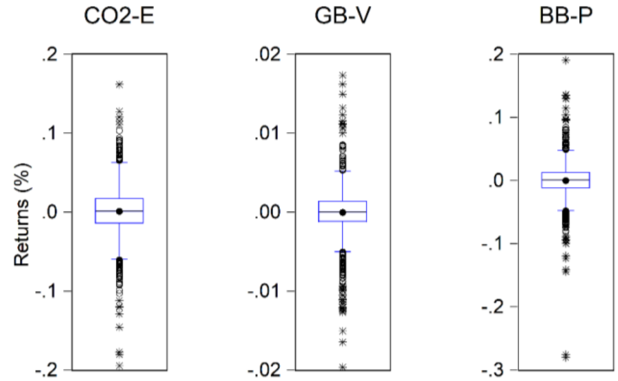
Table 4-2: List of variables.

Abbreviation	$\boldsymbol{CO2 - E}$	$\boldsymbol{GB - V}$	$\boldsymbol{BB - P}$
Variable	CO_2 futures price	Green Bond Index	Oil Brent price
Ticker	MO1 Comdty	GBEUTREU Index	CO1 Comdty
Description	CO_2 futures price, Euros per ton	Bloomberg MSCI Euro Green Bond Index Total Return Index Value Unhedged	Generic 1st Crude Oil, Brent

Source: Authors' own research.

According to the structure of the time series for the returns of the random variables considered for this study, Figure 4-4 shows that the most extended returns were the time series for Carbon Emissions ($CO2 - E$, min: -0. 194437 - max: 0.162035) (Figure 4-4a) and Brent Barrel Price ($BB - P$, min: -0.279762 - max: 0.190774) (Figure 4-4b). In contrast, the returns of the Green Bond Value Index ($GB - V$, min: -0.019640 - max: 0.017365) (Figure 4-4c) present returns that are more limited in magnitude. The high variation of the studied times series is because the period covered was volatile. According to Marín-Rodríguez et al. (2023), among the high volatility observed in these periods, several episodes of uncertainty can be mentioned: the FED's Taper Announcement and the oil prices crisis in 2014, the global COVID-19 pandemic at the end of 2019–2020, and the Russian invasion of Ukraine in February 2022.

Figure 4-4: Boxplots of returns of (a) CO_2 emissions, (b) green bonds, and (c) Brent oil.



(a) (b) (c)

Source: Authors' own research.

Additionally, following results obtained by Marín-Rodríguez et al. (2023), Table 4-3 depicts descriptive statistics of daily returns of the considered series computed as the first difference of the natural log of the prices or indexes. The average daily returns are close to zero for all series. The standard deviations reveal that green bonds are less volatile than CO_2 futures and Brent oil. All daily returns are negatively biased and leptokurtic consistent with heavy-tailed distortions. The Jarque–Bera (JB) Test strongly rejects the normality of the unconditional distribution of the return series and the non-stationarity tests [via Augmented Dickey-Fuller (ADF)] (Dickey & Fuller, 1979) evidence that all return series are stationary. Finally, the Ljung–Box Q-statistics (LBQ) indicate the presence of a serial correlation in both the return series and the squared return series; it is consistent with the existence of conditional heteroskedasticity effects.

Table 4-3: Summary statistics of daily returns.

Index	$\boldsymbol{CO2-E}$	$\boldsymbol{GB-V}$	$\boldsymbol{BB-P}$
Mean	0.001145	0.000004	−0.000063
Max	0.162	0.0196	0.1908
Min	−0.1944	−0.0196	−0.2798
Std. Dev.	0.0292	0.0027	0.0256
Skew.	−0.527	−0.164	−0.982
Kurt.	7.61	11.13	19.46
JB	2133.5 *	6315.4 *	26198.4 *
ADF	−50.34 *	−44.18 *	−47.16 *
LBQ (25)	38.42 [0.042]	61.73 [0]	48.36 [0.003]
LBQ2 (25)	306.21 [0]	1655.0 [0]	836.81 [0]

Notes: This table presents summary statistics of daily returns of CO_2 futures' returns ($CO2-E$), Green Bond Index ($GB-V$), and Brent oil prices ($BB-P$). The 1 January 2014—3 October 2022 sample yielded 2290 observations. (*) indicates the rejection of the null hypothesis at the 5% level for both the normality test (via Jarque-Bera) and unit root test [via Augmented Dickey-Fuller (ADF)], the ADF test is conducted with an intercept. LBQ (25) and LBQ2 (25) denote the Ljung–Box Q-statistics for serial correlation in the returns and squared returns series, respectively, computed using 25 lags, with p values reported in square brackets.

It is important to mention that for this study, just the first 256 lags were considered. When the authors tried to include lags 1 through 512 in order to make the results comparable with those obtained by Marín-Rodríguez et al. (2023) that includes analysis in the short, medium, and long-term, it was found that when 512 lags were considered, the correlation deteriorated considering the same parameters. Thus, long-term (LT) signals in the 256–512 days band were not included in this analysis because the models that include more than 256 lags deteriorated the correlation values of the forecast of the proposed series. Then four cycles are included: 1–4, 4–16, 16–64, and 64–256 daily bands. To better comprehend the results, the authors included in the short-term (ST) the signals between the 2–4 days and 4–16 bands, and in the medium-term (MT), the signals between the 16–64 days and 64–256 bands.

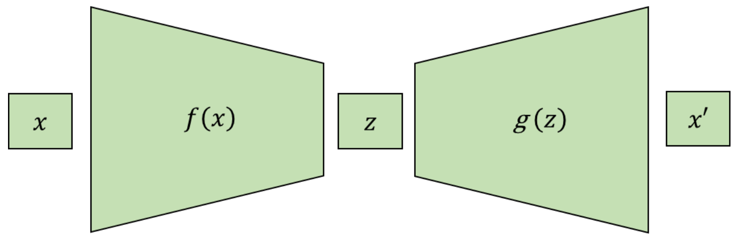
4.3.2. Fuzzy Logistic Autoencoder Model

For the characterization of the time series that represent the returns for the random variables of Carbon Emissions (CO2-E), Green Bonds (GB-V), and Brent Oil Price (BB-P), this article develops a hybrid neural model with a deep learning structure. It has two subsystems for adaptation and learning integrated into a single structure. A first subsystem will allow forecasting the returns' time series associated with a particular variable, considering the integration of the returns associated with the other variables. A second subsystem will allow the automatic classification by the level of impact of each independent effect associated with the fundamental lags of the return time series that significantly impact the predicted return time series forecast. Next, each subsystem used will be described.

- Forecast Subsystem

An autoencoder neural model is a neural model with a symmetric deep learning structure (Bengio, 2012), where the input data are used as a reference for the configuration of the proposed model (Charte et al., 2022a). In general, the autoencoder models allow the reduction of the complexity in the intrinsic structure of a data set (Dimensionality Reduction) using two internal mechanisms; the first mechanism allows the compression of the information (f(x): encoder), and the second mechanism allows the decompression of the information (g(z): decoder), or the reconstruction of the input data structure (Charte et al., 2018). Figure 4-5 shows the functional structure of the compression-decompression mechanisms that make up this model.

Figure 4-5: General structure of an autoencoder model



In general, an autoencoder model has a fully connected feed-forward neural network, which is denoted and defined as follows (Peña et al., 2020):

$$x_{io,k} = \sum_{j_{nn}=1}^{n_{nn}} w_{j_{nn},j_{nn-1}} \ldots w_{j_1,j_2}. \left(\sum_{j_o=1}^{n_o} \sum_{ii=1}^{n_e} w_{j,ii}. x_{ii,k} \right) \qquad (4.1)$$

Where $w_{j_{nn},j_{nn-1}}$ represents the internal connections between layer nn and layer $nn-1$; nn indicates the hidden layers ratio for the internal layer structure for the proposed model. n_{nn} indicates the $n-neurons$ for each of the $nn-layers$ that make up the model. $x_{ii,k}$ represents the input data to the model $(ii = 1,2, \ldots, ne)$. ne: indicates the number of input variables to the model $(ii - variable)$. According to the structure of the input data, the output values can be expressed as:

$$x_{ii,k} = \left[x_{CO_2,k}, x_{CO_2,k-1}, \ldots x_{CO_2,k-nr}, x_{GB,k}, x_{GB,k-1}, \ldots x_{GB,k-nr}, x_{BB,k}, x_{BB,k-1}, \ldots x_{BB,k-nr} \right] \qquad (4.2)$$

Where $x_{CO_2,k}$ represents the value of returns for the issuance time series of CO_2, $x_{GB,k}$ is the value of returns for the green bond time series GB), $x_{BB,k}$ indicates the value of the returns for the time series of the Brent Oil (BB), and finally, k is the number of time instants considered for this study, while nr, indicates the number of lags considered for each of the time series to be analyzed. The input-output values can be represented according to the proposed model's autoencoder structure.

$$x_{ii,k} = x_{io,k} \tag{4.3}$$

Where io indicates the number of output variables ($io - variable\text{:} io = ne$).

To evaluate the independent effects of each of the $ii - input$ variables regarding each of the $io - ouput$ variables, and without loss of generality, the proposed model can be expressed:

$$ys_{io,k} = \sum_{i_{ii}=1}^{n_e} C_{io,j} \left(\sum_{j_o=1}^{n_o} \sum_{ii=1}^{n_e} w_{j,ii} . x_{ii,k} \right) \tag{4.4}$$

Where $C_{io,j} . w_{j,ii}$ is known as the independent effects of the $ii - input$ variable concerning the $io - ouput$ variable.

For the structural modeling of the time series that represent the returns for each of the random variables, subsystem 1 integrates a logistic activation function, which is denoted and defined:

$$x_{io,k} = \mathrm{f}\left(ys_{io,k}\right) \tag{4.5}$$

Where $f(.)$ represents the logistic function, which denotes and defines according to the returns:

$$f\left(x_{ii,k}\right) = \frac{\mathrm{LS}}{1 + e^{-ys_{io,k}}} - \frac{LS}{2} \tag{4.6}$$

Where LS indicates the upper limit of returns. When the returns are bounded in an interval $(-100\%, 100\%)$, LS will take the value of 2 ($LS = 2$). For more extended performances, the value of LS can be defined in the interval $(1, +\infty)$. Additionally, $ys_{io,k}$ represents the intrinsic structure of the returns that make up the variable $x_{io,k}$ according to the structure of the forecast subsystem. In a general way, this term can be expressed:

$$ys_{io,k} = \sum_{i_{ii}=1}^{n_e} C_{io,j} \left(\sum_{j_o=1}^{n_o} \sum_{ii=1}^{n_e} w_{j,ii} . x_{ii,k} \right) \tag{4.7}$$

Equation (4.7) can be expressed as a function of the input variables as follows:

$$ys_{io,k} = C_{io,j}.w_{j,1}.x_{1,k} + C_{io,j}.w_{j,2}.x_{2,k} + \cdots + C_{io,j}.w_{j,ne}.x_{ne,k} \tag{4.8}$$

Where $C_{io,j}.w_{j,ne}$ represents the independent effects that make up the forecast model for an $io - ouput$ variable. According to Equation (4.5), which represents the activation function for the forecast subsystem, the activation function can be expressed as follows:

$$f(ys_{io,k}) = \frac{\mathrm{LS}}{1 + e^{-C_{io,j}.w_{j,1}.x_{1,k}}.e^{-C_{io,j}.w_{j,2}.x_{2,k}} \dots \dots \dots e^{-C_{io,j}.w_{j,ne}.x_{ne,k}}} - \frac{LS}{2} \tag{4.9}$$

For the analysis of the intrinsic structure of the returns associated with each random variable according to the independent effects associated with the fundamental lags of the time series, the activation function can be expressed:

$$f_{cdf}(ys_{io,k}) = \frac{1}{1 + e^{-C_{io,j}.w_{j,1}.x_{1,k}}.e^{-C_{io,j}.w_{j,2}.x_{2,k}} \dots \dots \dots e^{-C_{io,j}.w_{j,ne}.x_{ne,k}}} \tag{4.10}$$

Where $f_{cdf}(ys_{io,k})$ represents the structure of the cumulative distribution of returns according to the activation function. According to the previous Equation, the impact of each one of the fundamental delays on the modeling of the returns can be analyzed from the equilibrium point that the returns can reach. In this way, the term $e^{-C_{io,j}.w_{j,ii}.x_{ii,k}}$ is equal to unity, when the returns reach their breakeven $x_{ii,k-nr} = 0$. This makes it possible to isolate the impact of each of the ii-variables on an $io - ouput$ variable.

- Classification Subsystem

To automatically classify the impact of each of the challenges of the $ii - input$ variable, regarding each of the $io - ouput$ variables, the model integrates, for each variable, a Softmax function inspired by the structure of a Gaussian kernel function, which is denoted and defined:

$$K_{Softmax}\left(XC_{jc,iv}, (, C_{io,j}.w_{j,\mathrm{ii}})\right) = exp\left(-\frac{\left\|XC_{jc,iv} - C_{io,j}.w_{j,\mathrm{ii}}\right\|^2}{2.\sigma_{jc,iv}{}^2}\right) \tag{4.11}$$

Where $XC_{jc,iv}$ represents each of the centroids associated with the $jc - classification$ cluster for the $iv - variable$, jc allows the characterization of each of the independent effects at five levels or impact clusters $\{Very\,low,\ Low,\ Medium,\ High,\ Very\,High\}$, $C_{io,j}.w_{j,\mathrm{ii}}$ indicates the independent effect of the ii-variable concerning the io-variable.

For the configuration of the $K_{Softmax}$ function, the model incorporates a *k-medoids* algorithm, which adaptively classifies each of the return lags for one of the $iv - variables$. In general, the algorithm is denoted and defined:

1. The selection of the $jc - centroids$ a-priori is performed according to the first five (5) independent effects associated with each of the iv-characterization variables.
2. For each $k - record$, the model performs the estimation of the distance to each of the Kernels arranged for each $iv - variable$ according to Equation (4.9).
3. Subsequently, the selection of the minimum distance to each of the $jc - clusters$ associated with each of the iv-variables is performed as follows:

$$min:\left\{exp\left(-\frac{\left\|XC_{jc,iv} - C_{io,j}.w_{j,\mathrm{ii}}\right\|^2}{2.\,\sigma_{jc,iv}{}^2}\right)\right\} \quad (4.12)$$

4. The centroid is then recalculated $XC_{jc,iv}$ of each of the $jc - clusters$ associated with the shortest distance by estimating the mean as follows:

$$XC_{jc,iv} = \left(\frac{XC_{jc,iv} - C_{io,j}.w_{j,\mathrm{ii}}}{2}\right) \quad (4.13)$$

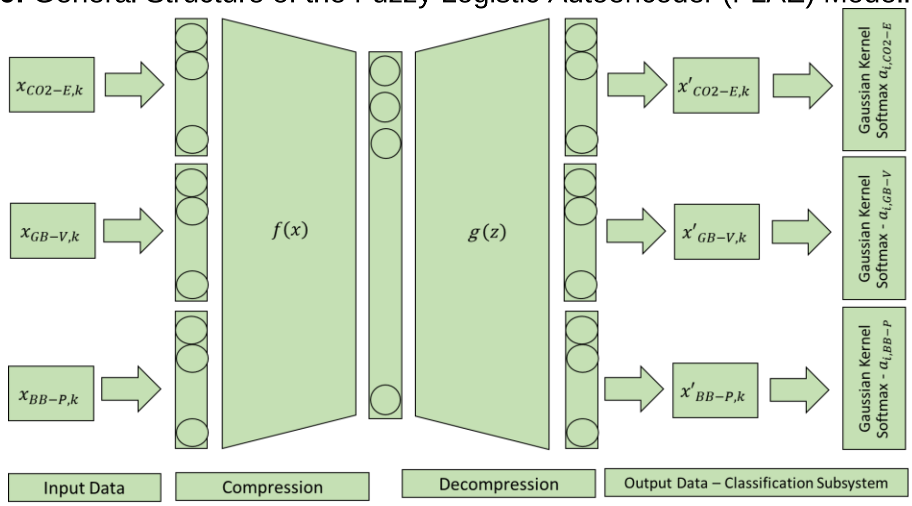
5. Finally, the estimation of the diameters of each of the centroids is performed, taking as reference the average of the distances of each of the $jc - clusters$ associated with each $iv - variables$ as follows:

$$\sigma_{jc} = \frac{1}{nc - 1}.\sum_{jcc=1}^{nc}\left\|XC_{jc,jcc} - XC_{jc,jcc}\right\| \quad (4.14)$$

Where nc indicates the number of centroids associated with each of the $iv - variables$.

The configuration process of the $K_{Softmax}$, unction can be carried out considering two strategies. A first fully supervised strategy adapts the centroids according to each of the records used to learn the proposed model. A second strategy, partially supervised, takes the final results obtained by the model against the estimation of the independent effects of the variables to carry out the configuration process of the later $K_{Softmax}$ function in a second phase (figure 4-6).

Figure 4-6: General Structure of the Fuzzy Logistic Autoencoder (FLAE) Model.



Source: Authors' own research.

- <u>Definitions and metrics</u>

Definition 1: Multivariate Logistic Function

For the characterization of variables as random variables using adaptive and learning models in terms of the structure of different random variables, the multivariate logistic function can be expressed as follows:

$$x_{io,k} = \frac{1}{1 + e^{-ys_{io,k}}} \tag{4.15}$$

Where $ys_{ii,o,k}$ represents the independent effects of a model for adaptation and learning according to the structure of a random variable $x_{io,k}$. According to the structure of an autoencoder neural model, this term can be expressed:

$$ys_{io,k} = C_{io,j}.w_{j,1}.x_{1,k} + C_{io,j}.w_{j,2}.x_{2,k} + \cdots + C_{io,j}.w_{j,ne}.x_{ne,k} \tag{4.16}$$

When the independent effects' structure takes values $ys_{io,k} > 0$, this gives rise to more extended cumulative distribution functions, with kurtosis coefficients that allow greater flexibility in the random variables model. When the structure of the independent effects takes values $ys_{ii,k} < 0$, this generates less flexibility in the representation of random variables.

Definition 2: Independent Structural Effects

Let $x_{ii,k}$ be a variable expressed as a random variable using the logistic activation function $x_{io,k}$, the structural effects of an input variable regarding an output variable can be expressed:

$$x_{io,k} = \frac{1}{1 + e^{-(C_{io,j} \cdot w_{j,1} \cdot x_{1,k} + C_{io,j} \cdot w_{j,2} \cdot x_{2,k} + \cdots + C_{io,j} \cdot w_{j,ne} \cdot x_{ne,k})}} \quad (4.17)$$

$$x_{io,k} = \frac{1}{1 + e^{-C_{io,j} \cdot w_{j,1} \cdot x_{1,k}} . e^{-C_{io,j} \cdot w_{j,2} \cdot x_{2,k}} \dots \dots \dots e^{-C_{io,j} \cdot w_{j,ne} \cdot x_{ne,k}}} \quad (4.18)$$

$$x_{io,k} = \frac{1}{1 + e^{-a_1 \cdot x_{1,k}} . e^{-a_2 \cdot x_{2,k}} \dots \dots \dots e^{-a_{ne} \cdot x_{ne,k}}} \quad (4.19)$$

In this way, the independent structural effect of a variable can be evaluated when at least one variable $x_{ii,k} \neq 0$. It is important to highlight that the positive independent effects can be classified into five levels of impact (Negative Low, Negative High, High, Positive High, Negative High).

These impact levels are defined in terms of the independent effects (a_i). Where $a_i \in (0{,}0.75)$ generates extended logistic functions of linear type (High), $a_i \epsilon (0.75{,}1)$ generates smooth canonical logistic functions (Positive High), and $a_i \epsilon [1, \infty)$ generates compressed logistic functions (Positive Low) (Gonzalez-Ruiz et al., 2019).

Definition 3: Blurred Impact Level

Let the function Softmax $K_{Softmax}$ defines the classification subsystem of the proposed model, the variables with a significant impact on the random output variables can be classified as follows:

$$x_{ii,k} \in \left\{ max \left\{ u_{jc,ii,k} = exp\left(-\frac{1}{2} \left(\frac{XC_{jc,ii} - x_{ii,k}}{\sigma} \right)^2 \right) \right\}; XC_{jc,ii} > 0 \right\} \quad (4.20)$$

$$ii = 1{,}2, \dots, ne; k = 1{,}2 \dots, ND$$

Definition 4: Structural Stability

An autoencoder model with a stacked deep learning structure is said to be structurally stable when the model has the ability to reconstruct the statistical structure of the cumulative distribution of an input random variable using a logistic activation function in the absence of an adaptation process and learning.

Definition 5: Dimensional Stability

An autoencoder model with a stacked deep learning structure is said to be dimensionally stable when an autoencoder-type neural model is sensitive to the magnitude of returns of a time series for a random input variable using a logistic activation function for this purpose and in the absence of a process of adaptation and learning. To evaluate the behavior of the proposed model against the characterization of the time series of the returns associated with the variables X_{iv}; the following metrics are proposed:

Metric 1: Mean Squared Error

They are defined as the mean of the squared errors with respect to each of the data that make up the input and output variables. The root means the square error and is denoted and defined as follows:

$$\mathcal{L}(x, x') = \frac{1}{n} . \sum_{k=1}^{n} \left(x_{ii,k} - x_{io,k}\right)^2 \tag{4.21}$$

For models by adaptation and learning, the learning height is defined in a general way:

$$\mathcal{L}(x, x') < 5 \times 10^{-p} \tag{4.22}$$

Where *p* indicates the number of significant figures to reach a precision with respect to the return structure.

Metric 2: Asymmetry coefficient

It is used to evaluate the joint impact of each independent effect that make up the proposed model. The coefficient of asymmetry can be evaluated as follows:

$$AC_{iv} = \frac{1}{ND} . \sum_{jc=1}^{nc_{iv}} ND_{jc,iv} . \frac{\left(XC_{jc,iv} - \overline{XC_{\iota v}}\right)^3}{\sigma_{iv}^3} \tag{4.23}$$

Where $ND_{jc,iv}$ represents the number of independent effects that make up the jc-cluster for the iv-variable. $\overline{XC}$ indicates the mean of the $jc-cluster$ centroids that make up the Softmax function for each $iv-variable$.

The coefficient of asymmetry allows evaluating the impact that a set of independent effects has on modeling the returns associated with a random variable. Negative Asymmetry Coefficients $AC_{iv} > 0$ will indicate the presence of significant independent effects.

Metric 3: Kurtosis coefficient

It allows evaluating the dispersion of the independent effects regarding the center of mass of the fuzzy sets that define the Gaussian Kernel used by the classification subsystem. The kurtosis coefficient can be defined as follows:

$$CK_{iv} = \frac{1}{ND}\sum_{jc=1}^{nc_{iv}} ND_{jc,iv} \cdot \frac{\left(XC_{jc,iv} - \overline{XC_{iv}}\right)^4}{\sigma_{iv}^4} - 3 \qquad (4.24)$$

The kurtosis coefficient will make it possible to evaluate the flexibility of a model regarding the characterization of the time series that represent the returns of the random study variables. Negative kurtosis values will result in more flexible models according to an activation function.

Metric 4: Wasserstein Distance (WD)

It allows evaluating the structural stability of a model by adaptation and learning against time series modeling using the logistic activation function (Panaretos & Zemel, 2019). Let $\tilde{A}$ (resp. $\tilde{B}$) be the cumulative distribution function or cumulative sum of A (resp. B), then the distance between activation functions can be estimated as the 1-norm, or Manhattan distance, of $\tilde{A}$ and $\tilde{B}$ as follows:

$$WD(A,B) = \left\|\tilde{A} - \tilde{B}\right\|_1 \qquad (4.25)$$

- Experimental validation

For the analysis and validation of the proposed model, the construction of the returns for the random carbon emissions variables $(CO2-E)$, value of green bonds (GB: Green Bonds, $GB-V$) and price of the Brent Oil Barrel Price (BB: Brent Barrel Price, $BB-P$), for the period between 2014 and 2022. After obtaining those time series, the characterization of its temporal structures was performed through a cross-prognosis of the returns using as a reference the methodology used by Charte et al. (2022) faced with the reduction of complexity in the modeling of dynamic systems using neuronal models with deep learning structure of the autoencoder type.

The cross-prognosis process was evaluated by contrasting the forecast of each performance **(Definition 2)**, taking different delays in time (NR): 10 delays for instant characterization (14 days); 64 delays for a very short-term characterization (2 months), 128 delays, for a short-term characterization (4 months); 256 delays, for a medium-term characterization (12 months); and a total of 512 delays for a long-term characterization. In this phase of experimentation, the model was subjected to a total of 500 iterations, an internal layer of neurons composed of a total of hidden non -neurons ($no = NR \times 3 \times ne/2$). The model takes 1000 data for each iteration to evaluate the returns' temporary random structure.

At this stage, the forecast will be evaluated regarding the correlation coefficient against the reference time series used for the model's configuration. For the generalization of learning, the proposed model will incorporate the logistics activation function described by Equation (4.6) to the Autoencoder model and will use the distance of Wassertein as an index to evaluate the capacity of this type of model to represent the intrinsic structure of returns for each of the random variables. Here, the model will reach correlation indexes above 75% on average, compared to the prognosis of returns, as well as Wasserstein indexes that are below 5% (5×10^{-2}) on average, so that this guarantees the structural stability of the model against the intrinsic structure of returns' modeling.

In the second stage, the evaluation of the proposed model was performed against the prognosis of the returns for each series of time individually, taking two neural models of reference under autoencoder structures (Charte et al., 2022). The first is a neuronal model of a stochastic type, which has been widely used to characterize random variables derived from the risk of an organization's business operations (S-ANFIS Stochastic Neural Fuzzy Integrated System) (Peña, Bonet, Lochmuller, Alejandro Patiño, et al., 2018). The second is a blurred neuronal model, which has been widely used for modeling Integrated Multirates Scenarios in the Financing of Infrastructure Projects (Fuzzy Neural Logistic Maps - FNLM) and which integrates logistics activation functions to evaluate the impact of random variables on these scenarios (Gonzalez-Ruiz et al., 2019).

According to the previous stage, the input neurons will be configured following the most promising period of 256 lags against the prognosis of returns (ne), and for the hidden layer, a 50% of the total input neurons ($no = ne \times 0.5$). In order to achieve reliability close to 99.9% in the modeling of the intrinsic structure of returns in accordance with the activation function that integrates the proposed model (Cramer et al., 2022; Peña, Bonet, Lochmuller, Alejandro Patiño, et al., 2018; Peña, Bonet, Lochmuller, Chiclana, et al., 2018), each model will be subjected to a total of 1000 iterations, and a total of 1000 data obtained randomly from the iteration of the total available data for the time series considered for this study ($ND = 2075$).

The fuzzy model proposed by Park and Seok (2007) was used to evaluate each one of the models. It integrates a total of eight statistical metrics to evaluate the behavior of models by adaptation and learning against the modeling of complex phenomena. According to the definitions established for this study **(Definition 4, Definition 5)**, these metrics were classified into structural stability metrics and dimensional stability metrics (Peña, Bonet, Lochmuller, Chiclana, et al., 2018). Among the structural stability metrics, the Geometric Mean Bias (MG), the Variance Mean Bias (VG), the Index of Agreement (IOA), and the Factor of Two (FAC2) stand out. Among the dimensional stability metrics, the Fractional Bias (FB), the Wasserstein Distance Index (WDI) (Çelik et al., 2021), the Unpaired Accuracy of the Peak Concentration (UAPC2), and the Mean Relative Error (MRE) stand out.

At this stage, the structural stability metrics are expected to reach values close to unity in order to ensure that the intrinsic structure of the random variables used for this study is maintained throughout the return forecast process. On the other hand, in order to guarantee the flexibility of the FLAE model against temporary changes in a time series (Gonzalez-Ruiz et al., 2019), it is expected that dimensional stability metrics reach values close to zero. It is important to note that each of the eight-performance metrics is evaluated by Park and Seok (2007) on a fuzzy-quantitative scale which establishes the following values: Good (G: 8.5), Over-Fair (OF: 6.0), Fair (F: 5.5), Under-Fair (UF: 5.0), Poor (P: 2.5). The maximum total score achieved by the model considering the eight metrics will be 68 points ($8 \times 8.5 = 68$), which may be represented as a percentage according to the score achieved by each one of the metrics.

In the third stage, the structural flexibility of the FLAE model is evaluated by taking as reference the neural evaluation models autoencoder S-ANFIS and autoencoder FNLM, as well as three flexibility parameters (Charte et al., 2022a, 2018). (i) hidden layers, which indicates the number of layers that make up a model with a stacked deep learning structure; (ii) dimensionality, which indicates the number of neurons that make up the first layer for a neural model with a deep learning structure; and, finally (iii) the Compression Index-IOA, which indicates the ability of the first layer of neurons to compress information while maintaining input-output Indexes of Agreement (IOAs) above 90% on average (Peña et al., 2022). After this structural evaluation process, the FLAE model will be evaluated in terms of its ability to represent the intrinsic structure of returns using, as the activation function, the logistic function integrating the activation function (Equation 4.9). Here, it is expected that the average, the variance, the skewness coefficient, and the kurtosis coefficient of the logistic functions used to forecast the returns for each random variable yr_v_r show the smallest percentage variations concerning the returns used as a reference for the configuration of the FLAE model yd_v_k.

Following **Definition 1, Definition 2, and Definition 3**, in the fourth stage, the impact of the independent effects a_i was evaluated with respect to each of the lags used for return forecasting, integrating into a single structure (FLAE model) each of the time series of the returns associated with each of the random variables considered for this study. In this case, three random variables (rv) were considered ($rv = 3$). At this stage of the process, the FLAE model is expected to generate a map of independent effects that shows the cross effect among the lags used to forecast returns for each one of the variables (Demir et al., 2021).

To evaluate this crossed impact on the return forecast, the independent effects will be automatically classified by magnitude, using the Gaussian Kernel structure (Classification Subsystem) configured at five impact levels (*Negative Low, Negative High, High, Positive High, Positive Low)* **(Definition 2, Definition 3)**. Independent effects with positive magnitudes are expected to have a greater impact on the forecast of returns for a particular variable. It is also expected that the Kernel functions reach asymmetry indexes close to zero (0), as well as extended kurtosis values, this in order to group the largest number of independent effects in the High & Positive High categories, which are closest to zero (0) in magnitude, this in order to guarantee the structural stability and flexibility of the proposed model against the return forecast (Gonzalez-Ruiz et al., 2019; Z. Liu et al., 2022).

4.4. Results and discussion

4.4.1. Experimental setup

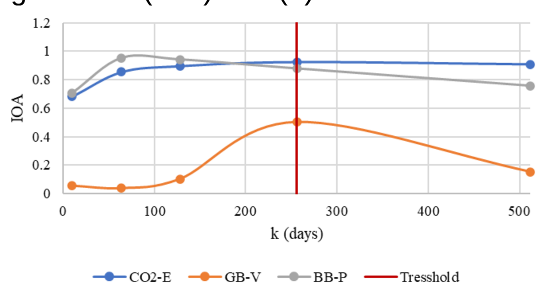
Table 4-4 and Figure 4-7 show the results achieved by the structure of the proposed model compared to the temporal characterization of the returns for each one of the random variables considered for this study, taking as reference different lags compared to the forecast.

Table 4-4: Characterization of the temporal structure of the returns – Deep learning neural models with autoencoder structure

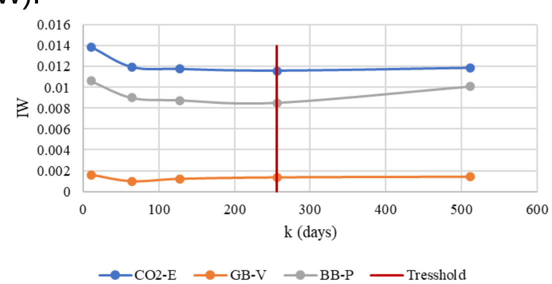
	Index of Agreement (IOA)				
Delays	**10**	**64**	**128**	**256**	**512**
CO2-E	0.681008	0.853972	0.895854	0.924988	0.909223
GB-V	0.054310	0.036850	0.102426	0.503362	0.152282
BB-P	0.705985	0.951362	0.940682	0.877384	0.756072
	Wassertein Index (IW)				
Delays	**10**	**64**	**128**	**256**	**512**
CO2-E	0.013901	0.011951	0.011758	0.011600	0.011869
GB-V	0.001603	0.001000	0.001219	0.001353	0.001416
BB-P	0.010628	0.009000	0.008758	0.008523	0.010104

Source: Authors' own research.

Figure 4-7: Behavior of the proposed model regarding the characterization of the temporal structure of the returns for each random variable of the different lags. (a) Index of Agreement (IOA) and (b) Wassertein Index (IW).



(a)



(b)

Source: Authors' own research.

Additionally, Table 4-4 and Figure 4-7 show that the FLAE model improved its performance as the number of lags increased until they reached a limit value of 256 lags (Tresshold); from this point, the correlation indexes deteriorated until they reached a total of 512 lags. It is important to highlight that the proposed model with 256 lags showed the most promising behavior regarding the return forecast for this number of lags for the random variable GB-V (IOA:0102426), which is why the analysis was carried out with this number of lags. It is important to highlight that the Wasserstein index was located in all cases below 5% on average, which also guarantees the good forecast performance of the logistic activation function compared to the modeling of the intrinsic structure of returns. The foregoing clearly shows the effect of the return forecast for a medium-term delay horizon.

Following the above, for the representation of the performance associated with the time series for the random variables considered for this study (CO2-E, GB-V, BB-P), the proposed models were configured to autoencoder structures for a total of 768 input neurons $ne = 256 \times 3$, for a unitary hidden layers and 50% dimensionality of the total input neurons ($no = ne \times 0.5$) (Peña et al., 2022). In the case of the autoencoder structure of the FLAE model, the input neurons determined the number of output neurons. It is important to emphasize that the S-ANFIS model incorporated logistic activation functions at the output according to **Definition 1 and Definition 2,** this in order to capture the intrinsic structure of forecast performance.

According to the structure of the random variables used for this study, Table 4-5 shows the results achieved by the models against the return forecast, taking as reference the structural stability indexes **(Definition 4)** and the dimensional stability indexes **(Definition 5)** mentioned above.

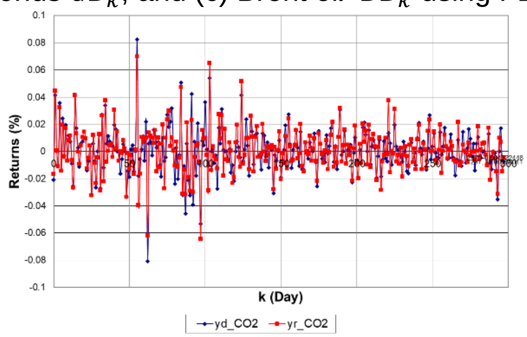
Table 4-5: Stability Analysis.

	Structural Stability																	
	FLAE						**S-ANFIS**						**FNLM**					
	yd_CO2		**yd_GB**		**yd_BB**		**yd_CO2**		**yd_GB**		**yd_BB**		**yd_CO2**		**yd_GB**		**yd_BB**	
MG	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G
VG	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G
IOA	1.000	G	0.045	P	1.000	G	0.998	G	0.046	P	0.998	G	0.988	G	0.042	P	0.989	G
FAC2	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G	1.000	G
	Dimensional Stability																	
	FLAE						**S-ANFIS**						**FNLM**					
	yd_CO2		**yd_GB**		**yd_BB**		**yd_CO2**		**yd_GB**		**yd_BB**		**yd_CO2**		**yd_GB**		**yd_BB**	
FB	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G
WDI	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G
UAPC2	0.001	G	0.004	G	0.002	G	-0.011	G	0.004	G	0.006	G	-0.005	G	0.003	G	-0.024	G
MRE	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G	0.000	G
ID	100		92.5		100		100		93		100		100		92.5		100	

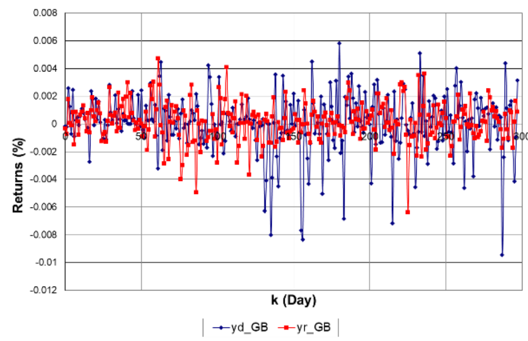
Source: Authors' own research.

Table 4-5 and Figure 4-8 show that the neural models reached average performance percentages of above 90% according to the fuzzy model proposed by Park and Seok (2007). The foregoing shows the good forecast performance shown by the neural models against the return forecast for each of the time series. The P (Poor) value reached by the models against the Index of Agreement (IOA) stands out concerning the return forecast for the GB-V series. However, the values reached by the models against the MG, VG indexes, and FAC2, account for the good forecast performance of the models concerning the identification of the average and the variation of the returns around it. It is important to underline that the distortion in structural stability was mainly due to the value reached by the IOA indicator for the GB_V time series, which indicates the presence of random temporary changes in returns during the time period considered for this series.

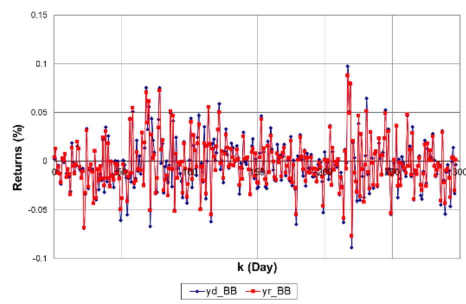
Figure 4-8: Time series reconstruction for returns of (a) CO_2 emissions $CO2_k$, (b) green bonds GB_k, and (c) Brent oil BB_k using FLAE model.



(a) CO2-E



(b) GB-V



(c) BB-P

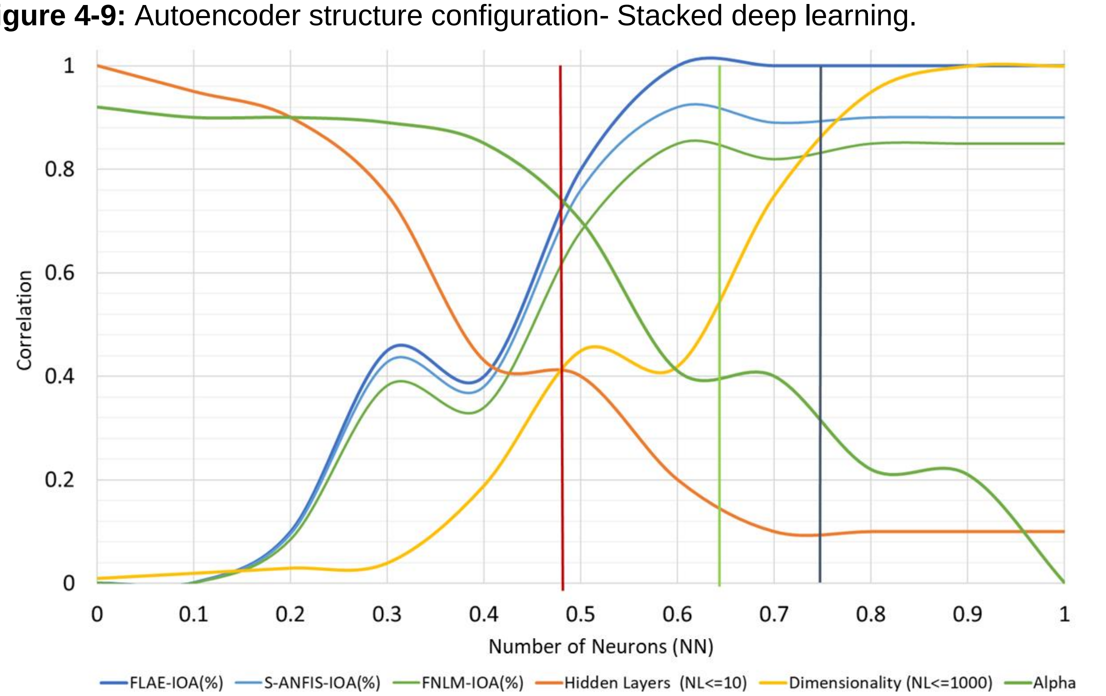
Source: Authors' own research.

Regarding the dimensional stability established by **Definition 4**, it is important to note that the FB, WDI, UAPC2, and MRE indexes obtained values that were below the level $|5| \times 10^{-4}$, which also corroborates the stability of the models against the forecast of the returns for the random variables considered for this study. The signs reached by the FB index stand out, which showed the tendency of the models to overestimate the returns, and also favored the flexibility of the models when modeling complex phenomena. Regarding the WDI, it is worth noting that the proposed model reached the minimum distances, which guarantees the good forecast performance of the FLAE model when it comes to characterizing the intrinsic structure of returns for each of the random variables considered for this study, thus according to the activation function integrating the model **(Definition 2)**. The values reached by the models against the IOA index show that the FLAE model returned the most promising results compared to the representation of the returns for the $GB - V$ variable; this is because of the flexibility of its structure which allows the integration of time series to model their behavior.

4.3.3. Results of the FLAE model

Figure 4-9 shows the behavior exhibited by the FLAE model, and by the S-ANFIS and FNLM evaluation models with autoencoder structure, compared to the return forecast for each one considered for this study, taking into account for them flexibility factors such as: hidden layers, dimensionality and Compression Index (IOA).

Figure 4-9: Autoencoder structure configuration- Stacked deep learning.



Source: Authors' own research.

In Figure 4-9, it can be seen how the IOAs are increasing, as the hidden layers and the learning factors (alpha) are decreasing. It is important to highlight that the IOAs were above 75% on average when the hidden layers and dimensionality reached the break-even point (Red Line). It is also emphasized that when the hidden layers reached unity (Blue Line), the dimensionality approached 80% ($\mathrm{no} \times 0.8$), and the neural models with autoencoder structure reached the equilibrium point in learning. Regarding the a priori dimensionality used to evaluate the FLAE (Green Line) model in its first stage ($\mathrm{no} \times 50\%$), it can be observed that the model reached IOAs close to 100%, which corroborates the good forecast performance exhibited by the model against the return forecast.

Following the above, Table 4-6 and Figure 4-10 show the behavior by the FLAE model, and its variations compared to the return forecast. This can be observed according to the logistic function that integrates the activation function. It is expected that, when the values are centered and are in the high and positive high categories, the activation function used by the proposed model has greater coverage of the solution space of the problem, unlike the low positive values, where these values rise more slender activation functions, with more limited coverage of the solution space of the problem; this can limit the process of forecasting the returns for a particular random variable.

Table 4-6: Variation in statistical characteristics of random variables (CO2-E, GB-V, BB-P)

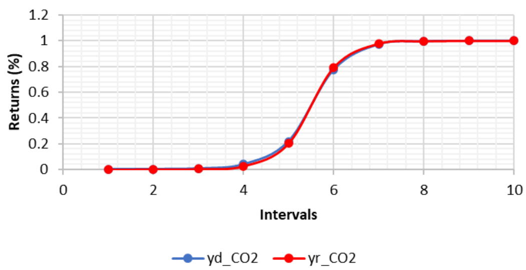
	yd_CO2	yr_CO2	Variation (%)	yd_GB	yr_GB	Variation (%)	yd_BB	yr_BB	Variation (%)
Mean	0.001138	0.001142	-0.32%	-0.000038	0.000025	166%	0.000054	0.000057	-4.96%
Variance	0.000840	0.000829	1.27%	0.000008	0.000004	48%	0.000712	0.000703	1.26%
Skew.	-0.412100	-0.402964	2.22%	-0.473464	0.449731	195%	-0.964248	-0.906411	6.00%
Kurt.	4.352971	4.260129	2.13%	6.502739	3.341896	49%	15.171825	14.260008	6.01%

Source: Authors' own research.

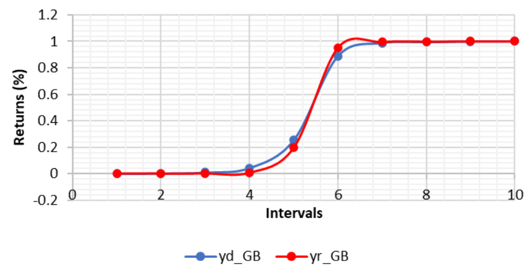
Additionally, although the negative values (negative low and negative high) allow a forecast of the returns associated with the time series of the random variables selected for this study, the activation function cannot be evaluated in these categories independently. This is because the topological structure changes in these scenarios, making it impossible to represent and analyze them as cumulative probability distributions using adaptation and learning models. Therefore, due to the activation function used, the model only works when it is in the presence of other random variables; this generates a dependency on the positive-signed variables. Thus, the analysis is focused on the results obtained in the high and positive high categories.

Additionally, Table 4-6 and Figure 4-10 show that by characterizing returns as logistic functions, FLAE model returns good forecast performance. Here, it can be observed that the variables with the smallest variations compared to indicators such as the average, the variance, the asymmetry coefficient, and the kurtosis were the CO2-E associated-returns, followed by the BB-P associated returns. It is important to highlight that these time series showed variations that were, on average, below 5%, unlike the variations for these indicators for the GB-V time series, which showed variations above 166% and 190% concerning the average and the asymmetry coefficient respectively; this again corroborates the temporal randomness in the values associated with the returns for this variable, despite the fact that, in general, the model was able to identify the intrinsic structure of the cumulative distributions for these variables through its activation function as demonstrated by MG, VG, and FAC2 (Table 4-5).

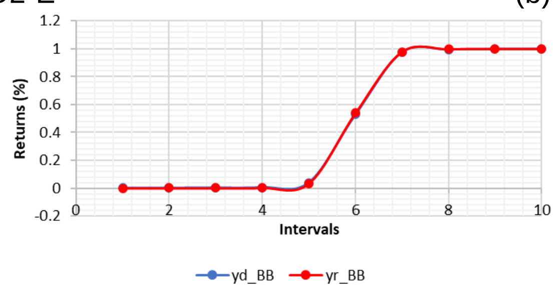
Figure 4-10: Intrinsic structure for returns according to the structure of the logistic function integrated into the FLAE model. (a) CO2 emissions, (b) green bonds, and (c) Brent oil.



(a) CO2-E



(b) GB-V

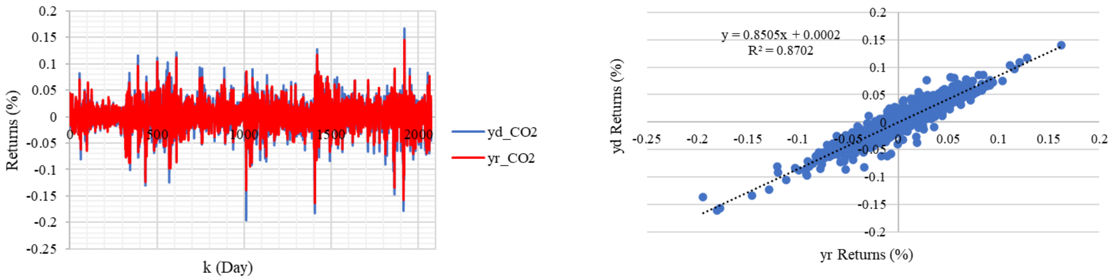


(c) BB-P

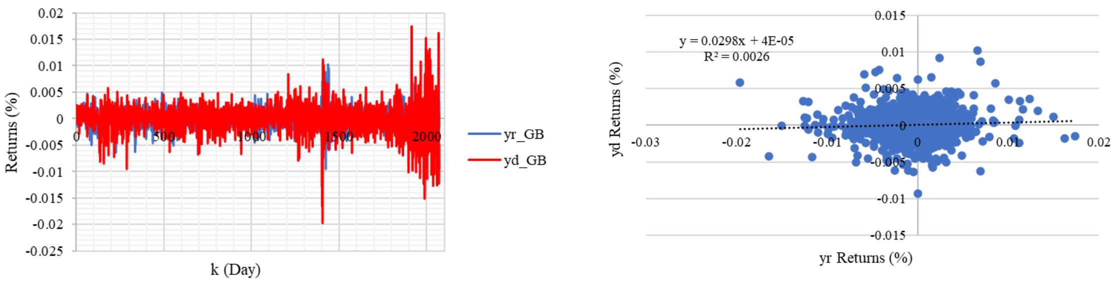
Source: Authors' own research.

On the other hand, Figure 4-11 shows the consolidated behavior of the forecast subsystem of the FLAE model against the performance forecast for a particular random variable, taking into account the independent effects associated with performance delays for the other random variables.

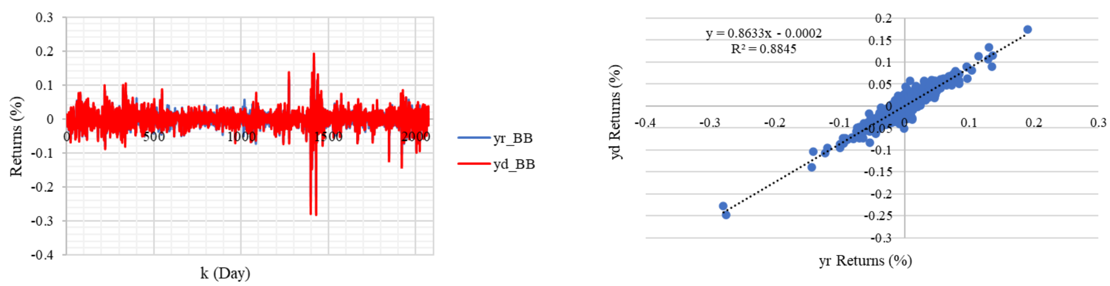
Figure 4-11: Consolidated behavior of the Fuzzy Logistic Autoencoder Model. Scatter Plot returns of (a) CO_2 emissions, (b) green bonds, and (c) Brent oil.



(a) CO2-E



(b) GB-V



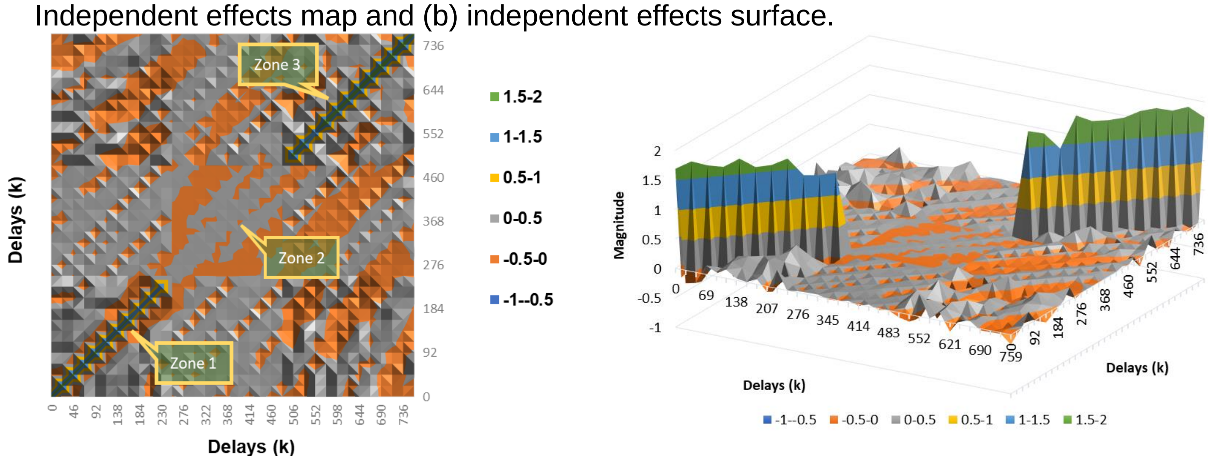
(c) BB-P

Source: Authors' own research.

Figure 4-12 shows that the model reached coefficients of determination (R^2) higher than 0.85 average against the forecast of the CO2-E returns and against the forecast of the BB-P returns, unlike the coefficient of determination for the GB-V return forecast, which only reached a value of 0.0026. The foregoing corroborates the random temporal behavior of the performance series for GB-V again.

For the cross-prognosis of the returns for each one of the random variables considered for this study, the proposed model will have three zones for the structure of the input and output neurons according to Equation (4.2). In this way, the first zone of neurons will correspond to the CO2-E returns (Zone 1: $ne_1 = 256$), the second zone of neurons will correspond to the GB-V returns (Zone 2: $ne_2 = 256$), while the third zone will correspond to the BB-P returns (Zone 3: $ne_3 = 256$). Alternatively, Figures 4-12a and 4-12b represent the map of independent effects by zones (a_i −IEs), where the magnitude of each effect represents the impact of a delay associated with a random variable, compared to the delays used in the forecast of the returns of a particular random variable. Figure 4-12a shows that the main diagonal of this map shows the dominance of the lags associated with the returns themselves for the forecast of the CO2-E returns and the BB-P price, as shown by Zone 1 and Zone 3, respectively. The interruption of the main diagonal for Zone 2 stands out, which does not present any independent effect that is relevant compared to the forecast of the GB-V returns; this indicates again the temporary random behavior that the returns present for this variable random, every time that main diagonal is interrupted (Figure 4-12a).

Figure 4-12: Map of independent effects (a_i) between lags of the time series of returns. (a) Independent effects map and (b) independent effects surface.



(a) (b)

Source: Authors' own research.

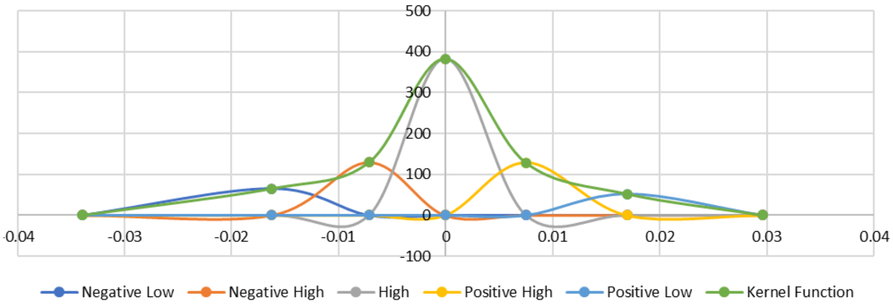
Table 4-7 and Figure 4-13 show the results obtained by the FLAE model against the characterization of the independent effects (a_i) associated with the return forecasts for each random variable included in this study **(Definition 1, Definition 2)**. Here, it can be seen that the connections associated with the return forecast for the CO2-E and BB-P random variables showed much larger magnitudes than the independent effects associated with the GB-V return forecast. It is important to emphasize that the magnitude of these effects was limited by the magnitude of the returns associated with this variable.

Table 4-7: Statistical characterization of independent effects in modeling returns for random variables. CO_2 emissions (CO2-E), green bonds (GB-V), and Brent oil (BB-P)

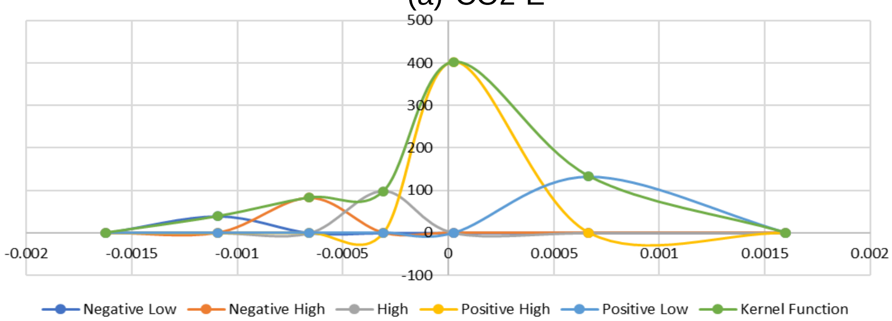
Kernel	ai_CO2	Lags	ai_GB	Lags	ai_BB	Lags
Negative Low	- 0.016264	65	- 0.001094	39	- 0.014809	64
Negative High	- 0.007175	129	- 0.000659	83	- 0.007406	118
High	- 0.000063	382	- 0.000309	98	- 0.000571	408
Positive High	0.007489	128	0.000027	403	0.006678	129
Positive Low	0.016927	52	0.000666	133	0.015664	37
Mean	- 0.000222		- 0.000037		- 0.000812	
Variance	0.000061		0.000000		0.000046	
Skew.	0.025947		- 0.320525		0.043244	
Kurt.	0.432398		0.148704		0.592242	

Source: Authors' own research.

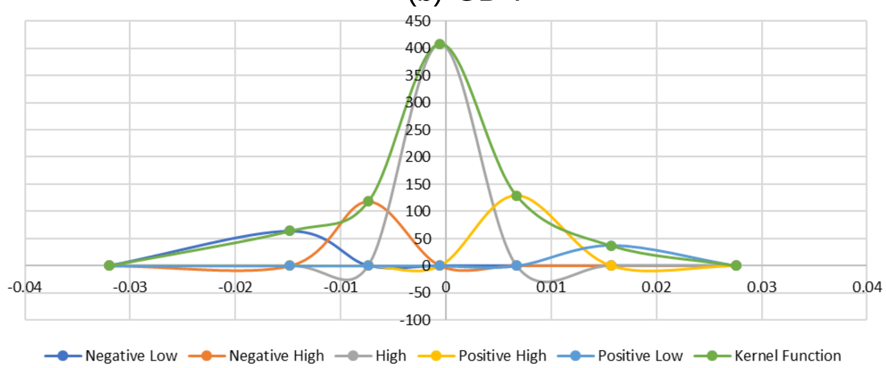
Figure 4-13: Kernel function - Structure of the independent effects in the modeling of the returns of (a) CO_2 emissions, (b) green bonds, and (c) Brent oil.



(a) CO2-E



(b) GB-V



(c) BB-P

Source: Authors' own research.

For the returns associated with the random variables CO2-E and BB-P, it is important to highlight that the largest number of their independent effects were located in the High and Positive High categories according to the structure of their Kernels (See appendices 1-6). This fact was promoted by asymmetry coefficients close to zero and extended kurtosis coefficients that added greater flexibility to the return forecast for these variables. The low variance and the value reached by the asymmetry coefficient for the Kernel GB-V favored the classification of a large part of the independent effects towards the Positive High and Positive Low categories, clearly evidencing the little effect that lags have for the Kernel GB-V return forecasting. They significantly limit the flexibility of the FLAE model when forecasting returns for the particular random variable itself, as shown by the interruption of the main diagonal that crosses Zone 2 of Independent Effects – MAP (Figures 4-12a and 4-12b).

4.4. Discussion

Classifying the results obtained in the short or medium term is essential to comprehend the results better. Thus, the authors included in the short-term (ST) the signals between the 2–4 days and 4–16 bands, and in the medium-term (MT), the signals between the 16–64 days and 64–256 bands.

Table 4-8 shows the number of significant lags for the returns forecast associated with the random variables considered in this study. Thus, Table 4-8 shows that the lags with the most significant impact (category - High) on the forecast of CO2-E returns and Brent oil returns (BB-P) were the lags associated with the GB-V random variable (252 lags), implying that, in the short-term (ST) and medium-term (MT), the Green Bond Index (GB-V) influenced the CO_2 futures' returns (CO2-E) and the oil returns (BB-P), with a negative relationship. These results have similar outcomes to the studies conducted by Mahmood et al., (2022), Mahmood & Furqan (2021), Marín-Rodríguez, González-Ruiz, & Botero (2022); Sadorsky (2009), and Zheng et al. (2021), who argued that it is expected that CO_2 futures' returns and oil returns show the same behavior against the Green Bond Index because, if oil prices rise, then the CO_2 emissions will increase too. In contrast, Marín-Rodríguez et al. (2023) found that green bonds influenced the CO_2 futures' returns and the oil returns negative in the short term, but in the medium term with a positive relationship.

This clearly shows the negative impact that GB-V lags are having on CO2-E and BB-P returns in international markets in the context of the transition towards cleaner energy, where the efforts for improving the environmental and financial sustainability of organizations are following the Sustainable Development Goals (SDGs). Then, this study utilizes key variables to examine the global goals of affordable and clean energy (Goal 7), sustainable cities and communities (Goal 11), responsible consumption and production (Goal 12), and climate action (Goal 13), which are central to the SDGs' aim of promoting long-term prosperity (Marín-Rodríguez et al., 2023). However, achieving these goals poses significant challenges due to the balancing, tensions, and trade-offs among the three pillars of sustainability based on the environmental, social, and economic domains (Giuliodori et al., 2022).

The second variable that positively influences the forecast of the CO_2 futures' returns (CO2-E) and Brent oil returns (BB-P) is the Brent oil returns (BB-P) with 71 and 96 lags, respectively. This result implies that Brent oil returns (BB-P) also have a positive impact in the short-term (ST) and medium-term (MT) for the forecast of CO2-E returns and Brent oil returns (BB-P) but considering fewer lags for the prediction (see appendices B and F). Thus, it can be seen that in the high category for the forecast of the returns of the CO2-E and BB-P returns, they generally kept the same lag structure. These results are according to Marín-Rodríguez, González-Ruiz, and Botero (2022a), who found that the correlation of oil price return with the CO_2 futures' returns is positive. However, the results of (Marín-Rodríguez et al., 2023) indicate that the relationship between oil price return with the CO_2 futures' returns is positive in the short and long term but can be positive or negative in the medium term, based on the reviewed period.

Finally, it is important to emphasize that the lag structure was similar to the forecast of the GB-V returns. However, the most significant impact was located in the Positive High category, which limited the model's flexibility in forecasting the GB-V returns. Regarding the modeling of the GB-V returns, it can be observed that the series' delays were not significant (category – High, appendix D) for its forecast. Therefore, for forecasting the returns of the GB-V series, the returns of the other two series (CO2-E and BB-P) were used, indicating the negative but smaller influence of the other two time series on its time structure in the short-term (ST) and medium-term (MT) (see appendices D and E). The results are according to (Marín-Rodríguez, González-Ruiz, & Botero, 2022) and Marín-Rodríguez et al. (2023), who found a negative relationship among oil price return and CO_2 futures' returns concerning green bonds.

Table 4-8: Number of significant time lags for the forecast of returns of CO_2 emissions, green bonds, and Brent oil

	CO2-E k		GB-V k		BB-P k	
	High	Positive High	High	Positive High	High	Positive High
CO2-E k-nr	59	51	42	59	60	29
GB-V k-nr	252	0	0	252	252	0
BB-P k-nr	71	77	56	92	96	100
Total	382	128	98	403	408	129

Source: Authors' own research.

Additionally, Table 4-8 shows no one-to-one correspondence of the CO2-E and BB-P time series compared to the return forecast for this return series (GB-V). In this way, Table 4-8 shows again, the temporary random variations that the time series presents for the GB-V returns, indicating that there is no proper temporary structure. One possible explanation for this phenomenon is the relative stability of green bond prices, which is why the return series includes a large number of zeros, limiting the prediction capability.

4.5. Conclusions

The FLAE model allowed the forecast of returns associated with three random variables CO_2 futures' returns (CO2-E), Green Bond Index (GB-V), and Brent oil prices (BB-P), integrating the series into a single structure of time that represent the returns for such variables. Due to its AE structure, the proposed model allowed identify the crossed lags (partial independent effects) with a greater impact on the returns forecast for each random variable. The effect that the lags associated with the time series of the GB-V returns had on the forecast of the CO2-E, and BB-P returns is highlighted, which shows the effect that green bonds are having on the issuance of CO_2 and the price of a barrel of oil in international markets, and the context of energy transition towards cleaner energy.

The proposed model integrated a novel activation function of the sigmoid type, which allowed, in a single neuronal structure, both the modeling of the intrinsic structure of the returns of a random variable (structural stability) and the modeling of the intrinsic structure of the returns of each random variable based on the independent effects associated with the lags of the other time series integrated into the FLAE model. In this way, the structure of the FLAE model becomes a reference model for studying cross-temporal effects among time series with temporal correlations according to their performance. The obtained results indicated that within the significant lags that contribute to the forecast of the CO2-E and BB-P returns series (category - High), as mentioned above, for the case of GB-V returns, lags ordered from time zero to lag 251 are included (appendices B and F), indicating that green bonds have a negative impact in the short and medium term to explain the forecasts of the CO_2 emissions (CO2-E) and Brent oil (BB-P) returns series. Alternatively, the BB-P and CO2-E lag returns series are also important to forecast the short, and medium-term lags of BB-P and CO2-E returns in the short and medium term, but in a smaller proportion (appendices B and F). In the case of the Green Bond Index (GB-V) return series forecasts (category - Positive High), their own lags ordered from zero to 251 are included, which indicates that the series is mainly random as it is highly dependent on impacts close to zero (which are included in the high positive category). However, Brent oil returns (BB-P), and CO_2 futures' (CO2-E) have a negative but smaller impact on its forecast.

The obtained results provide important policy implications. First, the issuance of green bonds has essential negative impacts in the short and medium term to explain the forecasts of the CO_2 emissions and Brent oil returns series. Furthermore, the relation between CO_2 emissions and Brent oil returns to forecast green bonds are also negative. Then, green bond issuances are a crucial element for the energy transition toward a low-carbon economy. This first result has two implications: (i) the negative bidirectional co-movements among CO_2 emissions and Brent oil returns series with respect to green bonds provide diversification opportunities for investors worldwide (Dutta et al., 2021; Marín-Rodríguez, González-Ruiz, & Botero, 2022; Reboredo & Ugolini, 2020). Additionally, (ii) policy-makers must strengthen their support for enterprise green bond issuance, and it is mandatory to continue making progress in this area (J. D. González-Ruiz et al., 2023; Marín-Rodríguez, González-Ruiz, & Botero, 2022).

Second, results indicate that Brent oil returns positively impact the short-term (ST) and medium-term (MT) forecasts for CO_2 futures' returns. This result can help forecast the CO_2 futures' price according to the oil price evolution in the international markets (Marín-Rodríguez, González-Ruiz, & Botero, 2022). Nevertheless, international energy markets can reflect climate change, uncertainty in green public policies, and changes in geopolitical situations (Jin et al., 2020; Marín-Rodríguez et al., 2023). Finally, it is important to emphasize that green bond forecasting depends on its lags. Furthermore, the other two series (CO_2 emissions and Brent oil returns series) also have an impact on the green bonds forecast but with a negative and more negligible influence in the short-term (ST) and medium-term (MT). The results are according to Marín-Rodríguez, González-Ruiz, & Botero (2022) and Marín-Rodríguez et al. (2023), who found a negative relationship between oil price return and CO_2 futures' returns concerning green bonds and have important implications for portfolio allocation.

As further work, it is important to validate the flexibility of the structure of the proposed FLAE model using time series with a clear temporal structural correlation among them in order to give greater importance to the independent effects that define the structure of an autoencoder model with a deep learning structure. In this sense, it is equally important to conduct studies to find independent effects with autoencoder models of greater hidden layers that help identify, with greater complexity, the effect that a time series has on the behavior of the associated returns with another variables.

Lastly, this study enlarges the discussion around the dynamic association among oil prices, green bonds, and CO_2 emissions using techniques from deep learning, such as the FLAE model. Machine learning models have been barely explored for this type of analysis, contributing to this gap in the literature. The results can guide the diversification potential of green bonds to CO_2 emissions and oil prices at different scale times. In this context, by understanding the connections among the studied variables, different actors such as researchers, managers, policy-makers, and decision-makers can gain insight into the impact of oil price shocks on sustainable practices to make informed decisions about investments and policies related to the co-movements among oil prices, green bonds, and CO_2 emissions.

5 Conclusions and recommendations

5.1 Conclusions

This study explores the dynamic relationship among green bonds, CO_2 emissions, and oil prices. Oil is a significant determinant of global economic performance, and its price's dynamics can affect the world's economy in several ways, such as market assets and economic production. In this way, an increase in oil prices will raise the cost of production of goods and services, leading to a rise in price levels and high inflation. Concerns about possible increases in price levels will produce uncertainty and negative sentiments in the financial markets, and the expected inflation will lower equity values. In addition, oil prices can set economic trends by driving gross domestic product growth (GDP). Hence, there is evidence of a linkage among the three variables analyzed: green bonds, CO_2 emissions, and oil price; it is due to the existing connection among them in industrial production, then the three variables considered represent the development of the economic activity in the present.

Understanding the interactions and dynamic relationships between green bonds, CO_2 emissions, and oil prices are paramount to ethical investors. This information is essential for gaining superior risk-adjusted returns through properly allocating a sustainable financial portfolio and managing risk (Dutta et al., 2021). The results of the negative co-movements between green bonds with oil prices and green bonds with CO_2 futures' prices have two major implications. First, negative correlations provide diversification opportunities for investors worldwide. Second, concerns policy-makers when oil prices and CO_2 futures' price increase, the Green Bonds Index is expected to decrease. Thus, green bonds appear as an attractive financial mechanism for environmentally friendly investors; issuers can employ this device to diversify their investor base and improve their environmental, social, and governance (ESG) scores (Dutta et al., 2021b; Reboredo & Ugolini, 2020). Furthermore, these results appear as an opportunity for policy-makers to design strategies for promoting eco-friendly policies that contribute to enlarging the supply of green bonds, allowing sustainable investment portfolios to be structured. Finally, the relation between the CO_2 futures' price and the oil price is mostly positive, which helps forecast the CO_2 futures' price according to the evolution of the oil price in the international markets.

The findings in this study extend several implications for researchers, managers, policymakers, and decision-makers. Thus, the negative relationship between oil prices and green bonds causes the financial markets to generate incentives to raise green financing in the context of higher oil prices. Additionally, the positive linkage between oil prices and CO_2 emissions generates that policy decisions on the transition of energy to a decarbonized economy should consider the incentives for generating green bond issuances, which are an essential instrument for the transition to a climate-resilient economy. These results are in line with Jin et al. (2020).

The findings are also relevant in the contribution for formulating green finance policies and supporting renewable investments. This is due to the negative relation founded between green bonds and CO_2 emissions. This topic acquires a particular interest in emerging countries where more outstanding efforts are required to expand the offer of these eco-friendly instruments. The preceding is because, for example, in the Latin American and Caribbean markets, investors in the local markets have a strong demand for this type of instrument. Additionally, the support from policymakers towards the generation of energy transition policies could facilitate and encourage the generation of renewable energies procuring the criteria of climate bond initiatives.

According to Jin et al. (2020), the findings also suggest that investors in green bond markets are sensitive to fluctuations in energy and carbon markets because the carbon market can reflect climate change, uncertainty in green public policies, and changes in geopolitical situations. Additionally, we can admit that the search for sustainable investments promoted for the climate change risk has increased the popularity of green bonds, contributing to the enhanced correlation among the green bond market, oil prices, and the carbon market. This phenomenon can explain that during the outbreak of COVID-19 and the recent Russian invasion of Ukraine in February 2022, a greater percentage of co-movement among green bonds, were driven by linkage connections among the markets (Tiwari et al., 2022).

Finally, for market players and decision-makers, the results can help to improve portfolio composition since we present the diversification potential of green bonds to CO_2 emissions and oil prices. Furthermore, based on the principal findings, several co-movements patterns in different frequency bands suggest that investors should determine the corresponding risk prevention strategies based on their investment time horizons. The above results can assist investors in making portfolio selection decisions within the Brent oil price, green bond markets, and carbon markets, as well as scale-conscious (or investment horizons-conscious) traders making trading decisions, as (Omane-Adjepong et al., 2019; Qureshi et al., 2020) mentioned.

The summary of the findings and policy implications can be presented as follows:

Findings:

- Green bonds have a negative relationship with CO_2 emissions and oil prices. However, these negative co-movements provide diversification opportunities for investors. Additionally, these results appear as an opportunity for policy-makers to design strategies for promoting eco-friendly policies that contribute to enlarging the supply of green bonds, allowing sustainable investment portfolios to be structured.
- Brent oil returns positively impact the short-term and medium-term forecasts for CO_2 futures' returns. This result can help forecast the CO_2 futures' price according to the oil price evolution in the international markets.
- Finally, it is important to emphasize that green bond forecasting depends on its lags. Furthermore, the other two series (CO_2 emissions and Brent oil returns series) also have an impact on the green bonds forecast but with a negative and more negligible influence in the short-term and medium-term.

Policy implications:

- The findings in this study extend several implications for researchers, managers, policymakers, and decision-makers. Thus, The negative relationship between oil prices and green bonds causes the financial markets to generate incentives to raise green financing in the context of higher oil prices.
- The positive linkage between oil prices and CO_2 emissions generates that policy decisions on the transition of energy to a decarbonized economy should consider the incentives for generating green bond issuances, which are an essential instrument for the transition to a climate-resilient economy.
- The findings are also relevant in the contribution for formulating green finance policies and supporting renewable investments. This is due to the negative relation founded between green bonds and CO_2 emissions. For example, investors have a strong

demand for this type of financial mechanism in the Latin American and Caribbean markets. Additionally, the support from policymakers towards the generation of energy transition policies could facilitate and encourage the generation of renewable energies procuring the criteria of climate bond initiatives.

- For market players and decision-makers, the results can help to improve portfolio composition since we present the diversification potential of green bonds to CO_2 emissions and oil prices.
- Finally, based on the principal findings, several co-movements patterns in different frequency bands suggest that investors should determine the corresponding risk prevention strategies based on their investment time horizons.

5.2 Recommendations

Despite the contributions of the present study, limitations should be acknowledged. First, the daily data are available only for developed markets such as Europe. This is mainly due to the lack of data for dynamic correlation studies among CO_2 emissions and green bond markets to contrast the results obtained in this analysis, for example, data from emerging markets. Second, the limited literature on green bond markets and their relations with oil prices and CO_2 emissions simultaneously to compare results.

Although this study enlarges the discussion around the dynamic association among oil prices, green bonds, and CO_2 emissions and addresses the diversification potential of green bonds to CO_2 emissions prices and oil prices in different frequency bands, a possible limitation of the study can be related to the data time-frequency. For example, some investors in energy markets and sustainable assets can prefer to make decisions over longer investment horizons, which is in line with (Saeed et al., 2021). Therefore, further research can address this limitation by using lower frequency data (i.e., weekly or monthly data) and considering the heterogeneity of investors over different investment horizons.

Lastly, this study enlarges the discussion around the dynamic association among oil prices, green bonds, and CO_2 emissions using techniques from deep learning, such as the FLAE model. Machine learning models have been barely explored for this type of analysis, contributing to this gap in the literature. The results can guide the diversification potential of green bonds to CO_2 emissions and oil prices at different scale times. In this context, by understanding the connections among the studied variables, different actors such as researchers, managers, policy-makers, and decision-makers can gain insight into the impact of oil price shocks on sustainable practices to make informed decisions about investments and policies related to the co-movements among oil prices, green bonds, and CO_2 emissions.

The above findings are relevant to investors and policy-makers keen to understand the dynamics of conditional correlations among green bonds, CO_2 prices, and oil prices, which can affect diversification strategies and the design of environmental policies. In this regard, given that green bonds are becoming an essential financial mechanism for achieving the SDGs, it is also mandatory to gain a better understanding of decision-makers perspectives in designing investment portfolios. Further research could also help to comprehend this issue deeply in this concern. Thus, there is great potential for further research on green bonds and their relationships with other financial assets, particularly those highly related to investment decisions, for example, stocks, which have been little explored. For this, machine learning models could be implemented. These studies could also be extended to the Latin American and Caribbean markets, where research on these issues is scarce. Furthermore, a hedging analysis can be conducted in further research of co-movements, their time-frequency domains, and investment horizons can have implications for dynamic hedging, asset allocation, and utility earnings. Finally, it is important to highlight that finance will be fully sustainable in the short term. In this scenario, green bonds play a pivotal role.

Additionally, as further work, it is important to validate the flexibility of the structure of the proposed FLAE model using time series with a clear temporal structural correlation among them in order to give greater importance to the independent effects that define the structure of an autoencoder model with a deep learning structure. In this sense, it is equally important to conduct studies to find independent effects with autoencoder models of greater hidden layers that help identify, with greater complexity, the effect that a time series has on the behavior of the associated returns with another variables.

A summary of the recommendations can be presented as follows:

<u>Limitations:</u>

- The daily data are available only for developed markets such as Europe. This is mainly due to the lack of data for dynamic correlation studies among CO_2 emissions and green bond markets to contrast the results obtained in this analysis, for example, data from emerging markets.

- The limited literature on green bond markets and their relations with oil prices and CO_2 emissions simultaneously compares results.
- A possible limitation of the study can be related to the data time-frequency. For example, some investors in energy markets and sustainable assets can prefer to make decisions over longer investment horizons.

Further research:

- Further research can address research by using lower frequency data (i.e., weekly or monthly data) and considering the heterogeneity of investors over different investment horizons.
- There is a great potential for further research on green bonds and their relationships with other financial assets, particularly those highly related to investment decisions, for example, stocks, which have been little explored. For this, machine learning models could be implemented.
- The studies could also be extended to the Latin American and Caribbean markets, where research on these issues is scarce.
- Hedging analysis can be conducted in further research of co-movements, their time-frequency domains, and investment horizons can have implications for dynamic hedging, asset allocation, and utility earnings.
- Green bonds will be a pivotal player in the global decarbonization scenario. Thus, analysis of the deep structure dependence of the green bond with its lags and other variables will be an interesting research topic.
- A hybrid DCDNNs (i.e. the DCC-GARCH-DNNs model) model, based on the RDNNs (Recurrent Deep Neural Networks) and DCC-GARCH models must be useful for contrast the obtained results in this study. For example, Ni & Xu (2023) show that the accuracy of the DCDNNs model is significantly higher than that of the DCC-GARCH model.
- It is important to validate the flexibility of the structure of the proposed FLAE model using time series with a clear temporal structural correlation among them in order to give greater importance to the independent effects that define the structure of an autoencoder model with a deep learning structure. In this sense, it is equally important to conduct studies to find independent effects with autoencoder models of greater hidden layers that help identify, with greater complexity, the effect that a time series has on the behavior of the associated returns with other variables.

Appendices

Appendix A. Dataset

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1	2/01/2014	4.74	100.00	107.78	-0.0250	0.0000	-0.0276
2	3/01/2014	4.72	100.00	106.89	-0.0042	0.0000	-0.0083
3	6/01/2014	4.64	100.00	106.73	-0.0171	0.0000	-0.0015
4	7/01/2014	4.69	100.00	107.35	0.0107	0.0000	0.0058
5	8/01/2014	4.58	100.00	107.15	-0.0237	0.0000	-0.0019
6	9/01/2014	4.51	100.00	106.39	-0.0154	0.0000	-0.0071
7	10/01/2014	4.53	100.00	107.25	0.0044	0.0000	0.0081
8	13/01/2014	4.63	100.00	106.75	0.0218	0.0000	-0.0047
9	14/01/2014	4.83	100.00	106.39	0.0423	0.0000	-0.0034
10	15/01/2014	4.82	100.00	107.13	-0.0021	0.0000	0.0069
11	16/01/2014	5.07	100.00	107.09	0.0506	0.0000	-0.0004
12	17/01/2014	5.07	100.00	106.48	0.0000	0.0000	-0.0057
13	20/01/2014	4.93	100.00	106.35	-0.0280	0.0000	-0.0012
14	21/01/2014	5.04	100.00	106.73	0.0221	0.0000	0.0036
15	22/01/2014	5.13	100.00	108.27	0.0177	0.0000	0.0143
16	23/01/2014	5.03	100.00	107.58	-0.0197	0.0000	-0.0064
17	24/01/2014	5.26	100.00	107.88	0.0447	0.0000	0.0028
18	27/01/2014	5.37	100.00	106.69	0.0207	0.0000	-0.0111
19	28/01/2014	5.52	100.00	107.41	0.0275	0.0000	0.0067
20	29/01/2014	5.5	100.00	107.85	-0.0036	0.0000	0.0041
21	30/01/2014	5.71	100.00	107.95	0.0375	0.0000	0.0009
22	31/01/2014	5.52	101.98	106.4	-0.0338	0.0196	-0.0145
23	3/02/2014	5.84	101.98	106.04	0.0564	0.0000	-0.0034
24	4/02/2014	5.82	101.98	105.78	-0.0034	0.0000	-0.0025
25	5/02/2014	6.07	101.98	106.25	0.0421	0.0000	0.0044
26	6/02/2014	6.44	101.98	107.19	0.0592	0.0000	0.0088
27	7/02/2014	6.42	101.98	109.57	-0.0031	0.0000	0.0220
28	10/02/2014	6.4	101.98	108.63	-0.0031	0.0000	-0.0086
29	11/02/2014	6.24	101.98	108.68	-0.0253	0.0000	0.0005
30	12/02/2014	6.35	101.98	108.79	0.0175	0.0000	0.0010

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
31	13/02/2014	6.38	101.98	108.73	0.0047	0.0000	-0.0006
32	14/02/2014	6.58	101.98	109.08	0.0309	0.0000	0.0032
33	17/02/2014	6.8	101.98	109.18	0.0329	0.0000	0.0009
34	18/02/2014	6.74	101.98	110.46	-0.0089	0.0000	0.0117
35	19/02/2014	6.91	101.98	110.47	0.0249	0.0000	0.0001
36	20/02/2014	6.98	101.98	110.3	0.0101	0.0000	-0.0015
37	21/02/2014	7.13	101.98	109.85	0.0213	0.0000	-0.0041
38	24/02/2014	7	101.98	110.64	-0.0184	0.0000	0.0072
39	25/02/2014	6.21	101.98	109.51	-0.1197	0.0000	-0.0103
40	26/02/2014	6.48	101.98	109.52	0.0426	0.0000	0.0001
41	27/02/2014	6.5	101.98	108.96	0.0031	0.0000	-0.0051
42	28/02/2014	7.06	102.31	109.07	0.0826	0.0033	0.0010
43	3/03/2014	6.61	102.31	111.2	-0.0659	0.0000	0.0193
44	4/03/2014	6.81	102.31	109.3	0.0298	0.0000	-0.0172
45	5/03/2014	6.77	102.31	107.76	-0.0059	0.0000	-0.0142
46	6/03/2014	6.8	102.31	108.1	0.0044	0.0000	0.0032
47	7/03/2014	6.9	102.31	109	0.0146	0.0000	0.0083
48	10/03/2014	6.89	102.31	108.08	-0.0015	0.0000	-0.0085
49	11/03/2014	6.82	102.31	108.55	-0.0102	0.0000	0.0043
50	12/03/2014	6.5	102.31	108.02	-0.0481	0.0000	-0.0049
51	13/03/2014	6.43	102.31	107.39	-0.0108	0.0000	-0.0058
52	14/03/2014	6.29	102.31	108.57	-0.0220	0.0000	0.0109
53	17/03/2014	5.87	102.31	106.24	-0.0691	0.0000	-0.0217
54	18/03/2014	5.75	102.31	106.79	-0.0207	0.0000	0.0052
55	19/03/2014	5.99	102.31	105.85	0.0409	0.0000	-0.0088
56	20/03/2014	6.01	102.31	106.45	0.0033	0.0000	0.0057
57	21/03/2014	6.18	102.31	106.92	0.0279	0.0000	0.0044
58	24/03/2014	5.86	102.31	106.81	-0.0532	0.0000	-0.0010
59	25/03/2014	5.85	102.31	106.99	-0.0017	0.0000	0.0017
60	26/03/2014	5.8	102.31	107.03	-0.0086	0.0000	0.0004
61	27/03/2014	5.17	102.31	107.83	-0.1150	0.0000	0.0074
62	28/03/2014	4.34	102.31	108.07	-0.1750	0.0000	0.0022
63	31/03/2014	4.64	102.94	107.76	0.0668	0.0061	-0.0029
64	1/04/2014	5.06	102.94	105.62	0.0867	0.0000	-0.0201
65	2/04/2014	4.85	102.94	104.79	-0.0424	0.0000	-0.0079
66	3/04/2014	4.87	102.94	106.15	0.0041	0.0000	0.0129
67	4/04/2014	4.7	102.94	106.72	-0.0355	0.0000	0.0054
68	7/04/2014	4.99	102.94	105.82	0.0599	0.0000	-0.0085
69	8/04/2014	4.87	102.94	107.67	-0.0243	0.0000	0.0173
70	9/04/2014	4.95	102.94	107.98	0.0163	0.0000	0.0029

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
71	10/04/2014	5.13	102.94	107.46	0.0357	0.0000	-0.0048
72	11/04/2014	5.33	102.94	107.33	0.0382	0.0000	-0.0012
73	14/04/2014	5.25	102.94	109.07	-0.0151	0.0000	0.0161
74	15/04/2014	5.55	102.94	108.74	0.0556	0.0000	-0.0030
75	16/04/2014	5.47	102.94	109.6	-0.0145	0.0000	0.0079
76	17/04/2014	5.56	102.94	109.53	0.0163	0.0000	-0.0006
77	18/04/2014	5.56	102.94	109.53	0.0000	0.0000	0.0000
78	21/04/2014	5.56	102.94	109.95	0.0000	0.0000	0.0038
79	22/04/2014	5.69	102.94	109.27	0.0231	0.0000	-0.0062
80	23/04/2014	5.68	102.94	109.11	-0.0018	0.0000	-0.0015
81	24/04/2014	5.73	102.94	110.33	0.0088	0.0000	0.0111
82	25/04/2014	5.08	102.94	109.58	-0.1204	0.0000	-0.0068
83	28/04/2014	5.22	102.94	108.12	0.0272	0.0000	-0.0134
84	29/04/2014	5.43	102.94	108.98	0.0394	0.0000	0.0079
85	30/04/2014	5.42	103.76	108.07	-0.0018	0.0079	-0.0084
86	1/05/2014	5.42	103.76	107.76	0.0000	0.0000	-0.0029
87	2/05/2014	5.2	103.76	108.59	-0.0414	0.0000	0.0077
88	5/05/2014	5.23	103.76	107.72	0.0058	0.0000	-0.0080
89	6/05/2014	5.24	103.76	107.06	0.0019	0.0000	-0.0061
90	7/05/2014	5.14	103.76	108.13	-0.0193	0.0000	0.0099
91	8/05/2014	5.15	103.76	108.04	0.0019	0.0000	-0.0008
92	9/05/2014	5.25	103.76	107.89	0.0192	0.0000	-0.0014
93	12/05/2014	5.31	103.76	108.41	0.0114	0.0000	0.0048
94	13/05/2014	5.3	103.76	109.24	-0.0019	0.0000	0.0076
95	14/05/2014	5.12	103.76	110.19	-0.0346	0.0000	0.0087
96	15/05/2014	4.78	103.76	110.44	-0.0687	0.0000	0.0023
97	16/05/2014	4.8	103.76	109.75	0.0042	0.0000	-0.0063
98	19/05/2014	4.7	103.76	109.37	-0.0211	0.0000	-0.0035
99	20/05/2014	4.84	103.76	109.69	0.0294	0.0000	0.0029
100	21/05/2014	5.12	103.76	110.55	0.0562	0.0000	0.0078
101	22/05/2014	5.16	103.76	110.36	0.0078	0.0000	-0.0017
102	23/05/2014	5.12	103.76	110.54	-0.0078	0.0000	0.0016
103	26/05/2014	5.09	103.76	110.32	-0.0059	0.0000	-0.0020
104	27/05/2014	5.17	103.76	110.02	0.0156	0.0000	-0.0027
105	28/05/2014	5.2	103.76	109.81	0.0058	0.0000	-0.0019
106	29/05/2014	5.2	103.76	109.97	0.0000	0.0000	0.0015
107	30/05/2014	5.05	105.05	109.41	-0.0293	0.0124	-0.0051
108	2/06/2014	5.14	105.05	108.83	0.0177	0.0000	-0.0053
109	3/06/2014	5.43	105.05	108.82	0.0549	0.0000	-0.0001
110	4/06/2014	5.39	105.05	108.4	-0.0074	0.0000	-0.0039

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
111	5/06/2014	5.54	105.05	108.79	0.0274	0.0000	0.0036
112	6/06/2014	5.44	105.05	108.61	-0.0182	0.0000	-0.0017
113	9/06/2014	5.53	105.05	109.99	0.0164	0.0000	0.0126
114	10/06/2014	5.49	105.05	109.52	-0.0073	0.0000	-0.0043
115	11/06/2014	5.36	105.05	109.95	-0.0240	0.0000	0.0039
116	12/06/2014	5.55	105.05	113.02	0.0348	0.0000	0.0275
117	13/06/2014	5.66	105.05	113.41	0.0196	0.0000	0.0034
118	16/06/2014	5.63	105.05	112.94	-0.0053	0.0000	-0.0042
119	17/06/2014	5.7	105.05	113.45	0.0124	0.0000	0.0045
120	18/06/2014	5.65	105.05	114.26	-0.0088	0.0000	0.0071
121	19/06/2014	5.54	105.05	115.06	-0.0197	0.0000	0.0070
122	20/06/2014	5.65	105.05	114.81	0.0197	0.0000	-0.0022
123	23/06/2014	5.79	105.05	114.12	0.0245	0.0000	-0.0060
124	24/06/2014	5.74	105.05	114.46	-0.0087	0.0000	0.0030
125	25/06/2014	5.71	105.05	114	-0.0052	0.0000	-0.0040
126	26/06/2014	5.7	105.05	113.21	-0.0018	0.0000	-0.0070
127	27/06/2014	5.76	105.05	113.3	0.0105	0.0000	0.0008
128	30/06/2014	5.81	106.07	112.36	0.0086	0.0097	-0.0083
129	1/07/2014	6.03	106.07	112.29	0.0372	0.0000	-0.0006
130	2/07/2014	6.09	106.07	111.24	0.0099	0.0000	-0.0094
131	3/07/2014	6.01	106.07	111	-0.0132	0.0000	-0.0022
132	4/07/2014	5.67	106.07	110.64	-0.0582	0.0000	-0.0032
133	7/07/2014	5.56	106.07	110.24	-0.0196	0.0000	-0.0036
134	8/07/2014	5.75	106.07	108.94	0.0336	0.0000	-0.0119
135	9/07/2014	5.81	106.07	108.28	0.0104	0.0000	-0.0061
136	10/07/2014	5.68	106.07	108.67	-0.0226	0.0000	0.0036
137	11/07/2014	5.74	106.07	106.66	0.0105	0.0000	-0.0187
138	14/07/2014	5.88	106.07	106.98	0.0241	0.0000	0.0030
139	15/07/2014	5.94	106.07	106.02	0.0102	0.0000	-0.0090
140	16/07/2014	6.04	106.07	105.85	0.0167	0.0000	-0.0016
141	17/07/2014	6.15	106.07	107.89	0.0180	0.0000	0.0191
142	18/07/2014	6	106.07	107.24	-0.0247	0.0000	-0.0060
143	21/07/2014	6.06	106.07	107.68	0.0100	0.0000	0.0041
144	22/07/2014	6.17	106.07	107.33	0.0180	0.0000	-0.0033
145	23/07/2014	6.17	106.07	108.03	0.0000	0.0000	0.0065
146	24/07/2014	6.05	106.07	107.07	-0.0196	0.0000	-0.0089
147	25/07/2014	6.13	106.07	108.39	0.0131	0.0000	0.0123
148	28/07/2014	6.19	106.07	107.57	0.0097	0.0000	-0.0076
149	29/07/2014	6.03	106.07	107.72	-0.0262	0.0000	0.0014
150	30/07/2014	6.13	106.07	106.51	0.0164	0.0000	-0.0113

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
151	31/07/2014	6.21	106.89	106.02	0.0130	0.0077	-0.0046
152	1/08/2014	6.27	106.89	104.84	0.0096	0.0000	-0.0112
153	4/08/2014	6.23	106.89	105.41	-0.0064	0.0000	0.0054
154	5/08/2014	6.2	106.89	104.61	-0.0048	0.0000	-0.0076
155	6/08/2014	6.21	106.89	104.59	0.0016	0.0000	-0.0002
156	7/08/2014	5.94	106.89	105.44	-0.0445	0.0000	0.0081
157	8/08/2014	5.97	106.89	105.02	0.0050	0.0000	-0.0040
158	11/08/2014	6.13	106.89	104.68	0.0264	0.0000	-0.0032
159	12/08/2014	6.11	106.89	103.02	-0.0033	0.0000	-0.0160
160	13/08/2014	6.23	106.89	104.28	0.0194	0.0000	0.0122
161	14/08/2014	6.23	106.89	102.01	0.0000	0.0000	-0.0220
162	15/08/2014	6.38	106.89	103.53	0.0238	0.0000	0.0148
163	18/08/2014	6.34	106.89	101.6	-0.0063	0.0000	-0.0188
164	19/08/2014	6.43	106.89	101.56	0.0141	0.0000	-0.0004
165	20/08/2014	6.41	106.89	102.28	-0.0031	0.0000	0.0071
166	21/08/2014	6.34	106.89	102.63	-0.0110	0.0000	0.0034
167	22/08/2014	6.35	106.89	102.29	0.0016	0.0000	-0.0033
168	25/08/2014	6.32	106.89	102.65	-0.0047	0.0000	0.0035
169	26/08/2014	6.29	106.89	102.5	-0.0048	0.0000	-0.0015
170	27/08/2014	6.35	106.89	102.72	0.0095	0.0000	0.0021
171	28/08/2014	6.43	106.89	102.46	0.0125	0.0000	-0.0025
172	29/08/2014	6.38	108.61	103.19	-0.0078	0.0159	0.0071
173	1/09/2014	6.39	108.61	102.79	0.0016	0.0000	-0.0039
174	2/09/2014	6.38	108.61	100.34	-0.0016	0.0000	-0.0241
175	3/09/2014	6.32	108.61	102.77	-0.0094	0.0000	0.0239
176	4/09/2014	6.11	108.61	101.83	-0.0338	0.0000	-0.0092
177	5/09/2014	6.26	108.61	100.82	0.0243	0.0000	-0.0100
178	8/09/2014	6.27	108.61	100.2	0.0016	0.0000	-0.0062
179	9/09/2014	6.12	108.61	99.16	-0.0242	0.0000	-0.0104
180	10/09/2014	6.08	108.61	98.04	-0.0066	0.0000	-0.0114
181	11/09/2014	6.1	108.61	98.08	0.0033	0.0000	0.0004
182	12/09/2014	6.04	108.61	97.11	-0.0099	0.0000	-0.0099
183	15/09/2014	5.91	108.61	96.65	-0.0218	0.0000	-0.0047
184	16/09/2014	5.79	108.61	99.05	-0.0205	0.0000	0.0245
185	17/09/2014	5.88	108.61	98.97	0.0154	0.0000	-0.0008
186	18/09/2014	5.97	108.61	97.7	0.0152	0.0000	-0.0129
187	19/09/2014	6.01	108.61	98.39	0.0067	0.0000	0.0070
188	22/09/2014	5.98	108.61	96.97	-0.0050	0.0000	-0.0145
189	23/09/2014	5.65	108.61	96.85	-0.0568	0.0000	-0.0012
190	24/09/2014	5.8	108.61	96.95	0.0262	0.0000	0.0010

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
191	25/09/2014	5.8	108.61	97	0.0000	0.0000	0.0005
192	26/09/2014	5.91	108.61	97	0.0188	0.0000	0.0000
193	29/09/2014	5.75	108.61	97.2	-0.0274	0.0000	0.0021
194	30/09/2014	5.84	108.93	94.67	0.0155	0.0029	-0.0264
195	1/10/2014	5.81	108.93	94.16	-0.0052	0.0000	-0.0054
196	2/10/2014	5.69	108.93	93.42	-0.0209	0.0000	-0.0079
197	3/10/2014	5.68	108.93	92.31	-0.0018	0.0000	-0.0120
198	6/10/2014	5.68	108.93	92.79	0.0000	0.0000	0.0052
199	7/10/2014	5.73	108.93	92.11	0.0088	0.0000	-0.0074
200	8/10/2014	6.05	108.93	91.38	0.0543	0.0000	-0.0080
201	9/10/2014	6.12	108.93	90.05	0.0115	0.0000	-0.0147
202	10/10/2014	6.04	108.93	90.21	-0.0132	0.0000	0.0018
203	13/10/2014	6.06	108.93	88.89	0.0033	0.0000	-0.0147
204	14/10/2014	6.08	109.36	85.04	0.0033	0.0039	-0.0443
205	15/10/2014	6.15	109.69	83.78	0.0114	0.0031	-0.0149
206	16/10/2014	6.21	109.00	84.47	0.0097	-0.0063	0.0082
207	17/10/2014	6.13	109.00	86.16	-0.0130	0.0000	0.0198
208	20/10/2014	6.14	109.07	85.4	0.0016	0.0006	-0.0089
209	21/10/2014	6.18	109.09	86.22	0.0065	0.0001	0.0096
210	22/10/2014	6.23	109.13	84.71	0.0081	0.0004	-0.0177
211	23/10/2014	6.34	108.99	86.83	0.0175	-0.0013	0.0247
212	24/10/2014	6.41	109.06	86.13	0.0110	0.0006	-0.0081
213	27/10/2014	6.29	109.17	85.83	-0.0189	0.0011	-0.0035
214	28/10/2014	6.16	109.15	86.03	-0.0209	-0.0002	0.0023
215	29/10/2014	6.42	109.13	87.12	0.0413	-0.0002	0.0126
216	30/10/2014	6.42	109.41	86.24	0.0000	0.0026	-0.0102
217	31/10/2014	6.35	109.55	85.86	-0.0110	0.0012	-0.0044
218	3/11/2014	6.58	109.47	84.78	0.0356	-0.0007	-0.0127
219	4/11/2014	6.49	109.74	82.82	-0.0138	0.0025	-0.0234
220	5/11/2014	6.65	109.65	82.95	0.0244	-0.0009	0.0016
221	6/11/2014	6.63	109.68	82.86	-0.0030	0.0003	-0.0011
222	7/11/2014	6.76	109.73	83.39	0.0194	0.0005	0.0064
223	10/11/2014	6.72	109.72	82.34	-0.0059	-0.0001	-0.0127
224	11/11/2014	6.8	109.78	81.67	0.0118	0.0006	-0.0082
225	12/11/2014	6.85	109.90	80.38	0.0073	0.0011	-0.0159
226	13/11/2014	6.79	109.99	77.92	-0.0088	0.0008	-0.0311
227	14/11/2014	6.62	110.03	79.41	-0.0254	0.0003	0.0189
228	17/11/2014	6.9	109.98	79.31	0.0414	-0.0004	-0.0013
229	18/11/2014	7.02	109.95	78.47	0.0172	-0.0003	-0.0106
230	19/11/2014	7.04	109.65	78.1	0.0028	-0.0027	-0.0047

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
231	20/11/2014	6.96	109.91	79.33	-0.0114	0.0024	0.0156
232	21/11/2014	7	110.11	80.36	0.0057	0.0018	0.0129
233	24/11/2014	7.05	110.10	79.68	0.0071	-0.0001	-0.0085
234	25/11/2014	7.12	110.30	78.33	0.0099	0.0018	-0.0171
235	26/11/2014	7.19	110.33	77.75	0.0098	0.0003	-0.0074
236	27/11/2014	7.09	110.51	72.58	-0.0140	0.0016	-0.0688
237	28/11/2014	7.04	110.52	70.15	-0.0071	0.0001	-0.0341
238	1/12/2014	7.07	110.40	72.54	0.0043	-0.0011	0.0335
239	2/12/2014	6.85	110.28	70.54	-0.0316	-0.0011	-0.0280
240	3/12/2014	6.89	110.31	69.92	0.0058	0.0003	-0.0088
241	4/12/2014	6.84	110.19	69.64	-0.0073	-0.0011	-0.0040
242	5/12/2014	6.66	110.18	69.07	-0.0267	-0.0001	-0.0082
243	8/12/2014	6.66	110.49	66.19	0.0000	0.0028	-0.0426
244	9/12/2014	6.74	110.58	66.84	0.0119	0.0008	0.0098
245	10/12/2014	6.56	110.62	64.24	-0.0271	0.0003	-0.0397
246	11/12/2014	6.74	110.69	63.68	0.0271	0.0006	-0.0088
247	12/12/2014	6.66	110.91	61.85	-0.0119	0.0021	-0.0292
248	15/12/2014	6.89	110.92	61.06	0.0340	0.0000	-0.0129
249	16/12/2014	6.93	111.04	59.86	0.0058	0.0011	-0.0198
250	17/12/2014	7.01	111.08	61.18	0.0115	0.0003	0.0218
251	18/12/2014	7.06	111.02	59.27	0.0071	-0.0005	-0.0317
252	19/12/2014	7.1	111.10	61.38	0.0056	0.0007	0.0350
253	22/12/2014	7.13	111.13	60.11	0.0042	0.0002	-0.0209
254	23/12/2014	7.27	111.16	61.69	0.0194	0.0003	0.0259
255	24/12/2014	7.39	111.16	60.24	0.0164	0.0000	-0.0238
256	25/12/2014	7.39	111.16	60.24	0.0000	0.0000	0.0000
257	26/12/2014	7.39	111.16	59.45	0.0000	0.0000	-0.0132
258	29/12/2014	7.27	111.43	57.88	-0.0164	0.0024	-0.0268
259	30/12/2014	7.23	111.48	57.9	-0.0055	0.0004	0.0003
260	31/12/2014	7.27	111.48	57.33	0.0055	0.0000	-0.0099
261	1/01/2015	7.27	111.48	57.33	0.0000	0.0000	0.0000
262	2/01/2015	7.03	111.72	56.42	-0.0336	0.0021	-0.0160
263	5/01/2015	6.93	111.69	53.11	-0.0143	-0.0002	-0.0605
264	6/01/2015	6.8	111.97	51.1	-0.0189	0.0024	-0.0386
265	7/01/2015	6.81	111.92	51.15	0.0015	-0.0004	0.0010
266	8/01/2015	6.84	111.81	50.96	0.0044	-0.0010	-0.0037
267	9/01/2015	6.74	111.96	50.11	-0.0147	0.0013	-0.0168
268	12/01/2015	6.74	111.99	47.43	0.0000	0.0003	-0.0550
269	13/01/2015	7.32	112.01	46.59	0.0826	0.0002	-0.0179
270	14/01/2015	7.19	112.35	48.69	-0.0179	0.0030	0.0441

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
271	15/01/2015	7.15	112.38	47.67	-0.0056	0.0003	-0.0212
272	16/01/2015	7.16	112.41	50.17	0.0014	0.0002	0.0511
273	19/01/2015	7.24	112.56	48.84	0.0111	0.0014	-0.0269
274	20/01/2015	7.19	112.47	47.99	-0.0069	-0.0008	-0.0176
275	21/01/2015	7.35	112.11	49.03	0.0220	-0.0032	0.0214
276	22/01/2015	6.78	112.49	48.52	-0.0807	0.0034	-0.0105
277	23/01/2015	6.82	112.99	48.79	0.0059	0.0045	0.0055
278	26/01/2015	6.87	112.78	48.16	0.0073	-0.0019	-0.0130
279	27/01/2015	6.85	112.91	49.6	-0.0029	0.0011	0.0295
280	28/01/2015	6.96	113.02	48.47	0.0159	0.0010	-0.0230
281	29/01/2015	7.07	112.88	49.13	0.0157	-0.0012	0.0135
282	30/01/2015	7.09	113.12	52.99	0.0028	0.0021	0.0756
283	2/02/2015	7.14	113.18	54.75	0.0070	0.0005	0.0327
284	3/02/2015	7.07	113.09	57.91	-0.0099	-0.0008	0.0561
285	4/02/2015	6.94	113.00	54.16	-0.0186	-0.0008	-0.0669
286	5/02/2015	7.01	113.02	56.57	0.0100	0.0002	0.0435
287	6/02/2015	6.96	112.98	57.8	-0.0072	-0.0003	0.0215
288	9/02/2015	6.93	113.10	58.34	-0.0043	0.0011	0.0093
289	10/02/2015	7.12	112.98	56.43	0.0270	-0.0011	-0.0333
290	11/02/2015	7.25	113.07	54.66	0.0181	0.0007	-0.0319
291	12/02/2015	7.41	113.27	57.05	0.0218	0.0018	0.0428
292	13/02/2015	7.65	113.23	61.52	0.0319	-0.0003	0.0754
293	16/02/2015	7.66	113.23	61.4	0.0013	0.0000	-0.0020
294	17/02/2015	7.48	113.08	62.53	-0.0238	-0.0014	0.0182
295	18/02/2015	7.5	113.07	60.53	0.0027	0.0000	-0.0325
296	19/02/2015	7.35	113.09	60.21	-0.0202	0.0002	-0.0053
297	20/02/2015	7.33	113.21	60.22	-0.0027	0.0010	0.0002
298	23/02/2015	7.71	113.29	58.9	0.0505	0.0008	-0.0222
299	24/02/2015	7.47	113.32	58.66	-0.0316	0.0003	-0.0041
300	25/02/2015	7.39	113.57	61.63	-0.0108	0.0022	0.0494
301	26/02/2015	7.06	113.71	60.05	-0.0457	0.0013	-0.0260
302	27/02/2015	7.1	113.55	62.58	0.0056	-0.0015	0.0413
303	2/03/2015	6.95	113.43	59.54	-0.0214	-0.0010	-0.0498
304	3/03/2015	6.73	113.38	61.02	-0.0322	-0.0005	0.0246
305	4/03/2015	7.02	113.21	60.55	0.0422	-0.0014	-0.0077
306	5/03/2015	6.75	113.24	60.48	-0.0392	0.0002	-0.0012
307	6/03/2015	6.8	113.05	59.73	0.0074	-0.0017	-0.0125
308	9/03/2015	6.68	113.53	58.53	-0.0178	0.0042	-0.0203
309	10/03/2015	6.82	113.91	56.39	0.0207	0.0034	-0.0372
310	11/03/2015	6.76	114.08	57.54	-0.0088	0.0014	0.0202

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
311	12/03/2015	6.41	113.81	57.08	-0.0532	-0.0023	-0.0080
312	13/03/2015	6.46	113.81	54.67	0.0078	0.0000	-0.0431
313	16/03/2015	6.49	113.74	53.44	0.0046	-0.0006	-0.0228
314	17/03/2015	6.73	113.63	53.51	0.0363	-0.0010	0.0013
315	18/03/2015	6.74	114.01	55.91	0.0015	0.0034	0.0439
316	19/03/2015	6.67	114.01	54.43	-0.0104	0.0000	-0.0268
317	20/03/2015	7.04	114.02	55.32	0.0540	0.0001	0.0162
318	23/03/2015	7.04	113.78	55.92	0.0000	-0.0021	0.0108
319	24/03/2015	7.05	113.65	55.11	0.0014	-0.0012	-0.0146
320	25/03/2015	6.99	113.73	56.48	-0.0085	0.0007	0.0246
321	26/03/2015	6.97	113.81	59.19	-0.0029	0.0007	0.0469
322	27/03/2015	6.78	113.83	56.41	-0.0276	0.0002	-0.0481
323	30/03/2015	6.9	113.77	56.29	0.0175	-0.0005	-0.0021
324	31/03/2015	6.94	113.91	55.11	0.0058	0.0012	-0.0212
325	1/04/2015	7.16	113.96	57.1	0.0312	0.0005	0.0355
326	2/04/2015	7.17	113.86	54.95	0.0014	-0.0009	-0.0384
327	3/04/2015	7.17	113.86	54.95	0.0000	0.0000	0.0000
328	6/04/2015	7.17	113.86	58.12	0.0000	0.0000	0.0561
329	7/04/2015	7.13	113.90	59.1	-0.0056	0.0003	0.0167
330	8/04/2015	7.14	114.06	55.55	0.0014	0.0014	-0.0619
331	9/04/2015	7.03	114.07	56.57	-0.0155	0.0001	0.0182
332	10/04/2015	6.96	114.11	57.87	-0.0100	0.0003	0.0227
333	13/04/2015	6.81	114.17	57.93	-0.0218	0.0005	0.0010
334	14/04/2015	6.81	114.38	58.43	0.0000	0.0018	0.0086
335	15/04/2015	6.86	114.42	60.32	0.0073	0.0003	0.0318
336	16/04/2015	6.88	114.42	63.98	0.0029	0.0000	0.0589
337	17/04/2015	6.85	114.39	63.45	-0.0044	-0.0003	-0.0083
338	20/04/2015	7.14	114.42	63.45	0.0415	0.0003	0.0000
339	21/04/2015	7.09	114.28	62.08	-0.0070	-0.0012	-0.0218
340	22/04/2015	7.1	113.99	62.73	0.0014	-0.0026	0.0104
341	23/04/2015	7.27	114.00	64.85	0.0237	0.0001	0.0332
342	24/04/2015	7.3	113.98	65.28	0.0041	-0.0002	0.0066
343	27/04/2015	7.17	113.96	64.83	-0.0180	-0.0001	-0.0069
344	28/04/2015	7.36	114.01	64.64	0.0262	0.0004	-0.0029
345	29/04/2015	7.47	113.30	65.84	0.0148	-0.0063	0.0184
346	30/04/2015	7.4	112.83	66.78	-0.0094	-0.0041	0.0142
347	1/05/2015	7.49	112.84	66.46	0.0121	0.0000	-0.0048
348	4/05/2015	7.59	112.84	66.45	0.0133	0.0000	-0.0002
349	5/05/2015	7.56	111.94	67.52	-0.0040	-0.0080	0.0160
350	6/05/2015	7.54	111.50	67.77	-0.0026	-0.0039	0.0037

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
351	7/05/2015	7.44	111.51	65.54	-0.0134	0.0001	-0.0335
352	8/05/2015	7.54	111.91	65.39	0.0134	0.0036	-0.0023
353	11/05/2015	7.63	111.65	64.91	0.0119	-0.0023	-0.0074
354	12/05/2015	7.6	111.15	66.86	-0.0039	-0.0045	0.0296
355	13/05/2015	7.65	111.04	66.81	0.0066	-0.0010	-0.0007
356	14/05/2015	7.56	110.96	66.59	-0.0118	-0.0007	-0.0033
357	15/05/2015	7.59	111.35	66.81	0.0040	0.0035	0.0033
358	18/05/2015	7.6	111.28	66.27	0.0013	-0.0006	-0.0081
359	19/05/2015	7.37	111.46	64.02	-0.0307	0.0016	-0.0345
360	20/05/2015	7.35	111.41	65.03	-0.0027	-0.0005	0.0157
361	21/05/2015	7.3	111.32	66.54	-0.0068	-0.0009	0.0230
362	22/05/2015	7.3	111.47	65.37	0.0000	0.0014	-0.0177
363	25/05/2015	7.36	111.47	65.52	0.0082	0.0000	0.0023
364	26/05/2015	7.22	111.72	63.72	-0.0192	0.0022	-0.0279
365	27/05/2015	7.17	111.70	62.06	-0.0069	-0.0002	-0.0264
366	28/05/2015	7.18	111.74	62.58	0.0014	0.0004	0.0083
367	29/05/2015	7.32	111.93	65.56	0.0193	0.0017	0.0465
368	1/06/2015	7.24	111.86	64.88	-0.0110	-0.0006	-0.0104
369	2/06/2015	7.44	111.01	65.49	0.0272	-0.0077	0.0094
370	3/06/2015	7.48	110.08	63.8	0.0054	-0.0083	-0.0261
371	4/06/2015	7.39	110.20	62.03	-0.0121	0.0010	-0.0281
372	5/06/2015	7.4	110.11	63.31	0.0014	-0.0008	0.0204
373	8/06/2015	7.44	109.84	62.69	0.0054	-0.0025	-0.0098
374	9/06/2015	7.56	109.36	64.88	0.0160	-0.0043	0.0343
375	10/06/2015	7.58	109.21	65.7	0.0026	-0.0014	0.0126
376	11/06/2015	7.5	109.70	65.11	-0.0106	0.0045	-0.0090
377	12/06/2015	7.61	109.87	63.87	0.0146	0.0015	-0.0192
378	15/06/2015	7.51	109.79	62.61	-0.0132	-0.0007	-0.0199
379	16/06/2015	7.41	109.77	63.7	-0.0134	-0.0002	0.0173
380	17/06/2015	7.46	109.78	63.87	0.0067	0.0001	0.0027
381	18/06/2015	7.45	109.70	64.26	-0.0013	-0.0007	0.0061
382	19/06/2015	7.41	109.92	63.02	-0.0054	0.0020	-0.0195
383	22/06/2015	7.46	109.37	63.34	0.0067	-0.0051	0.0051
384	23/06/2015	7.48	109.52	64.45	0.0027	0.0014	0.0174
385	24/06/2015	7.48	109.60	63.49	0.0000	0.0008	-0.0150
386	25/06/2015	7.58	109.52	63.2	0.0133	-0.0007	-0.0046
387	26/06/2015	7.52	109.24	63.26	-0.0079	-0.0026	0.0009
388	29/06/2015	7.33	109.57	62.01	-0.0256	0.0030	-0.0200
389	30/06/2015	7.44	109.70	63.59	0.0149	0.0013	0.0252
390	1/07/2015	7.48	109.58	62.01	0.0054	-0.0012	-0.0252

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
391	2/07/2015	7.44	109.38	62.07	-0.0054	-0.0017	0.0010
392	3/07/2015	7.43	109.73	60.32	-0.0013	0.0031	-0.0286
393	6/07/2015	7.37	109.74	56.54	-0.0081	0.0001	-0.0647
394	7/07/2015	7.46	110.38	56.85	0.0121	0.0058	0.0055
395	8/07/2015	7.45	110.15	57.05	-0.0013	-0.0021	0.0035
396	9/07/2015	7.48	110.02	58.61	0.0040	-0.0012	0.0270
397	10/07/2015	7.61	109.27	58.73	0.0172	-0.0068	0.0020
398	13/07/2015	7.78	109.48	57.85	0.0221	0.0019	-0.0151
399	14/07/2015	7.72	109.63	58.51	-0.0077	0.0013	0.0113
400	15/07/2015	7.75	110.01	57.05	0.0039	0.0034	-0.0253
401	16/07/2015	7.65	110.05	57.51	-0.0130	0.0004	0.0080
402	17/07/2015	7.73	110.45	57.1	0.0104	0.0036	-0.0072
403	20/07/2015	7.97	110.65	56.65	0.0306	0.0019	-0.0079
404	21/07/2015	7.95	110.59	57.04	-0.0025	-0.0006	0.0069
405	22/07/2015	7.95	110.76	56.13	0.0000	0.0015	-0.0161
406	23/07/2015	8.07	110.74	55.27	0.0150	-0.0002	-0.0154
407	24/07/2015	8	111.04	54.62	-0.0087	0.0027	-0.0118
408	27/07/2015	8.01	111.06	53.47	0.0012	0.0002	-0.0213
409	28/07/2015	8.01	111.04	53.3	0.0000	-0.0002	-0.0032
410	29/07/2015	8.05	110.97	53.38	0.0050	-0.0006	0.0015
411	30/07/2015	7.87	111.23	53.31	-0.0226	0.0023	-0.0013
412	31/07/2015	7.86	111.28	52.21	-0.0013	0.0005	-0.0208
413	3/08/2015	7.94	111.35	49.52	0.0101	0.0006	-0.0529
414	4/08/2015	7.89	111.35	49.99	-0.0063	0.0000	0.0094
415	5/08/2015	7.82	110.87	49.59	-0.0089	-0.0043	-0.0080
416	6/08/2015	7.83	111.01	49.52	0.0013	0.0012	-0.0014
417	7/08/2015	7.77	111.32	48.61	-0.0077	0.0029	-0.0185
418	10/08/2015	7.91	111.16	50.41	0.0179	-0.0015	0.0364
419	11/08/2015	8.08	111.51	49.18	0.0213	0.0032	-0.0247
420	12/08/2015	8.18	111.59	49.66	0.0123	0.0007	0.0097
421	13/08/2015	8.18	111.44	49.22	0.0000	-0.0013	-0.0089
422	14/08/2015	8.31	111.30	49.03	0.0158	-0.0013	-0.0039
423	17/08/2015	8.23	111.42	48.74	-0.0097	0.0011	-0.0059
424	18/08/2015	8.26	111.34	48.81	0.0036	-0.0008	0.0014
425	19/08/2015	8.33	111.36	47.16	0.0084	0.0002	-0.0344
426	20/08/2015	8.35	111.60	46.62	0.0024	0.0021	-0.0115
427	21/08/2015	8.19	111.54	45.46	-0.0193	-0.0005	-0.0252
428	24/08/2015	8.16	111.44	42.69	-0.0037	-0.0009	-0.0629
429	25/08/2015	8.23	110.64	43.21	0.0085	-0.0072	0.0121
430	26/08/2015	8.08	110.90	43.14	-0.0184	0.0023	-0.0016

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
431	27/08/2015	8.03	110.77	47.56	-0.0062	-0.0012	0.0975
432	28/08/2015	8.09	110.81	50.05	0.0074	0.0003	0.0510
433	31/08/2015	8.05	110.53	54.15	-0.0050	-0.0025	0.0787
434	1/09/2015	7.99	110.38	49.56	-0.0075	-0.0014	-0.0886
435	2/09/2015	8.1	110.43	50.5	0.0137	0.0004	0.0188
436	3/09/2015	8.15	110.75	50.68	0.0062	0.0029	0.0036
437	4/09/2015	8.07	111.02	49.61	-0.0099	0.0025	-0.0213
438	7/09/2015	8.06	111.02	47.63	-0.0012	-0.0001	-0.0407
439	8/09/2015	8.22	110.96	49.52	0.0197	-0.0005	0.0389
440	9/09/2015	8.25	110.88	47.58	0.0036	-0.0008	-0.0400
441	10/09/2015	8.26	110.93	48.89	0.0012	0.0005	0.0272
442	11/09/2015	8.24	111.10	48.14	-0.0024	0.0015	-0.0155
443	14/09/2015	8.21	111.02	46.37	-0.0036	-0.0007	-0.0375
444	15/09/2015	8.15	110.52	46.63	-0.0073	-0.0046	0.0056
445	16/09/2015	8.21	110.33	49.75	0.0073	-0.0017	0.0648
446	17/09/2015	8.21	110.26	49.08	0.0000	-0.0006	-0.0136
447	18/09/2015	8.09	110.83	47.47	-0.0147	0.0051	-0.0334
448	21/09/2015	7.96	110.77	48.92	-0.0162	-0.0006	0.0301
449	22/09/2015	8	111.16	49.08	0.0050	0.0035	0.0033
450	23/09/2015	8.05	111.06	47.75	0.0062	-0.0009	-0.0275
451	24/09/2015	7.99	111.08	48.17	-0.0075	0.0002	0.0088
452	25/09/2015	7.98	110.76	48.6	-0.0013	-0.0029	0.0089
453	28/09/2015	7.9	110.95	47.34	-0.0101	0.0017	-0.0263
454	29/09/2015	7.98	110.93	48.23	0.0101	-0.0002	0.0186
455	30/09/2015	8.15	110.98	48.37	0.0211	0.0005	0.0029
456	1/10/2015	8.17	111.21	47.69	0.0025	0.0020	-0.0142
457	2/10/2015	8.15	111.42	48.13	-0.0025	0.0019	0.0092
458	5/10/2015	8.21	111.22	49.25	0.0073	-0.0018	0.0230
459	6/10/2015	8.22	111.08	51.92	0.0012	-0.0013	0.0528
460	7/10/2015	8.11	111.09	51.33	-0.0135	0.0001	-0.0114
461	8/10/2015	8.13	111.19	53.05	0.0025	0.0010	0.0330
462	9/10/2015	8.35	111.06	52.65	0.0267	-0.0012	-0.0076
463	12/10/2015	8.3	111.28	49.86	-0.0060	0.0020	-0.0544
464	13/10/2015	8.33	111.20	49.24	0.0036	-0.0007	-0.0125
465	14/10/2015	8.44	111.49	49.15	0.0131	0.0025	-0.0018
466	15/10/2015	8.43	111.42	48.71	-0.0012	-0.0006	-0.0090
467	16/10/2015	8.39	111.49	50.46	-0.0048	0.0006	0.0353
468	19/10/2015	8.35	111.43	48.61	-0.0048	-0.0006	-0.0374
469	20/10/2015	8.47	111.11	48.71	0.0143	-0.0029	0.0021
470	21/10/2015	8.45	111.42	47.85	-0.0024	0.0028	-0.0178

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
471	22/10/2015	8.48	111.87	48.08	0.0035	0.0040	0.0048
472	23/10/2015	8.63	111.92	47.99	0.0175	0.0005	-0.0019
473	26/10/2015	8.66	112.06	47.54	0.0035	0.0013	-0.0094
474	27/10/2015	8.61	112.41	46.81	-0.0058	0.0030	-0.0155
475	28/10/2015	8.57	112.46	49.05	-0.0047	0.0005	0.0467
476	29/10/2015	8.68	111.94	48.8	0.0128	-0.0046	-0.0051
477	30/10/2015	8.64	111.96	49.56	-0.0046	0.0002	0.0155
478	2/11/2015	8.6	111.74	48.79	-0.0046	-0.0020	-0.0157
479	3/11/2015	8.45	111.77	50.54	-0.0176	0.0003	0.0352
480	4/11/2015	8.4	111.74	48.58	-0.0059	-0.0003	-0.0396
481	5/11/2015	8.47	111.79	47.98	0.0083	0.0004	-0.0124
482	6/11/2015	8.41	111.36	47.42	-0.0071	-0.0038	-0.0117
483	9/11/2015	8.32	111.56	47.19	-0.0108	0.0018	-0.0049
484	10/11/2015	8.44	111.81	47.44	0.0143	0.0022	0.0053
485	11/11/2015	8.44	111.94	45.81	0.0000	0.0011	-0.0350
486	12/11/2015	8.37	111.92	44.06	-0.0083	-0.0002	-0.0390
487	13/11/2015	8.39	112.13	43.61	0.0024	0.0019	-0.0103
488	16/11/2015	8.53	112.24	44.56	0.0165	0.0010	0.0216
489	17/11/2015	8.61	112.30	43.57	0.0093	0.0006	-0.0225
490	18/11/2015	8.58	112.43	44.14	-0.0035	0.0011	0.0130
491	19/11/2015	8.63	112.56	44.18	0.0058	0.0012	0.0009
492	20/11/2015	8.51	112.65	44.66	-0.0140	0.0007	0.0108
493	23/11/2015	8.56	112.44	44.83	0.0059	-0.0018	0.0038
494	24/11/2015	8.65	112.55	46.12	0.0105	0.0009	0.0284
495	25/11/2015	8.62	112.72	46.17	-0.0035	0.0015	0.0011
496	26/11/2015	8.58	112.70	45.46	-0.0047	-0.0002	-0.0155
497	27/11/2015	8.58	112.84	44.86	0.0000	0.0012	-0.0133
498	30/11/2015	8.58	112.71	44.61	0.0000	-0.0011	-0.0056
499	1/12/2015	8.56	112.77	44.44	-0.0023	0.0006	-0.0038
500	2/12/2015	8.48	112.83	42.49	-0.0094	0.0005	-0.0449
501	3/12/2015	8.59	111.77	43.84	0.0129	-0.0094	0.0313
502	4/12/2015	8.52	111.50	43	-0.0082	-0.0024	-0.0193
503	7/12/2015	8.41	111.99	40.73	-0.0130	0.0044	-0.0542
504	8/12/2015	8.41	112.12	40.26	0.0000	0.0011	-0.0116
505	9/12/2015	8.4	111.98	40.11	-0.0012	-0.0012	-0.0037
506	10/12/2015	8.36	112.14	39.73	-0.0048	0.0014	-0.0095
507	11/12/2015	8.07	112.32	37.93	-0.0353	0.0017	-0.0464
508	14/12/2015	8.07	112.13	37.92	0.0000	-0.0018	-0.0003
509	15/12/2015	8.21	111.66	38.45	0.0172	-0.0041	0.0139
510	16/12/2015	8.16	111.56	37.19	-0.0061	-0.0010	-0.0333

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
511	17/12/2015	8.1	111.91	37.06	-0.0074	0.0032	-0.0035
512	18/12/2015	8.09	112.15	36.88	-0.0012	0.0021	-0.0049
513	21/12/2015	8.22	112.13	36.35	0.0159	-0.0001	-0.0145
514	22/12/2015	8.28	111.81	36.11	0.0073	-0.0029	-0.0066
515	23/12/2015	8.25	111.61	37.36	-0.0036	-0.0018	0.0340
516	24/12/2015	8.21	111.62	37.89	-0.0049	0.0000	0.0141
517	25/12/2015	8.21	111.62	37.89	0.0000	0.0000	0.0000
518	28/12/2015	8.33	111.62	36.62	0.0145	0.0000	-0.0341
519	29/12/2015	8.3	111.64	37.79	-0.0036	0.0002	0.0314
520	30/12/2015	8.24	111.69	36.46	-0.0073	0.0004	-0.0358
521	31/12/2015	8.25	111.69	37.28	0.0012	0.0000	0.0222
522	1/01/2016	8.25	111.69	37.28	0.0000	0.0000	0.0000
523	4/01/2016	8.07	111.96	37.22	-0.0221	0.0024	-0.0016
524	5/01/2016	8.02	112.13	36.42	-0.0062	0.0015	-0.0217
525	6/01/2016	7.77	112.36	34.23	-0.0317	0.0020	-0.0620
526	7/01/2016	7.56	112.13	33.75	-0.0274	-0.0020	-0.0141
527	8/01/2016	7.42	112.27	33.55	-0.0187	0.0013	-0.0059
528	11/01/2016	7.14	112.16	31.55	-0.0385	-0.0010	-0.0615
529	12/01/2016	7.11	112.13	30.86	-0.0042	-0.0003	-0.0221
530	13/01/2016	7.25	112.26	30.31	0.0195	0.0012	-0.0180
531	14/01/2016	7.1	112.15	31.03	-0.0209	-0.0010	0.0235
532	15/01/2016	6.68	112.27	28.94	-0.0610	0.0011	-0.0697
533	18/01/2016	6.73	112.18	28.55	0.0075	-0.0008	-0.0136
534	19/01/2016	6.82	112.14	28.76	0.0133	-0.0003	0.0073
535	20/01/2016	6.32	112.39	27.88	-0.0761	0.0021	-0.0311
536	21/01/2016	6.18	112.64	29.25	-0.0224	0.0022	0.0480
537	22/01/2016	6.33	112.61	32.18	0.0240	-0.0002	0.0955
538	25/01/2016	5.88	112.64	30.5	-0.0737	0.0003	-0.0536
539	26/01/2016	6.08	112.78	31.8	0.0334	0.0012	0.0417
540	27/01/2016	5.91	112.78	33.1	-0.0284	0.0000	0.0401
541	28/01/2016	6.07	112.95	33.89	0.0267	0.0016	0.0236
542	29/01/2016	6.05	113.36	34.74	-0.0033	0.0036	0.0248
543	1/02/2016	5.69	113.30	34.24	-0.0613	-0.0005	-0.0145
544	2/02/2016	5.82	113.44	32.72	0.0226	0.0012	-0.0454
545	3/02/2016	5.62	113.63	35.04	-0.0350	0.0016	0.0685
546	4/02/2016	5.6	113.46	34.46	-0.0036	-0.0015	-0.0167
547	5/02/2016	5.54	113.45	34.06	-0.0108	0.0000	-0.0117
548	8/02/2016	5.23	113.71	32.88	-0.0576	0.0023	-0.0353
549	9/02/2016	4.95	113.59	30.32	-0.0550	-0.0010	-0.0811
550	10/02/2016	4.87	113.57	30.84	-0.0163	-0.0002	0.0170

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
551	11/02/2016	4.73	113.78	30.06	-0.0292	0.0019	-0.0256
552	12/02/2016	5.05	113.39	33.36	0.0655	-0.0035	0.1042
553	15/02/2016	4.79	113.53	33.39	-0.0529	0.0012	0.0009
554	16/02/2016	4.68	113.40	32.18	-0.0232	-0.0011	-0.0369
555	17/02/2016	5.08	113.40	34.5	0.0820	0.0000	0.0696
556	18/02/2016	5.25	113.68	34.28	0.0329	0.0024	-0.0064
557	19/02/2016	5.16	113.76	33.01	-0.0173	0.0007	-0.0378
558	22/02/2016	5.41	113.91	34.69	0.0473	0.0013	0.0496
559	23/02/2016	4.9	113.86	33.27	-0.0990	-0.0004	-0.0418
560	24/02/2016	4.86	114.05	34.41	-0.0082	0.0016	0.0337
561	25/02/2016	5.07	114.09	35.29	0.0423	0.0004	0.0253
562	26/02/2016	4.99	114.12	35.1	-0.0159	0.0002	-0.0054
563	29/02/2016	5	114.39	35.97	0.0020	0.0024	0.0245
564	1/03/2016	4.99	114.26	36.81	-0.0020	-0.0011	0.0231
565	2/03/2016	4.95	114.03	36.93	-0.0080	-0.0021	0.0033
566	3/03/2016	4.88	114.18	37.07	-0.0142	0.0014	0.0038
567	4/03/2016	4.92	114.00	38.72	0.0082	-0.0016	0.0435
568	7/03/2016	5.09	114.08	40.84	0.0340	0.0007	0.0533
569	8/03/2016	5.01	114.29	39.65	-0.0158	0.0018	-0.0296
570	9/03/2016	5.07	113.97	41.07	0.0119	-0.0028	0.0352
571	10/03/2016	4.9	113.63	40.05	-0.0341	-0.0030	-0.0251
572	11/03/2016	4.98	114.06	40.39	0.0162	0.0038	0.0085
573	14/03/2016	4.85	114.20	39.53	-0.0265	0.0012	-0.0215
574	15/03/2016	4.85	114.02	38.74	0.0000	-0.0016	-0.0202
575	16/03/2016	4.95	114.18	40.33	0.0204	0.0014	0.0402
576	17/03/2016	4.99	114.48	41.54	0.0080	0.0026	0.0296
577	18/03/2016	4.93	114.56	41.2	-0.0121	0.0007	-0.0082
578	21/03/2016	4.86	114.60	41.54	-0.0143	0.0003	0.0082
579	22/03/2016	4.81	114.65	41.79	-0.0103	0.0005	0.0060
580	23/03/2016	4.79	114.74	40.47	-0.0042	0.0007	-0.0321
581	24/03/2016	4.84	114.84	40.44	0.0104	0.0009	-0.0007
582	25/03/2016	4.84	114.84	40.44	0.0000	0.0000	0.0000
583	28/03/2016	4.84	114.84	40.27	0.0000	0.0000	-0.0042
584	29/03/2016	4.77	115.08	39.14	-0.0146	0.0021	-0.0285
585	30/03/2016	4.95	115.02	39.26	0.0370	-0.0005	0.0031
586	31/03/2016	5.2	115.06	39.6	0.0493	0.0004	0.0086
587	1/04/2016	5.16	115.18	38.67	-0.0077	0.0010	-0.0238
588	4/04/2016	5.32	115.26	37.69	0.0305	0.0007	-0.0257
589	5/04/2016	5.23	115.46	37.87	-0.0171	0.0018	0.0048
590	6/04/2016	5.3	115.39	39.84	0.0133	-0.0006	0.0507

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
591	7/04/2016	5.27	115.51	39.43	-0.0057	0.0010	-0.0103
592	8/04/2016	5.41	115.42	41.94	0.0262	-0.0007	0.0617
593	11/04/2016	5.57	115.37	42.83	0.0291	-0.0005	0.0210
594	12/04/2016	5.58	115.18	44.69	0.0018	-0.0016	0.0425
595	13/04/2016	5.53	115.26	44.18	-0.0090	0.0006	-0.0115
596	14/04/2016	5.6	115.18	43.84	0.0126	-0.0007	-0.0077
597	15/04/2016	5.47	115.33	43.1	-0.0235	0.0013	-0.0170
598	18/04/2016	5.46	115.21	42.91	-0.0018	-0.0010	-0.0044
599	19/04/2016	5.56	115.11	44.03	0.0181	-0.0008	0.0258
600	20/04/2016	5.54	115.27	45.8	-0.0036	0.0014	0.0394
601	21/04/2016	5.74	114.88	44.53	0.0355	-0.0034	-0.0281
602	22/04/2016	5.96	114.93	45.11	0.0376	0.0004	0.0129
603	25/04/2016	5.89	114.82	44.48	-0.0118	-0.0009	-0.0141
604	26/04/2016	6.61	114.61	45.74	0.1153	-0.0019	0.0279
605	27/04/2016	6.83	114.66	47.18	0.0327	0.0004	0.0310
606	28/04/2016	6.33	114.81	48.14	-0.0760	0.0014	0.0201
607	29/04/2016	6.17	114.60	48.13	-0.0256	-0.0019	-0.0002
608	2/05/2016	6.1	114.60	45.83	-0.0114	0.0000	-0.0490
609	3/05/2016	5.98	115.06	44.97	-0.0199	0.0040	-0.0189
610	4/05/2016	6.12	115.03	44.62	0.0231	-0.0003	-0.0078
611	5/05/2016	6.19	115.19	45.01	0.0114	0.0014	0.0087
612	6/05/2016	5.85	115.29	45.37	-0.0565	0.0009	0.0080
613	9/05/2016	5.69	115.38	43.63	-0.0277	0.0008	-0.0391
614	10/05/2016	5.89	115.40	45.52	0.0345	0.0001	0.0424
615	11/05/2016	6.01	115.36	47.6	0.0202	-0.0003	0.0447
616	12/05/2016	5.8	115.19	48.08	-0.0356	-0.0015	0.0100
617	13/05/2016	5.84	115.28	47.83	0.0069	0.0007	-0.0052
618	16/05/2016	6.1	115.18	48.97	0.0436	-0.0009	0.0236
619	17/05/2016	6.04	115.22	49.28	-0.0099	0.0004	0.0063
620	18/05/2016	6.05	115.05	48.93	0.0017	-0.0015	-0.0071
621	19/05/2016	5.98	115.03	48.81	-0.0116	-0.0002	-0.0025
622	20/05/2016	5.95	115.01	48.72	-0.0050	-0.0002	-0.0018
623	23/05/2016	5.72	114.96	48.35	-0.0394	-0.0004	-0.0076
624	24/05/2016	5.78	115.01	48.61	0.0104	0.0005	0.0054
625	25/05/2016	5.85	115.18	49.74	0.0120	0.0015	0.0230
626	26/05/2016	6.01	115.24	49.59	0.0270	0.0005	-0.0030
627	27/05/2016	6.02	115.23	49.32	0.0017	0.0000	-0.0055
628	30/05/2016	6.1	115.23	49.76	0.0132	0.0000	0.0089
629	31/05/2016	6.08	115.24	49.69	-0.0033	0.0000	-0.0014
630	1/06/2016	5.95	115.34	49.72	-0.0216	0.0009	0.0006

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
631	2/06/2016	6.01	115.41	50.04	0.0100	0.0006	0.0064
632	3/06/2016	5.93	115.67	49.64	-0.0134	0.0023	-0.0080
633	6/06/2016	6.19	115.61	50.55	0.0429	-0.0006	0.0182
634	7/06/2016	6.1	115.75	51.44	-0.0146	0.0012	0.0175
635	8/06/2016	6.09	115.76	52.51	-0.0016	0.0001	0.0206
636	9/06/2016	6.1	115.88	51.95	0.0016	0.0011	-0.0107
637	10/06/2016	5.94	115.97	50.54	-0.0266	0.0008	-0.0275
638	13/06/2016	5.84	115.90	50.35	-0.0170	-0.0006	-0.0038
639	14/06/2016	5.84	116.03	49.83	0.0000	0.0011	-0.0104
640	15/06/2016	5.89	116.08	48.97	0.0085	0.0004	-0.0174
641	16/06/2016	5.7	116.12	47.19	-0.0328	0.0003	-0.0370
642	17/06/2016	5.66	116.03	49.17	-0.0070	-0.0007	0.0411
643	20/06/2016	5.84	115.88	50.65	0.0313	-0.0013	0.0297
644	21/06/2016	5.54	115.92	50.62	-0.0527	0.0003	-0.0006
645	22/06/2016	5.67	115.86	49.88	0.0232	-0.0005	-0.0147
646	23/06/2016	5.63	115.78	50.91	-0.0071	-0.0007	0.0204
647	24/06/2016	4.95	116.15	48.41	-0.1287	0.0032	-0.0504
648	27/06/2016	4.76	116.37	47.16	-0.0391	0.0019	-0.0262
649	28/06/2016	4.69	116.56	48.58	-0.0148	0.0016	0.0297
650	29/06/2016	4.52	116.63	50.61	-0.0369	0.0006	0.0409
651	30/06/2016	4.47	116.75	49.68	-0.0111	0.0010	-0.0185
652	1/07/2016	4.62	116.94	50.35	0.0330	0.0017	0.0134
653	4/07/2016	4.97	117.13	50.1	0.0730	0.0016	-0.0050
654	5/07/2016	4.71	117.41	47.96	-0.0537	0.0024	-0.0437
655	6/07/2016	4.59	117.44	48.8	-0.0258	0.0002	0.0174
656	7/07/2016	4.58	117.45	46.4	-0.0022	0.0001	-0.0504
657	8/07/2016	4.55	117.62	46.76	-0.0066	0.0014	0.0077
658	11/07/2016	4.43	117.63	46.25	-0.0267	0.0001	-0.0110
659	12/07/2016	4.63	117.40	48.47	0.0442	-0.0020	0.0469
660	13/07/2016	4.79	117.74	46.26	0.0340	0.0029	-0.0467
661	14/07/2016	4.78	117.57	47.37	-0.0021	-0.0014	0.0237
662	15/07/2016	4.93	117.40	47.61	0.0309	-0.0015	0.0051
663	18/07/2016	4.85	117.61	46.96	-0.0164	0.0018	-0.0137
664	19/07/2016	4.67	117.68	46.66	-0.0378	0.0007	-0.0064
665	20/07/2016	4.69	117.69	47.17	0.0043	0.0001	0.0109
666	21/07/2016	4.65	117.58	46.2	-0.0086	-0.0010	-0.0208
667	22/07/2016	4.56	117.67	45.69	-0.0195	0.0007	-0.0111
668	25/07/2016	4.59	117.82	44.72	0.0066	0.0013	-0.0215
669	26/07/2016	4.51	117.75	44.87	-0.0176	-0.0006	0.0033
670	27/07/2016	4.53	118.04	43.47	0.0044	0.0024	-0.0317

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
671	28/07/2016	4.48	117.99	42.7	-0.0111	-0.0004	-0.0179
672	29/07/2016	4.42	118.15	42.46	-0.0135	0.0014	-0.0056
673	1/08/2016	4.37	118.04	42.14	-0.0114	-0.0010	-0.0076
674	2/08/2016	4.41	117.70	41.8	0.0091	-0.0029	-0.0081
675	3/08/2016	4.63	117.75	43.1	0.0487	0.0005	0.0306
676	4/08/2016	4.69	118.15	44.29	0.0129	0.0034	0.0272
677	5/08/2016	4.72	117.98	44.27	0.0064	-0.0014	-0.0005
678	8/08/2016	4.94	118.00	45.39	0.0456	0.0001	0.0250
679	9/08/2016	4.87	118.13	44.98	-0.0143	0.0011	-0.0091
680	10/08/2016	4.76	118.33	44.05	-0.0228	0.0016	-0.0209
681	11/08/2016	4.87	118.25	46.04	0.0228	-0.0006	0.0442
682	12/08/2016	4.89	118.28	46.97	0.0041	0.0002	0.0200
683	15/08/2016	4.8	118.08	48.35	-0.0186	-0.0017	0.0290
684	16/08/2016	4.69	117.86	49.23	-0.0232	-0.0018	0.0180
685	17/08/2016	4.48	117.98	49.85	-0.0458	0.0010	0.0125
686	18/08/2016	4.68	118.15	50.89	0.0437	0.0015	0.0206
687	19/08/2016	4.76	117.95	50.88	0.0169	-0.0017	-0.0002
688	22/08/2016	4.89	118.14	49.16	0.0269	0.0016	-0.0344
689	23/08/2016	4.7	118.21	49.96	-0.0396	0.0006	0.0161
690	24/08/2016	4.6	118.17	49.05	-0.0215	-0.0004	-0.0184
691	25/08/2016	4.7	118.10	49.67	0.0215	-0.0006	0.0126
692	26/08/2016	4.69	118.19	49.92	-0.0021	0.0008	0.0050
693	29/08/2016	4.69	118.19	49.26	0.0000	0.0000	-0.0133
694	30/08/2016	4.54	118.20	48.37	-0.0325	0.0000	-0.0182
695	31/08/2016	4.46	118.07	47.04	-0.0178	-0.0011	-0.0279
696	1/09/2016	4.37	118.06	45.45	-0.0204	-0.0001	-0.0344
697	2/09/2016	4.08	117.90	46.83	-0.0687	-0.0014	0.0299
698	5/09/2016	3.93	118.03	47.63	-0.0375	0.0011	0.0169
699	6/09/2016	4.13	118.38	47.26	0.0496	0.0030	-0.0078
700	7/09/2016	4.01	118.46	47.98	-0.0295	0.0008	0.0151
701	8/09/2016	4.08	118.11	49.99	0.0173	-0.0030	0.0410
702	9/09/2016	4.08	117.66	48.01	0.0000	-0.0038	-0.0404
703	12/09/2016	4.03	117.49	48.32	-0.0123	-0.0015	0.0064
704	13/09/2016	4.02	117.47	47.1	-0.0025	-0.0001	-0.0256
705	14/09/2016	3.98	117.56	45.85	-0.0100	0.0008	-0.0269
706	15/09/2016	4.14	117.53	46.59	0.0394	-0.0002	0.0160
707	16/09/2016	4.36	117.69	45.77	0.0518	0.0013	-0.0178
708	19/09/2016	4.4	117.59	45.95	0.0091	-0.0008	0.0039
709	20/09/2016	4.16	117.79	45.88	-0.0561	0.0017	-0.0015
710	21/09/2016	4.21	117.62	46.83	0.0119	-0.0014	0.0205

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
711	22/09/2016	4.42	118.16	47.65	0.0487	0.0046	0.0174
712	23/09/2016	4.54	118.11	45.89	0.0268	-0.0005	-0.0376
713	26/09/2016	4.62	118.26	47.35	0.0175	0.0013	0.0313
714	27/09/2016	4.43	118.41	45.97	-0.0420	0.0012	-0.0296
715	28/09/2016	4.95	118.49	48.69	0.1110	0.0006	0.0575
716	29/09/2016	5.02	118.30	49.24	0.0140	-0.0016	0.0112
717	30/09/2016	4.96	118.25	49.06	-0.0120	-0.0004	-0.0037
718	3/10/2016	5.31	118.11	50.89	0.0682	-0.0012	0.0366
719	4/10/2016	5.21	118.09	50.87	-0.0190	-0.0002	-0.0004
720	5/10/2016	5.48	117.64	51.86	0.0505	-0.0038	0.0193
721	6/10/2016	5.86	117.63	52.51	0.0670	-0.0001	0.0125
722	7/10/2016	5.69	117.51	51.93	-0.0294	-0.0010	-0.0111
723	10/10/2016	5.66	117.28	53.14	-0.0053	-0.0020	0.0230
724	11/10/2016	5.43	117.39	52.41	-0.0415	0.0010	-0.0138
725	12/10/2016	5.52	117.22	51.81	0.0164	-0.0014	-0.0115
726	13/10/2016	5.65	117.39	52.03	0.0233	0.0014	0.0042
727	14/10/2016	5.81	117.31	51.95	0.0279	-0.0007	-0.0015
728	17/10/2016	5.87	117.33	51.52	0.0103	0.0002	-0.0083
729	18/10/2016	5.95	117.47	51.68	0.0135	0.0011	0.0031
730	19/10/2016	5.67	117.50	52.67	-0.0482	0.0003	0.0190
731	20/10/2016	5.58	117.65	51.38	-0.0160	0.0013	-0.0248
732	21/10/2016	5.89	117.61	51.78	0.0541	-0.0004	0.0078
733	24/10/2016	5.81	117.51	51.46	-0.0137	-0.0008	-0.0062
734	25/10/2016	5.81	117.52	50.79	0.0000	0.0001	-0.0131
735	26/10/2016	5.94	117.12	49.98	0.0221	-0.0034	-0.0161
736	27/10/2016	5.81	116.68	50.47	-0.0221	-0.0038	0.0098
737	28/10/2016	5.88	116.70	49.71	0.0120	0.0002	-0.0152
738	31/10/2016	5.9	116.75	48.3	0.0034	0.0004	-0.0288
739	1/11/2016	6.03	116.58	48.14	0.0218	-0.0015	-0.0033
740	2/11/2016	6.24	116.88	46.86	0.0342	0.0026	-0.0269
741	3/11/2016	6.5	116.65	46.35	0.0408	-0.0019	-0.0109
742	4/11/2016	6.41	116.81	45.58	-0.0139	0.0013	-0.0168
743	7/11/2016	6.23	116.75	46.15	-0.0285	-0.0005	0.0124
744	8/11/2016	6.15	116.56	46.04	-0.0129	-0.0016	-0.0024
745	9/11/2016	6.13	116.52	46.36	-0.0033	-0.0004	0.0069
746	10/11/2016	5.92	115.79	45.84	-0.0349	-0.0062	-0.0113
747	11/11/2016	5.67	115.52	44.75	-0.0431	-0.0023	-0.0241
748	14/11/2016	5.41	115.18	44.43	-0.0469	-0.0030	-0.0072
749	15/11/2016	5.74	115.41	46.95	0.0592	0.0020	0.0552
750	16/11/2016	5.55	115.22	46.63	-0.0337	-0.0017	-0.0068

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
751	17/11/2016	5.9	115.31	46.49	0.0612	0.0008	-0.0030
752	18/11/2016	5.58	115.08	46.86	-0.0558	-0.0020	0.0079
753	21/11/2016	5.48	115.11	48.9	-0.0181	0.0003	0.0426
754	22/11/2016	5.51	115.40	49.12	0.0055	0.0025	0.0045
755	23/11/2016	5.39	115.14	48.95	-0.0220	-0.0023	-0.0035
756	24/11/2016	5.34	115.21	49	-0.0093	0.0006	0.0010
757	25/11/2016	5	115.25	47.24	-0.0658	0.0003	-0.0366
758	28/11/2016	4.74	115.52	48.24	-0.0534	0.0023	0.0209
759	29/11/2016	4.56	115.38	46.38	-0.0387	-0.0012	-0.0393
760	30/11/2016	4.58	115.15	50.47	0.0044	-0.0020	0.0845
761	1/12/2016	4.46	114.77	53.94	-0.0266	-0.0033	0.0665
762	2/12/2016	4.3	115.04	54.46	-0.0365	0.0023	0.0096
763	5/12/2016	4.37	114.77	54.94	0.0161	-0.0023	0.0088
764	6/12/2016	4.5	114.54	53.93	0.0293	-0.0019	-0.0186
765	7/12/2016	4.3	114.74	53	-0.0455	0.0017	-0.0174
766	8/12/2016	4.61	114.52	53.89	0.0696	-0.0019	0.0167
767	9/12/2016	4.46	114.77	54.33	-0.0331	0.0022	0.0081
768	12/12/2016	4.87	114.39	55.69	0.0879	-0.0033	0.0247
769	13/12/2016	4.79	114.74	55.72	-0.0166	0.0031	0.0005
770	14/12/2016	5.01	115.09	53.9	0.0449	0.0030	-0.0332
771	15/12/2016	4.84	114.66	54.02	-0.0345	-0.0037	0.0022
772	16/12/2016	4.93	114.88	55.21	0.0184	0.0019	0.0218
773	19/12/2016	5.09	115.32	54.92	0.0319	0.0038	-0.0053
774	20/12/2016	5.24	115.25	55.35	0.0290	-0.0006	0.0078
775	21/12/2016	5.81	115.37	54.46	0.1033	0.0011	-0.0162
776	22/12/2016	6.08	115.24	55.05	0.0454	-0.0011	0.0108
777	23/12/2016	6.23	115.42	55.16	0.0244	0.0016	0.0020
778	26/12/2016	6.23	115.42	55.16	0.0000	0.0000	0.0000
779	27/12/2016	6.33	115.42	56.09	0.0159	0.0000	0.0167
780	28/12/2016	6.33	115.61	56.22	0.0000	0.0016	0.0023
781	29/12/2016	6.36	115.81	56.14	0.0047	0.0017	-0.0014
782	30/12/2016	6.55	115.60	56.82	0.0294	-0.0018	0.0120
783	2/01/2017	6.12	115.60	56.82	-0.0679	0.0000	0.0000
784	3/01/2017	5.43	115.23	55.47	-0.1196	-0.0032	-0.0240
785	4/01/2017	5.72	115.18	56.46	0.0520	-0.0004	0.0177
786	5/01/2017	5.29	115.29	56.89	-0.0782	0.0009	0.0076
787	6/01/2017	5.05	115.02	57.1	-0.0464	-0.0023	0.0037
788	9/01/2017	5.27	115.09	54.94	0.0426	0.0006	-0.0386
789	10/01/2017	5.51	115.15	53.64	0.0445	0.0005	-0.0239
790	11/01/2017	5.52	115.27	55.1	0.0018	0.0011	0.0269

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
791	12/01/2017	5.04	115.36	56.01	-0.0910	0.0008	0.0164
792	13/01/2017	5.04	115.18	55.45	0.0000	-0.0016	-0.0100
793	16/01/2017	4.7	115.22	55.86	-0.0698	0.0003	0.0074
794	17/01/2017	5	115.32	55.47	0.0619	0.0008	-0.0070
795	18/01/2017	4.84	115.09	53.92	-0.0325	-0.0020	-0.0283
796	19/01/2017	5.2	114.87	54.16	0.0717	-0.0019	0.0044
797	20/01/2017	5.42	114.53	55.49	0.0414	-0.0030	0.0243
798	23/01/2017	5.31	114.88	55.23	-0.0205	0.0031	-0.0047
799	24/01/2017	5.07	114.75	55.44	-0.0463	-0.0011	0.0038
800	25/01/2017	4.97	114.31	55.08	-0.0199	-0.0038	-0.0065
801	26/01/2017	5.19	114.11	56.24	0.0433	-0.0018	0.0208
802	27/01/2017	4.92	114.22	55.52	-0.0534	0.0010	-0.0129
803	30/01/2017	5.16	114.28	55.23	0.0476	0.0005	-0.0052
804	31/01/2017	5.35	114.32	55.7	0.0362	0.0004	0.0085
805	1/02/2017	5.27	113.93	56.8	-0.0151	-0.0035	0.0196
806	2/02/2017	5.22	114.37	56.56	-0.0095	0.0039	-0.0042
807	3/02/2017	5.15	114.21	56.81	-0.0135	-0.0014	0.0044
808	6/02/2017	5.09	114.09	55.72	-0.0117	-0.0010	-0.0194
809	7/02/2017	5.16	114.18	55.05	0.0137	0.0008	-0.0121
810	8/02/2017	5.21	114.75	55.12	0.0096	0.0050	0.0013
811	9/02/2017	5.28	114.89	55.63	0.0133	0.0012	0.0092
812	10/02/2017	5.12	114.49	56.7	-0.0308	-0.0034	0.0191
813	13/02/2017	4.9	114.49	55.59	-0.0439	-0.0001	-0.0198
814	14/02/2017	5.13	114.30	55.97	0.0459	-0.0016	0.0068
815	15/02/2017	5.06	114.18	55.75	-0.0137	-0.0010	-0.0039
816	16/02/2017	4.93	114.62	55.65	-0.0260	0.0038	-0.0018
817	17/02/2017	4.97	114.76	55.81	0.0081	0.0013	0.0029
818	20/02/2017	5.08	114.78	56.18	0.0219	0.0001	0.0066
819	21/02/2017	5.04	114.60	56.66	-0.0079	-0.0016	0.0085
820	22/02/2017	5.06	115.02	55.84	0.0040	0.0037	-0.0146
821	23/02/2017	5.34	115.42	56.58	0.0539	0.0034	0.0132
822	24/02/2017	5.38	115.88	55.99	0.0075	0.0040	-0.0105
823	27/02/2017	5.19	115.97	55.93	-0.0360	0.0009	-0.0011
824	28/02/2017	5.23	115.94	55.59	0.0077	-0.0003	-0.0061
825	1/03/2017	5.9	115.45	56.36	0.1205	-0.0042	0.0138
826	2/03/2017	5.46	115.36	55.08	-0.0775	-0.0008	-0.0230
827	3/03/2017	5.59	115.06	55.9	0.0235	-0.0026	0.0148
828	6/03/2017	5.48	115.05	56.01	-0.0199	0.0000	0.0020
829	7/03/2017	5.37	115.18	55.92	-0.0203	0.0012	-0.0016
830	8/03/2017	5.23	114.71	53.11	-0.0264	-0.0041	-0.0516

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
831	9/03/2017	5.12	114.37	52.19	-0.0213	-0.0029	-0.0175
832	10/03/2017	5.16	113.89	51.37	0.0078	-0.0042	-0.0158
833	13/03/2017	5.15	114.17	51.35	-0.0019	0.0024	-0.0004
834	14/03/2017	5.1	114.31	50.92	-0.0098	0.0012	-0.0084
835	15/03/2017	5.19	114.71	51.81	0.0175	0.0035	0.0173
836	16/03/2017	5.14	114.41	51.74	-0.0097	-0.0026	-0.0014
837	17/03/2017	5.13	114.39	51.76	-0.0019	-0.0001	0.0004
838	20/03/2017	4.99	114.36	51.62	-0.0277	-0.0003	-0.0027
839	21/03/2017	4.93	114.35	50.96	-0.0121	-0.0001	-0.0129
840	22/03/2017	4.96	114.75	50.64	0.0061	0.0035	-0.0063
841	23/03/2017	4.97	114.68	50.56	0.0020	-0.0006	-0.0016
842	24/03/2017	4.76	114.91	50.8	-0.0432	0.0020	0.0047
843	27/03/2017	4.62	114.95	50.75	-0.0299	0.0004	-0.0010
844	28/03/2017	4.74	115.14	51.33	0.0256	0.0016	0.0114
845	29/03/2017	4.76	115.34	52.42	0.0042	0.0018	0.0210
846	30/03/2017	4.92	115.30	52.96	0.0331	-0.0003	0.0102
847	31/03/2017	4.69	115.17	52.83	-0.0479	-0.0011	-0.0025
848	3/04/2017	4.87	115.44	53.12	0.0377	0.0023	0.0055
849	4/04/2017	4.65	115.71	54.17	-0.0462	0.0023	0.0196
850	5/04/2017	4.82	115.66	54.36	0.0359	-0.0005	0.0035
851	6/04/2017	5.06	115.76	54.89	0.0486	0.0009	0.0097
852	7/04/2017	4.89	115.99	55.24	-0.0342	0.0019	0.0064
853	10/04/2017	4.79	115.87	55.98	-0.0207	-0.0010	0.0133
854	11/04/2017	4.87	115.89	56.23	0.0166	0.0002	0.0045
855	12/04/2017	4.93	116.02	55.86	0.0122	0.0011	-0.0066
856	13/04/2017	4.95	116.21	55.89	0.0040	0.0016	0.0005
857	14/04/2017	4.95	116.21	55.89	0.0000	0.0000	0.0000
858	17/04/2017	4.95	116.21	55.36	0.0000	0.0000	-0.0095
859	18/04/2017	4.86	116.30	54.89	-0.0183	0.0008	-0.0085
860	19/04/2017	4.83	116.22	52.93	-0.0062	-0.0007	-0.0364
861	20/04/2017	4.75	116.19	52.99	-0.0167	-0.0002	0.0011
862	21/04/2017	4.57	116.03	51.96	-0.0386	-0.0014	-0.0196
863	24/04/2017	4.64	116.11	51.6	0.0152	0.0007	-0.0070
864	25/04/2017	4.5	115.80	52.1	-0.0306	-0.0027	0.0096
865	26/04/2017	4.61	115.95	51.82	0.0242	0.0013	-0.0054
866	27/04/2017	4.55	116.37	51.44	-0.0131	0.0036	-0.0074
867	28/04/2017	4.57	116.25	51.73	0.0044	-0.0011	0.0056
868	1/05/2017	4.57	116.25	51.52	0.0000	0.0000	-0.0041
869	2/05/2017	4.45	116.31	50.46	-0.0266	0.0005	-0.0208
870	3/05/2017	4.4	116.37	50.79	-0.0113	0.0006	0.0065

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
871	4/05/2017	4.52	116.10	48.38	0.0269	-0.0024	-0.0486
872	5/05/2017	4.58	115.92	49.1	0.0132	-0.0015	0.0148
873	8/05/2017	4.42	115.96	49.34	-0.0356	0.0004	0.0049
874	9/05/2017	4.52	115.81	48.73	0.0224	-0.0013	-0.0124
875	10/05/2017	4.45	116.08	50.22	-0.0156	0.0023	0.0301
876	11/05/2017	4.35	115.84	50.77	-0.0227	-0.0021	0.0109
877	12/05/2017	4.46	116.13	50.84	0.0250	0.0025	0.0014
878	15/05/2017	4.39	115.84	51.82	-0.0158	-0.0025	0.0191
879	16/05/2017	4.54	115.86	51.65	0.0336	0.0002	-0.0033
880	17/05/2017	4.58	116.19	52.21	0.0088	0.0028	0.0108
881	18/05/2017	4.76	116.37	52.51	0.0385	0.0016	0.0057
882	19/05/2017	4.85	116.28	53.61	0.0187	-0.0008	0.0207
883	22/05/2017	4.9	116.03	53.87	0.0103	-0.0021	0.0048
884	23/05/2017	4.75	116.03	54.15	-0.0311	0.0000	0.0052
885	24/05/2017	4.91	115.99	53.96	0.0331	-0.0003	-0.0035
886	25/05/2017	4.98	116.30	51.46	0.0142	0.0027	-0.0474
887	26/05/2017	5.19	116.62	52.15	0.0413	0.0027	0.0133
888	29/05/2017	5.17	116.62	52.29	-0.0039	0.0000	0.0027
889	30/05/2017	5.14	116.85	51.84	-0.0058	0.0020	-0.0086
890	31/05/2017	4.98	116.90	50.31	-0.0316	0.0004	-0.0300
891	1/06/2017	5.08	116.80	50.63	0.0199	-0.0009	0.0063
892	2/06/2017	5.16	116.98	49.95	0.0156	0.0015	-0.0135
893	5/06/2017	5.17	116.87	49.47	0.0019	-0.0009	-0.0097
894	6/06/2017	4.97	117.19	50.12	-0.0395	0.0027	0.0131
895	7/06/2017	4.87	117.16	48.06	-0.0203	-0.0002	-0.0420
896	8/06/2017	5.04	117.29	47.86	0.0343	0.0011	-0.0042
897	9/06/2017	5.04	117.25	48.15	0.0000	-0.0003	0.0060
898	12/06/2017	4.91	117.53	48.29	-0.0261	0.0024	0.0029
899	13/06/2017	5	117.50	48.72	0.0182	-0.0003	0.0089
900	14/06/2017	4.93	117.83	47	-0.0141	0.0028	-0.0359
901	15/06/2017	4.95	117.41	46.92	0.0040	-0.0035	-0.0017
902	16/06/2017	4.87	117.48	47.37	-0.0163	0.0006	0.0095
903	19/06/2017	4.92	117.51	46.91	0.0102	0.0002	-0.0098
904	20/06/2017	4.94	117.72	46.02	0.0041	0.0018	-0.0192
905	21/06/2017	4.87	117.81	44.82	-0.0143	0.0007	-0.0264
906	22/06/2017	4.86	117.86	45.22	-0.0021	0.0004	0.0089
907	23/06/2017	4.86	117.74	45.54	0.0000	-0.0010	0.0071
908	26/06/2017	4.77	117.78	45.83	-0.0187	0.0003	0.0063
909	27/06/2017	4.93	116.98	46.65	0.0330	-0.0067	0.0177
910	28/06/2017	4.93	116.94	47.31	0.0000	-0.0004	0.0140

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
911	29/06/2017	5.06	116.19	47.42	0.0260	-0.0064	0.0023
912	30/06/2017	5.02	116.04	47.92	-0.0079	-0.0013	0.0105
913	3/07/2017	5.13	115.91	49.68	0.0217	-0.0011	0.0361
914	4/07/2017	5.11	116.00	49.61	-0.0039	0.0008	-0.0014
915	5/07/2017	5.04	116.13	47.79	-0.0138	0.0012	-0.0374
916	6/07/2017	5.23	115.38	48.11	0.0370	-0.0065	0.0067
917	7/07/2017	5.33	115.35	46.71	0.0189	-0.0003	-0.0295
918	10/07/2017	5.39	115.65	46.88	0.0112	0.0026	0.0036
919	11/07/2017	5.32	115.47	47.52	-0.0131	-0.0015	0.0136
920	12/07/2017	5.47	115.92	47.74	0.0278	0.0039	0.0046
921	13/07/2017	5.35	115.80	48.42	-0.0222	-0.0010	0.0141
922	14/07/2017	5.41	115.85	48.91	0.0112	0.0004	0.0101
923	17/07/2017	5.43	116.01	48.42	0.0037	0.0015	-0.0101
924	18/07/2017	5.45	116.21	48.84	0.0037	0.0017	0.0086
925	19/07/2017	5.38	116.48	49.7	-0.0129	0.0024	0.0175
926	20/07/2017	5.29	116.47	49.3	-0.0169	-0.0001	-0.0081
927	21/07/2017	5.08	116.75	48.06	-0.0405	0.0024	-0.0255
928	24/07/2017	5.13	116.81	48.6	0.0098	0.0005	0.0112
929	25/07/2017	5.15	116.25	50.2	0.0039	-0.0048	0.0324
930	26/07/2017	5.24	116.31	50.97	0.0173	0.0006	0.0152
931	27/07/2017	5.13	116.50	51.49	-0.0212	0.0016	0.0102
932	28/07/2017	5.17	116.38	52.52	0.0078	-0.0010	0.0198
933	31/07/2017	5.22	116.44	52.65	0.0096	0.0005	0.0025
934	1/08/2017	5.29	117.00	51.78	0.0133	0.0048	-0.0167
935	2/08/2017	5.42	117.02	52.36	0.0243	0.0002	0.0111
936	3/08/2017	5.42	117.24	52.01	0.0000	0.0019	-0.0067
937	4/08/2017	5.34	117.10	52.42	-0.0149	-0.0012	0.0079
938	7/08/2017	5.26	117.18	52.37	-0.0151	0.0006	-0.0010
939	8/08/2017	5.26	117.02	52.14	0.0000	-0.0014	-0.0044
940	9/08/2017	5.36	117.43	52.7	0.0188	0.0035	0.0107
941	10/08/2017	5.36	117.54	51.9	0.0000	0.0009	-0.0153
942	11/08/2017	5.38	117.78	52.1	0.0037	0.0020	0.0038
943	14/08/2017	5.51	117.56	50.73	0.0239	-0.0018	-0.0266
944	15/08/2017	5.52	117.35	50.8	0.0018	-0.0018	0.0014
945	16/08/2017	5.79	117.22	50.27	0.0478	-0.0011	-0.0105
946	17/08/2017	5.8	117.30	51.03	0.0017	0.0007	0.0150
947	18/08/2017	5.81	117.57	52.72	0.0017	0.0022	0.0326
948	21/08/2017	5.74	117.59	51.66	-0.0121	0.0002	-0.0203
949	22/08/2017	5.77	117.54	51.87	0.0052	-0.0005	0.0041
950	23/08/2017	5.94	117.72	52.57	0.0290	0.0016	0.0134

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
951	24/08/2017	5.94	117.62	52.04	0.0000	-0.0009	-0.0101
952	25/08/2017	6.08	117.58	52.41	0.0233	-0.0004	0.0071
953	28/08/2017	6.09	117.58	51.89	0.0016	0.0000	-0.0100
954	29/08/2017	6.03	117.95	52	-0.0099	0.0032	0.0021
955	30/08/2017	6.02	117.79	50.86	-0.0017	-0.0014	-0.0222
956	31/08/2017	5.93	117.77	52.38	-0.0151	-0.0002	0.0294
957	1/09/2017	5.82	117.52	52.75	-0.0187	-0.0021	0.0070
958	4/09/2017	5.91	117.58	52.34	0.0153	0.0005	-0.0078
959	5/09/2017	6.49	117.87	53.38	0.0936	0.0025	0.0197
960	6/09/2017	6.69	117.81	54.2	0.0304	-0.0005	0.0152
961	7/09/2017	6.89	118.05	54.49	0.0295	0.0020	0.0053
962	8/09/2017	7.06	117.92	53.78	0.0244	-0.0011	-0.0131
963	11/09/2017	6.87	117.85	53.84	-0.0273	-0.0007	0.0011
964	12/09/2017	6.86	117.30	54.27	-0.0015	-0.0046	0.0080
965	13/09/2017	7.09	117.32	55.16	0.0330	0.0001	0.0163
966	14/09/2017	7.09	117.23	55.47	0.0000	-0.0007	0.0056
967	15/09/2017	6.94	117.10	55.62	-0.0214	-0.0011	0.0027
968	18/09/2017	6.72	116.97	55.48	-0.0322	-0.0011	-0.0025
969	19/09/2017	7.02	117.11	55.14	0.0437	0.0012	-0.0061
970	20/09/2017	6.9	117.24	56.29	-0.0172	0.0011	0.0206
971	21/09/2017	6.55	117.13	56.43	-0.0521	-0.0009	0.0025
972	22/09/2017	6.64	117.15	56.86	0.0136	0.0001	0.0076
973	25/09/2017	7.27	117.55	59.02	0.0906	0.0034	0.0373
974	26/09/2017	6.98	117.44	58.44	-0.0407	-0.0010	-0.0099
975	27/09/2017	6.93	117.02	57.9	-0.0072	-0.0035	-0.0093
976	28/09/2017	6.96	116.86	57.41	0.0043	-0.0013	-0.0085
977	29/09/2017	7.07	117.02	57.54	0.0157	0.0014	0.0023
978	2/10/2017	6.94	117.14	56.12	-0.0186	0.0010	-0.0250
979	3/10/2017	7	117.04	56	0.0086	-0.0008	-0.0021
980	4/10/2017	6.9	117.11	55.8	-0.0144	0.0006	-0.0036
981	5/10/2017	6.89	117.13	57	-0.0015	0.0002	0.0213
982	6/10/2017	7	117.11	55.62	0.0158	-0.0002	-0.0245
983	9/10/2017	6.96	117.32	55.79	-0.0057	0.0018	0.0031
984	10/10/2017	7.39	117.34	56.61	0.0599	0.0001	0.0146
985	11/10/2017	7.38	117.22	56.94	-0.0014	-0.0010	0.0058
986	12/10/2017	7.41	117.34	56.25	0.0041	0.0010	-0.0122
987	13/10/2017	7.32	117.70	57.17	-0.0122	0.0031	0.0162
988	16/10/2017	7.36	117.99	57.82	0.0054	0.0024	0.0113
989	17/10/2017	7.42	118.10	57.88	0.0081	0.0010	0.0010
990	18/10/2017	7.81	117.87	58.15	0.0512	-0.0020	0.0047

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
991	19/10/2017	7.65	117.87	57.23	-0.0207	0.0000	-0.0159
992	20/10/2017	7.57	117.40	57.75	-0.0105	-0.0040	0.0090
993	23/10/2017	7.44	117.60	57.37	-0.0173	0.0018	-0.0066
994	24/10/2017	7.47	117.28	58.33	0.0040	-0.0028	0.0166
995	25/10/2017	7.4	117.24	58.44	-0.0094	-0.0003	0.0019
996	26/10/2017	7.2	117.57	59.3	-0.0274	0.0028	0.0146
997	27/10/2017	7.17	117.99	60.44	-0.0042	0.0035	0.0190
998	30/10/2017	7.14	118.29	60.9	-0.0042	0.0025	0.0076
999	31/10/2017	7.37	118.45	61.37	0.0317	0.0014	0.0077
1000	1/11/2017	7.51	118.44	60.49	0.0188	0.0000	-0.0144
1001	2/11/2017	7.66	118.49	60.62	0.0198	0.0004	0.0021
1002	3/11/2017	7.88	118.51	62.07	0.0283	0.0002	0.0236
1003	6/11/2017	7.92	118.73	64.27	0.0051	0.0019	0.0348
1004	7/11/2017	7.75	118.88	63.69	-0.0217	0.0012	-0.0091
1005	8/11/2017	7.72	118.91	63.49	-0.0039	0.0003	-0.0031
1006	9/11/2017	7.55	118.38	63.93	-0.0223	-0.0045	0.0069
1007	10/11/2017	7.4	118.10	63.52	-0.0201	-0.0023	-0.0064
1008	13/11/2017	7.35	118.06	63.16	-0.0068	-0.0004	-0.0057
1009	14/11/2017	7.39	118.24	62.21	0.0054	0.0015	-0.0152
1010	15/11/2017	7.69	118.34	61.87	0.0398	0.0009	-0.0055
1011	16/11/2017	7.5	118.35	61.36	-0.0250	0.0001	-0.0083
1012	17/11/2017	7.48	118.45	62.72	-0.0027	0.0009	0.0219
1013	20/11/2017	7.44	118.56	62.22	-0.0054	0.0009	-0.0080
1014	21/11/2017	7.39	118.78	62.57	-0.0067	0.0018	0.0056
1015	22/11/2017	7.37	118.76	63.32	-0.0027	-0.0001	0.0119
1016	23/11/2017	7.66	118.78	63.55	0.0386	0.0001	0.0036
1017	24/11/2017	7.77	118.63	63.86	0.0143	-0.0012	0.0049
1018	27/11/2017	7.7	118.81	63.84	-0.0090	0.0015	-0.0003
1019	28/11/2017	7.59	118.81	63.61	-0.0144	0.0000	-0.0036
1020	29/11/2017	7.7	118.44	63.11	0.0144	-0.0032	-0.0079
1021	30/11/2017	7.53	118.61	63.57	-0.0223	0.0015	0.0073
1022	1/12/2017	7.68	119.19	63.73	0.0197	0.0048	0.0025
1023	4/12/2017	7.55	118.95	62.45	-0.0171	-0.0020	-0.0203
1024	5/12/2017	7.43	119.11	62.86	-0.0160	0.0014	0.0065
1025	6/12/2017	7.27	119.32	61.22	-0.0218	0.0017	-0.0264
1026	7/12/2017	7.35	119.35	62.2	0.0109	0.0003	0.0159
1027	8/12/2017	7.14	119.22	63.4	-0.0290	-0.0011	0.0191
1028	11/12/2017	7.2	119.30	64.69	0.0084	0.0007	0.0201
1029	12/12/2017	7.14	119.10	63.34	-0.0084	-0.0017	-0.0211
1030	13/12/2017	7.07	119.07	62.44	-0.0099	-0.0002	-0.0143

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1031	14/12/2017	7.09	119.09	63.31	0.0028	0.0001	0.0138
1032	15/12/2017	7.18	119.22	63.23	0.0126	0.0011	-0.0013
1033	18/12/2017	7.39	119.23	63.41	0.0288	0.0001	0.0028
1034	19/12/2017	7.52	118.63	63.8	0.0174	-0.0050	0.0061
1035	20/12/2017	7.79	118.25	64.56	0.0353	-0.0032	0.0118
1036	21/12/2017	8	118.24	64.9	0.0266	-0.0001	0.0053
1037	22/12/2017	8.16	118.23	65.25	0.0198	-0.0001	0.0054
1038	25/12/2017	8.16	118.23	65.25	0.0000	0.0000	0.0000
1039	26/12/2017	8.16	118.23	67.02	0.0000	0.0000	0.0268
1040	27/12/2017	8.14	118.46	66.44	-0.0025	0.0019	-0.0087
1041	28/12/2017	8.18	118.10	66.72	0.0049	-0.0030	0.0042
1042	29/12/2017	8.15	117.96	66.87	-0.0037	-0.0012	0.0022
1043	1/01/2018	8.15	117.96	66.87	0.0000	0.0000	0.0000
1044	2/01/2018	7.78	117.74	66.57	-0.0465	-0.0019	-0.0045
1045	3/01/2018	7.81	117.94	67.84	0.0038	0.0017	0.0189
1046	4/01/2018	7.75	117.99	68.07	-0.0077	0.0004	0.0034
1047	5/01/2018	7.76	117.98	67.62	0.0013	0.0000	-0.0066
1048	8/01/2018	7.64	118.11	67.78	-0.0156	0.0011	0.0024
1049	9/01/2018	7.76	117.80	68.82	0.0156	-0.0026	0.0152
1050	10/01/2018	7.87	117.68	69.2	0.0141	-0.0010	0.0055
1051	11/01/2018	7.8	117.27	69.26	-0.0089	-0.0035	0.0009
1052	12/01/2018	7.84	117.33	69.87	0.0051	0.0005	0.0088
1053	15/01/2018	7.78	117.31	70.26	-0.0077	-0.0001	0.0056
1054	16/01/2018	8.03	117.59	69.15	0.0316	0.0023	-0.0159
1055	17/01/2018	8.16	117.65	69.38	0.0161	0.0005	0.0033
1056	18/01/2018	8.47	117.51	69.31	0.0373	-0.0012	-0.0010
1057	19/01/2018	8.74	117.54	68.61	0.0314	0.0003	-0.0102
1058	22/01/2018	8.73	117.65	69.03	-0.0011	0.0009	0.0061
1059	23/01/2018	8.99	117.68	69.96	0.0293	0.0003	0.0134
1060	24/01/2018	9.43	117.47	70.53	0.0478	-0.0018	0.0081
1061	25/01/2018	9.22	117.34	70.42	-0.0225	-0.0011	-0.0016
1062	26/01/2018	9.07	117.23	70.52	-0.0164	-0.0009	0.0014
1063	29/01/2018	8.98	116.73	69.46	-0.0100	-0.0043	-0.0151
1064	30/01/2018	8.86	116.80	69.02	-0.0135	0.0005	-0.0064
1065	31/01/2018	9.26	116.87	69.05	0.0442	0.0006	0.0004
1066	1/02/2018	9.25	116.80	69.65	-0.0011	-0.0006	0.0087
1067	2/02/2018	8.94	116.51	68.58	-0.0341	-0.0025	-0.0155
1068	5/02/2018	9.05	116.58	67.62	0.0122	0.0006	-0.0141
1069	6/02/2018	8.78	116.94	66.86	-0.0303	0.0031	-0.0113
1070	7/02/2018	8.97	116.77	65.51	0.0214	-0.0015	-0.0204

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1071	8/02/2018	9.1	116.54	64.81	0.0144	-0.0020	-0.0107
1072	9/02/2018	9.21	116.62	62.79	0.0120	0.0008	-0.0317
1073	12/02/2018	9.46	116.62	62.59	0.0268	0.0000	-0.0032
1074	13/02/2018	9.87	116.50	62.72	0.0424	-0.0011	0.0021
1075	14/02/2018	9.58	116.44	64.36	-0.0298	-0.0005	0.0258
1076	15/02/2018	9.52	116.38	64.33	-0.0063	-0.0005	-0.0005
1077	16/02/2018	9.5	116.73	64.84	-0.0021	0.0030	0.0079
1078	19/02/2018	9.86	116.50	65.67	0.0372	-0.0020	0.0127
1079	20/02/2018	9.7	116.51	65.25	-0.0164	0.0001	-0.0064
1080	21/02/2018	9.54	116.58	65.42	-0.0166	0.0005	0.0026
1081	22/02/2018	9.7	116.66	66.39	0.0166	0.0007	0.0147
1082	23/02/2018	9.79	117.02	67.31	0.0092	0.0031	0.0138
1083	26/02/2018	9.61	117.08	67.5	-0.0186	0.0005	0.0028
1084	27/02/2018	10.13	116.97	66.63	0.0527	-0.0010	-0.0130
1085	28/02/2018	10.08	117.13	65.78	-0.0049	0.0014	-0.0128
1086	1/03/2018	9.97	117.21	63.83	-0.0110	0.0007	-0.0301
1087	2/03/2018	10.12	117.18	64.37	0.0149	-0.0003	0.0084
1088	5/03/2018	10.34	117.21	65.54	0.0215	0.0003	0.0180
1089	6/03/2018	10.45	116.91	65.79	0.0106	-0.0025	0.0038
1090	7/03/2018	10.62	117.08	64.34	0.0161	0.0014	-0.0223
1091	8/03/2018	11.1	117.31	63.61	0.0442	0.0020	-0.0114
1092	9/03/2018	11.1	117.14	65.49	0.0000	-0.0014	0.0291
1093	12/03/2018	11.06	117.36	64.95	-0.0036	0.0018	-0.0083
1094	13/03/2018	11.38	117.44	64.64	0.0285	0.0007	-0.0048
1095	14/03/2018	11.16	117.61	64.89	-0.0195	0.0014	0.0039
1096	15/03/2018	11.16	117.62	65.12	0.0000	0.0001	0.0035
1097	16/03/2018	11.15	117.60	66.21	-0.0009	-0.0001	0.0166
1098	19/03/2018	11.04	117.55	66.05	-0.0099	-0.0005	-0.0024
1099	20/03/2018	11.52	117.46	67.42	0.0426	-0.0007	0.0205
1100	21/03/2018	12.62	117.38	69.47	0.0912	-0.0007	0.0300
1101	22/03/2018	12.31	117.94	68.91	-0.0249	0.0047	-0.0081
1102	23/03/2018	12.58	117.85	70.45	0.0217	-0.0008	0.0221
1103	26/03/2018	12.96	117.82	70.12	0.0298	-0.0003	-0.0047
1104	27/03/2018	13.65	118.02	70.11	0.0519	0.0018	-0.0001
1105	28/03/2018	12.96	118.03	69.53	-0.0519	0.0000	-0.0083
1106	29/03/2018	13.26	118.07	70.27	0.0229	0.0003	0.0106
1107	30/03/2018	13.26	118.07	70.27	0.0000	0.0000	0.0000
1108	2/04/2018	13.26	118.08	67.64	0.0000	0.0001	-0.0381
1109	3/04/2018	13.27	118.00	68.12	0.0008	-0.0007	0.0071
1110	4/04/2018	13.03	118.12	68.02	-0.0183	0.0011	-0.0015

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1111	5/04/2018	12.61	117.87	68.33	-0.0328	-0.0021	0.0045
1112	6/04/2018	12.96	118.06	67.11	0.0274	0.0016	-0.0180
1113	9/04/2018	13.3	118.00	68.65	0.0259	-0.0005	0.0227
1114	10/04/2018	13.35	117.86	71.04	0.0038	-0.0011	0.0342
1115	11/04/2018	13.4	118.12	72.06	0.0037	0.0022	0.0143
1116	12/04/2018	13.56	117.99	72.02	0.0119	-0.0011	-0.0006
1117	13/04/2018	13.91	118.06	72.58	0.0255	0.0006	0.0077
1118	16/04/2018	13.97	117.99	71.42	0.0043	-0.0006	-0.0161
1119	17/04/2018	13.71	118.15	71.58	-0.0188	0.0014	0.0022
1120	18/04/2018	13.86	118.05	73.48	0.0109	-0.0009	0.0262
1121	19/04/2018	13.43	117.58	73.78	-0.0315	-0.0040	0.0041
1122	20/04/2018	13.02	117.53	74.06	-0.0310	-0.0004	0.0038
1123	23/04/2018	12.86	117.34	74.71	-0.0124	-0.0017	0.0087
1124	24/04/2018	13.2	117.30	73.86	0.0261	-0.0003	-0.0114
1125	25/04/2018	13.23	117.23	74	0.0023	-0.0006	0.0019
1126	26/04/2018	13.46	117.55	74.74	0.0172	0.0027	0.0100
1127	27/04/2018	13.53	117.74	74.64	0.0052	0.0016	-0.0013
1128	30/04/2018	13.56	117.77	75.17	0.0022	0.0002	0.0071
1129	1/05/2018	13.35	117.77	73.13	-0.0156	0.0000	-0.0275
1130	2/05/2018	13.02	117.67	73.36	-0.0250	-0.0009	0.0031
1131	3/05/2018	12.92	117.97	73.62	-0.0077	0.0026	0.0035
1132	4/05/2018	12.98	117.84	74.87	0.0046	-0.0011	0.0168
1133	7/05/2018	13.58	117.84	76.17	0.0452	0.0000	0.0172
1134	8/05/2018	13.56	117.68	74.85	-0.0015	-0.0014	-0.0175
1135	9/05/2018	13.96	117.68	77.21	0.0291	0.0001	0.0310
1136	10/05/2018	14.57	117.79	77.47	0.0428	0.0009	0.0034
1137	11/05/2018	14.6	117.71	77.12	0.0021	-0.0007	-0.0045
1138	14/05/2018	14.6	117.34	78.23	0.0000	-0.0031	0.0143
1139	15/05/2018	14.29	117.11	78.43	-0.0215	-0.0019	0.0026
1140	16/05/2018	15.15	117.18	79.28	0.0584	0.0006	0.0108
1141	17/05/2018	15.27	116.97	79.3	0.0079	-0.0018	0.0003
1142	18/05/2018	15.22	117.28	78.51	-0.0033	0.0026	-0.0100
1143	21/05/2018	15.53	117.34	79.22	0.0202	0.0005	0.0090
1144	22/05/2018	15.92	117.14	79.57	0.0248	-0.0016	0.0044
1145	23/05/2018	15.98	117.30	79.8	0.0038	0.0013	0.0029
1146	24/05/2018	16.26	117.62	78.79	0.0174	0.0027	-0.0127
1147	25/05/2018	15.97	117.87	76.44	-0.0180	0.0022	-0.0303
1148	28/05/2018	16.28	117.87	75.3	0.0192	0.0000	-0.0150
1149	29/05/2018	16.27	118.19	75.39	-0.0006	0.0027	0.0012
1150	30/05/2018	15.81	117.79	77.5	-0.0287	-0.0034	0.0276

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1151	31/05/2018	14.88	118.15	77.59	-0.0606	0.0031	0.0012
1152	1/06/2018	15.26	117.91	76.79	0.0252	-0.0020	-0.0104
1153	4/06/2018	16.1	117.82	75.29	0.0536	-0.0007	-0.0197
1154	5/06/2018	15.74	118.06	75.38	-0.0226	0.0020	0.0012
1155	6/06/2018	15.9	117.29	75.36	0.0101	-0.0066	-0.0003
1156	7/06/2018	15.97	117.02	77.32	0.0044	-0.0023	0.0257
1157	8/06/2018	15.79	117.24	76.46	-0.0113	0.0018	-0.0112
1158	11/06/2018	15.46	116.98	76.46	-0.0211	-0.0022	0.0000
1159	12/06/2018	15.12	117.08	75.88	-0.0222	0.0009	-0.0076
1160	13/06/2018	15.28	117.34	76.74	0.0105	0.0022	0.0113
1161	14/06/2018	14.88	117.80	75.94	-0.0265	0.0038	-0.0105
1162	15/06/2018	14.5	118.11	73.44	-0.0259	0.0027	-0.0335
1163	18/06/2018	14.57	118.11	75.34	0.0048	0.0000	0.0255
1164	19/06/2018	14.21	118.29	75.08	-0.0250	0.0015	-0.0035
1165	20/06/2018	14.47	118.24	74.74	0.0181	-0.0004	-0.0045
1166	21/06/2018	14.78	118.35	73.05	0.0212	0.0009	-0.0229
1167	22/06/2018	15.09	118.26	75.55	0.0208	-0.0007	0.0337
1168	25/06/2018	14.99	118.22	74.73	-0.0066	-0.0003	-0.0109
1169	26/06/2018	15.01	117.99	76.31	0.0013	-0.0020	0.0209
1170	27/06/2018	15.24	118.16	77.62	0.0152	0.0014	0.0170
1171	28/06/2018	14.99	118.25	77.85	-0.0165	0.0008	0.0030
1172	29/06/2018	14.98	118.52	79.44	-0.0007	0.0022	0.0202
1173	2/07/2018	15.06	118.60	77.3	0.0053	0.0007	-0.0273
1174	3/07/2018	15.09	118.69	77.76	0.0020	0.0007	0.0059
1175	4/07/2018	15.51	118.61	78.24	0.0275	-0.0007	0.0062
1176	5/07/2018	15.67	118.70	77.39	0.0103	0.0008	-0.0109
1177	6/07/2018	15.69	118.73	77.11	0.0013	0.0002	-0.0036
1178	9/07/2018	15.99	118.62	78.07	0.0189	-0.0009	0.0124
1179	10/07/2018	16.04	118.59	78.86	0.0031	-0.0003	0.0101
1180	11/07/2018	16.31	118.64	73.4	0.0167	0.0004	-0.0718
1181	12/07/2018	16.08	118.78	74.45	-0.0142	0.0012	0.0142
1182	13/07/2018	16.05	118.93	75.33	-0.0019	0.0013	0.0118
1183	16/07/2018	15.92	118.64	71.84	-0.0081	-0.0025	-0.0474
1184	17/07/2018	16.07	118.89	72.16	0.0094	0.0021	0.0044
1185	18/07/2018	16.4	118.90	72.9	0.0203	0.0001	0.0102
1186	19/07/2018	16.85	118.90	72.58	0.0271	0.0000	-0.0044
1187	20/07/2018	17.06	118.54	73.07	0.0124	-0.0030	0.0067
1188	23/07/2018	17.38	118.30	73.06	0.0186	-0.0020	-0.0001
1189	24/07/2018	17.09	118.48	73.44	-0.0168	0.0015	0.0052
1190	25/07/2018	17.33	118.58	73.93	0.0139	0.0009	0.0066

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1191	26/07/2018	17.28	118.51	74.54	-0.0029	-0.0006	0.0082
1192	27/07/2018	17.11	118.47	74.29	-0.0099	-0.0003	-0.0034
1193	30/07/2018	17.03	118.09	74.97	-0.0047	-0.0032	0.0091
1194	31/07/2018	17.38	118.28	74.25	0.0203	0.0015	-0.0097
1195	1/08/2018	17.76	117.90	72.39	0.0216	-0.0032	-0.0254
1196	2/08/2018	17.61	118.00	73.45	-0.0085	0.0009	0.0145
1197	3/08/2018	17.65	118.38	73.21	0.0023	0.0032	-0.0033
1198	6/08/2018	17.55	118.60	73.75	-0.0057	0.0018	0.0073
1199	7/08/2018	17.49	118.46	74.65	-0.0034	-0.0011	0.0121
1200	8/08/2018	17.38	118.49	72.28	-0.0063	0.0002	-0.0323
1201	9/08/2018	17.58	118.64	72.07	0.0114	0.0013	-0.0029
1202	10/08/2018	17.87	119.00	72.81	0.0164	0.0030	0.0102
1203	13/08/2018	18.04	118.88	72.61	0.0095	-0.0010	-0.0028
1204	14/08/2018	18.14	118.85	72.46	0.0055	-0.0002	-0.0021
1205	15/08/2018	18.07	119.04	70.76	-0.0039	0.0016	-0.0237
1206	16/08/2018	17.97	118.94	71.43	-0.0055	-0.0008	0.0094
1207	17/08/2018	18.12	119.01	71.83	0.0083	0.0006	0.0056
1208	20/08/2018	18.47	119.06	72.21	0.0191	0.0004	0.0053
1209	21/08/2018	19.29	118.88	72.63	0.0434	-0.0016	0.0058
1210	22/08/2018	19.78	118.73	74.78	0.0251	-0.0013	0.0292
1211	23/08/2018	20.36	118.75	74.73	0.0289	0.0002	-0.0007
1212	24/08/2018	20.65	118.73	75.82	0.0141	-0.0002	0.0145
1213	27/08/2018	21.28	118.73	76.21	0.0301	0.0000	0.0051
1214	28/08/2018	20.65	118.38	75.95	-0.0301	-0.0029	-0.0034
1215	29/08/2018	21.02	118.21	77.14	0.0178	-0.0014	0.0155
1216	30/08/2018	21.13	118.56	77.77	0.0052	0.0030	0.0081
1217	31/08/2018	21.06	118.64	77.42	-0.0033	0.0006	-0.0045
1218	3/09/2018	20.12	118.53	78.15	-0.0457	-0.0009	0.0094
1219	4/09/2018	20.14	118.42	78.17	0.0010	-0.0010	0.0003
1220	5/09/2018	20.34	118.16	77.27	0.0099	-0.0021	-0.0116
1221	6/09/2018	21.44	118.42	76.5	0.0527	0.0022	-0.0100
1222	7/09/2018	23.19	118.22	76.83	0.0785	-0.0017	0.0043
1223	10/09/2018	25.19	118.18	77.37	0.0827	-0.0003	0.0070
1224	11/09/2018	24.13	117.99	79.06	-0.0430	-0.0016	0.0216
1225	12/09/2018	22.92	118.15	79.74	-0.0514	0.0014	0.0086
1226	13/09/2018	18.87	118.09	78.18	-0.1944	-0.0005	-0.0198
1227	14/09/2018	19.94	117.93	78.09	0.0552	-0.0014	-0.0012
1228	17/09/2018	20.9	117.90	78.05	0.0470	-0.0002	-0.0005
1229	18/09/2018	20.19	117.80	79.03	-0.0346	-0.0009	0.0125
1230	19/09/2018	21.43	117.74	79.4	0.0596	-0.0005	0.0047

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1231	20/09/2018	21.98	117.78	78.7	0.0253	0.0003	-0.0089
1232	21/09/2018	22.08	117.93	78.8	0.0045	0.0013	0.0013
1233	24/09/2018	22.37	117.54	81.2	0.0130	-0.0033	0.0300
1234	25/09/2018	21.25	117.31	81.87	-0.0514	-0.0019	0.0082
1235	26/09/2018	20.24	117.42	81.34	-0.0487	0.0009	-0.0065
1236	27/09/2018	20.83	117.42	81.72	0.0287	0.0000	0.0047
1237	28/09/2018	21.21	117.74	82.72	0.0181	0.0027	0.0122
1238	1/10/2018	21.37	117.63	84.98	0.0075	-0.0009	0.0270
1239	2/10/2018	20.98	117.93	84.8	-0.0184	0.0025	-0.0021
1240	3/10/2018	21.18	117.70	86.29	0.0095	-0.0019	0.0174
1241	4/10/2018	21.34	117.28	84.58	0.0075	-0.0036	-0.0200
1242	5/10/2018	22.16	117.07	84.16	0.0377	-0.0018	-0.0050
1243	8/10/2018	21.94	117.15	83.91	-0.0100	0.0007	-0.0030
1244	9/10/2018	20.79	117.21	85	-0.0538	0.0005	0.0129
1245	10/10/2018	19.46	117.08	83.09	-0.0661	-0.0011	-0.0227
1246	11/10/2018	19.87	117.22	80.26	0.0208	0.0011	-0.0347
1247	12/10/2018	20.37	117.31	80.43	0.0249	0.0008	0.0021
1248	15/10/2018	18.58	117.30	80.78	-0.0920	0.0000	0.0043
1249	16/10/2018	19.29	117.46	81.41	0.0375	0.0013	0.0078
1250	17/10/2018	19.27	117.68	80.05	-0.0010	0.0019	-0.0168
1251	18/10/2018	19.74	117.74	79.29	0.0241	0.0005	-0.0095
1252	19/10/2018	19.71	117.58	79.78	-0.0015	-0.0013	0.0062
1253	22/10/2018	19	117.65	79.83	-0.0367	0.0006	0.0006
1254	23/10/2018	19.23	117.87	76.44	0.0120	0.0019	-0.0434
1255	24/10/2018	19.61	118.03	76.17	0.0196	0.0013	-0.0035
1256	25/10/2018	19.08	117.98	76.89	-0.0274	-0.0004	0.0094
1257	26/10/2018	18.28	118.26	77.62	-0.0428	0.0024	0.0094
1258	29/10/2018	16.68	118.04	77.34	-0.0916	-0.0018	-0.0036
1259	30/10/2018	16.02	118.06	75.91	-0.0404	0.0001	-0.0187
1260	31/10/2018	16.36	118.02	75.47	0.0210	-0.0004	-0.0058
1261	1/11/2018	15.62	117.89	72.89	-0.0463	-0.0011	-0.0348
1262	2/11/2018	17.08	117.74	72.83	0.0894	-0.0013	-0.0008
1263	5/11/2018	17.23	117.77	73.17	0.0087	0.0002	0.0047
1264	6/11/2018	17.57	117.75	72.13	0.0195	-0.0002	-0.0143
1265	7/11/2018	18.62	117.67	72.07	0.0580	-0.0006	-0.0008
1266	8/11/2018	19.56	117.61	70.65	0.0493	-0.0006	-0.0199
1267	9/11/2018	19.5	117.88	70.18	-0.0031	0.0023	-0.0067
1268	12/11/2018	20.5	117.98	70.12	0.0500	0.0009	-0.0009
1269	13/11/2018	20.14	117.84	65.47	-0.0177	-0.0012	-0.0686
1270	14/11/2018	19.73	117.77	66.12	-0.0206	-0.0006	0.0099

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1271	15/11/2018	19	117.93	66.62	-0.0377	0.0014	0.0075
1272	16/11/2018	19.11	117.76	66.76	0.0058	-0.0014	0.0021
1273	19/11/2018	18.93	117.61	66.79	-0.0095	-0.0013	0.0004
1274	20/11/2018	19.46	117.68	62.53	0.0276	0.0007	-0.0659
1275	21/11/2018	20.49	117.61	63.48	0.0516	-0.0006	0.0151
1276	22/11/2018	20.92	117.66	62.6	0.0208	0.0005	-0.0140
1277	23/11/2018	20.21	117.91	58.8	-0.0345	0.0021	-0.0626
1278	26/11/2018	19.83	117.78	60.48	-0.0190	-0.0011	0.0282
1279	27/11/2018	19.6	117.86	60.21	-0.0117	0.0007	-0.0045
1280	28/11/2018	19.29	117.78	58.76	-0.0159	-0.0007	-0.0244
1281	29/11/2018	20.02	118.05	59.51	0.0371	0.0023	0.0127
1282	30/11/2018	20.5	118.15	58.71	0.0237	0.0009	-0.0135
1283	3/12/2018	20.63	118.07	61.69	0.0063	-0.0007	0.0495
1284	4/12/2018	20.73	118.34	62.08	0.0048	0.0022	0.0063
1285	5/12/2018	19.67	118.17	61.56	-0.0525	-0.0014	-0.0084
1286	6/12/2018	19.99	118.43	60.06	0.0161	0.0022	-0.0247
1287	7/12/2018	20.29	118.16	61.67	0.0149	-0.0022	0.0265
1288	10/12/2018	20.86	118.21	59.97	0.0277	0.0004	-0.0280
1289	11/12/2018	20.16	118.14	60.2	-0.0341	-0.0006	0.0038
1290	12/12/2018	21.47	118.05	60.15	0.0630	-0.0007	-0.0008
1291	13/12/2018	22.32	118.07	61.45	0.0388	0.0002	0.0214
1292	14/12/2018	23.37	118.19	60.28	0.0460	0.0010	-0.0192
1293	17/12/2018	24.26	118.11	59.61	0.0374	-0.0007	-0.0112
1294	18/12/2018	24.09	118.24	56.26	-0.0070	0.0012	-0.0578
1295	19/12/2018	24.38	118.26	57.24	0.0120	0.0002	0.0173
1296	20/12/2018	24.23	118.46	54.35	-0.0062	0.0016	-0.0518
1297	21/12/2018	24.65	118.27	53.82	0.0172	-0.0015	-0.0098
1298	24/12/2018	24.9	118.29	50.47	0.0101	0.0001	-0.0643
1299	25/12/2018	24.9	118.29	50.47	0.0000	0.0000	0.0000
1300	26/12/2018	24.9	118.29	54.47	0.0000	0.0000	0.0763
1301	27/12/2018	24.73	118.48	52.16	-0.0069	0.0016	-0.0433
1302	28/12/2018	24.7	118.35	52.2	-0.0012	-0.0011	0.0008
1303	31/12/2018	24.73	118.36	53.8	0.0012	0.0001	0.0302
1304	1/01/2019	24.73	118.36	53.8	0.0000	0.0000	0.0000
1305	2/01/2019	25.06	118.80	54.91	0.0133	0.0037	0.0204
1306	3/01/2019	23.08	118.75	55.95	-0.0823	-0.0004	0.0188
1307	4/01/2019	23.54	118.29	57.06	0.0197	-0.0039	0.0196
1308	7/01/2019	22.09	118.08	57.33	-0.0636	-0.0018	0.0047
1309	8/01/2019	22.68	117.93	58.72	0.0264	-0.0013	0.0240
1310	9/01/2019	21.87	118.12	61.44	-0.0364	0.0016	0.0453

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1311	10/01/2019	21.95	118.24	61.68	0.0037	0.0010	0.0039
1312	11/01/2019	22.6	118.36	60.48	0.0292	0.0011	-0.0196
1313	14/01/2019	22.41	118.50	58.99	-0.0084	0.0012	-0.0249
1314	15/01/2019	22.49	118.69	60.64	0.0036	0.0016	0.0276
1315	16/01/2019	23.25	118.61	61.32	0.0332	-0.0007	0.0112
1316	17/01/2019	23.51	118.52	61.18	0.0111	-0.0008	-0.0023
1317	18/01/2019	24.69	118.45	62.7	0.0490	-0.0006	0.0245
1318	21/01/2019	24.3	118.48	62.74	-0.0159	0.0003	0.0006
1319	22/01/2019	25.03	118.68	61.5	0.0296	0.0017	-0.0200
1320	23/01/2019	24.55	118.76	61.14	-0.0194	0.0006	-0.0059
1321	24/01/2019	23.9	119.20	61.09	-0.0268	0.0037	-0.0008
1322	25/01/2019	23.78	119.18	61.64	-0.0050	-0.0002	0.0090
1323	28/01/2019	22.62	119.07	59.93	-0.0500	-0.0009	-0.0281
1324	29/01/2019	23.24	119.14	61.32	0.0270	0.0005	0.0229
1325	30/01/2019	22.91	119.27	61.65	-0.0143	0.0011	0.0054
1326	31/01/2019	22.16	119.70	61.89	-0.0333	0.0036	0.0039
1327	1/02/2019	21.85	119.61	62.75	-0.0141	-0.0008	0.0138
1328	4/02/2019	22.92	119.53	62.51	0.0478	-0.0006	-0.0038
1329	5/02/2019	23.03	119.72	61.98	0.0048	0.0016	-0.0085
1330	6/02/2019	23.56	119.83	62.69	0.0228	0.0009	0.0114
1331	7/02/2019	23.34	120.11	61.63	-0.0094	0.0023	-0.0171
1332	8/02/2019	22.24	120.17	62.1	-0.0483	0.0005	0.0076
1333	11/02/2019	22.27	120.01	61.51	0.0013	-0.0013	-0.0095
1334	12/02/2019	20.58	119.93	62.42	-0.0789	-0.0007	0.0147
1335	13/02/2019	20.83	120.01	63.61	0.0121	0.0007	0.0189
1336	14/02/2019	19.68	120.20	64.57	-0.0568	0.0016	0.0150
1337	15/02/2019	20.31	120.15	66.25	0.0315	-0.0004	0.0257
1338	18/02/2019	19.9	120.16	66.5	-0.0204	0.0000	0.0038
1339	19/02/2019	20.1	120.28	66.45	0.0100	0.0010	-0.0008
1340	20/02/2019	20.37	120.39	67.08	0.0133	0.0009	0.0094
1341	21/02/2019	18.71	120.19	67.07	-0.0850	-0.0017	-0.0001
1342	22/02/2019	18.85	120.41	67.12	0.0075	0.0018	0.0007
1343	25/02/2019	19.15	120.36	64.76	0.0158	-0.0004	-0.0358
1344	26/02/2019	19.56	120.32	65.21	0.0212	-0.0003	0.0069
1345	27/02/2019	21.17	120.14	66.39	0.0791	-0.0016	0.0179
1346	28/02/2019	21.59	120.02	66.03	0.0196	-0.0009	-0.0054
1347	1/03/2019	22.18	119.93	65.07	0.0270	-0.0008	-0.0146
1348	4/03/2019	23.03	120.11	65.67	0.0376	0.0016	0.0092
1349	5/03/2019	22.83	120.11	65.86	-0.0087	0.0000	0.0029
1350	6/03/2019	22.04	120.43	65.99	-0.0352	0.0027	0.0020

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1351	7/03/2019	23.17	120.97	66.3	0.0500	0.0045	0.0047
1352	8/03/2019	22.91	121.04	65.74	-0.0113	0.0005	-0.0085
1353	11/03/2019	22.18	121.06	66.58	-0.0324	0.0002	0.0127
1354	12/03/2019	22.22	121.02	66.67	0.0018	-0.0003	0.0014
1355	13/03/2019	22.17	121.06	67.55	-0.0023	0.0003	0.0131
1356	14/03/2019	22.63	121.09	67.23	0.0205	0.0002	-0.0047
1357	15/03/2019	22.36	121.21	67.16	-0.0120	0.0010	-0.0010
1358	18/03/2019	21.71	121.41	67.54	-0.0295	0.0016	0.0056
1359	19/03/2019	21.01	121.38	67.61	-0.0328	-0.0003	0.0010
1360	20/03/2019	21.53	121.45	68.5	0.0244	0.0006	0.0131
1361	21/03/2019	20.83	121.87	67.86	-0.0331	0.0034	-0.0094
1362	22/03/2019	20.56	122.41	67.03	-0.0130	0.0045	-0.0123
1363	25/03/2019	20.83	122.32	67.21	0.0130	-0.0007	0.0027
1364	26/03/2019	21.47	122.31	67.97	0.0303	-0.0001	0.0112
1365	27/03/2019	21.78	122.94	67.83	0.0143	0.0051	-0.0021
1366	28/03/2019	22.19	122.75	67.82	0.0186	-0.0015	-0.0001
1367	29/03/2019	21.47	122.69	68.39	-0.0330	-0.0005	0.0084
1368	1/04/2019	21.85	122.31	69.01	0.0175	-0.0031	0.0090
1369	2/04/2019	21.95	122.57	69.37	0.0046	0.0021	0.0052
1370	3/04/2019	23.1	122.22	69.31	0.0511	-0.0029	-0.0009
1371	4/04/2019	24.38	122.41	69.4	0.0539	0.0016	0.0013
1372	5/04/2019	24.54	122.47	70.34	0.0065	0.0004	0.0135
1373	8/04/2019	24.25	122.47	71.1	-0.0119	0.0001	0.0107
1374	9/04/2019	25.47	122.56	70.61	0.0491	0.0007	-0.0069
1375	10/04/2019	26.07	122.80	71.73	0.0233	0.0020	0.0157
1376	11/04/2019	27.26	122.69	70.83	0.0446	-0.0009	-0.0126
1377	12/04/2019	26.52	122.19	71.55	-0.0275	-0.0041	0.0101
1378	15/04/2019	26.75	122.16	71.18	0.0086	-0.0003	-0.0052
1379	16/04/2019	26.94	122.15	71.72	0.0071	-0.0001	0.0076
1380	17/04/2019	27.4	122.07	71.62	0.0169	-0.0007	-0.0014
1381	18/04/2019	26.83	122.57	71.97	-0.0210	0.0041	0.0049
1382	19/04/2019	26.83	122.57	71.97	0.0000	0.0000	0.0000
1383	22/04/2019	26.83	122.57	74.04	0.0000	0.0000	0.0284
1384	23/04/2019	27.47	122.39	74.51	0.0236	-0.0015	0.0063
1385	24/04/2019	27.34	122.89	74.57	-0.0047	0.0041	0.0008
1386	25/04/2019	27.21	122.76	74.35	-0.0048	-0.0011	-0.0030
1387	26/04/2019	25.78	122.89	72.15	-0.0540	0.0010	-0.0300
1388	29/04/2019	26.31	122.86	72.04	0.0204	-0.0002	-0.0015
1389	30/04/2019	26.22	122.87	72.8	-0.0034	0.0001	0.0105
1390	1/05/2019	25.71	122.87	72.18	-0.0196	0.0000	-0.0086

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1391	2/05/2019	24.63	122.87	70.75	-0.0429	0.0000	-0.0200
1392	3/05/2019	25.13	122.94	70.85	0.0201	0.0005	0.0014
1393	6/05/2019	25.26	122.94	71.24	0.0052	0.0000	0.0055
1394	7/05/2019	26.33	123.17	69.88	0.0415	0.0019	-0.0193
1395	8/05/2019	26.83	123.15	70.37	0.0188	-0.0002	0.0070
1396	9/05/2019	26.43	122.99	70.39	-0.0150	-0.0013	0.0003
1397	10/05/2019	25.55	122.98	70.62	-0.0339	-0.0001	0.0033
1398	13/05/2019	24.96	123.05	70.23	-0.0234	0.0006	-0.0055
1399	14/05/2019	25.82	123.12	71.24	0.0339	0.0005	0.0143
1400	15/05/2019	25.9	123.30	71.77	0.0031	0.0015	0.0074
1401	16/05/2019	25.5	123.35	72.62	-0.0156	0.0004	0.0118
1402	17/05/2019	24.93	123.39	72.21	-0.0226	0.0004	-0.0057
1403	20/05/2019	25.13	123.20	71.97	0.0080	-0.0015	-0.0033
1404	21/05/2019	25.32	123.01	72.18	0.0075	-0.0016	0.0029
1405	22/05/2019	26.3	123.09	70.99	0.0380	0.0007	-0.0166
1406	23/05/2019	25.99	123.19	67.76	-0.0119	0.0007	-0.0466
1407	24/05/2019	25.4	123.23	68.69	-0.0230	0.0004	0.0136
1408	27/05/2019	25.51	123.23	70.11	0.0043	0.0000	0.0205
1409	28/05/2019	25.4	123.49	70.11	-0.0043	0.0021	0.0000
1410	29/05/2019	25.45	123.66	69.45	0.0020	0.0014	-0.0095
1411	30/05/2019	25.22	123.64	66.87	-0.0091	-0.0002	-0.0379
1412	31/05/2019	24.39	123.90	64.49	-0.0335	0.0021	-0.0362
1413	3/06/2019	23.67	124.00	61.28	-0.0300	0.0009	-0.0511
1414	4/06/2019	24.49	124.22	61.97	0.0341	0.0017	0.0112
1415	5/06/2019	24.18	124.54	60.63	-0.0127	0.0026	-0.0219
1416	6/06/2019	23.91	124.85	61.67	-0.0112	0.0025	0.0170
1417	7/06/2019	24.44	125.29	63.29	0.0219	0.0035	0.0259
1418	10/06/2019	25.13	124.80	62.29	0.0278	-0.0039	-0.0159
1419	11/06/2019	24.91	125.08	62.29	-0.0088	0.0023	0.0000
1420	12/06/2019	24.75	125.10	59.97	-0.0064	0.0002	-0.0380
1421	13/06/2019	24.9	125.16	61.31	0.0060	0.0004	0.0221
1422	14/06/2019	24.99	125.44	62.01	0.0036	0.0022	0.0114
1423	17/06/2019	24.96	125.28	60.94	-0.0012	-0.0013	-0.0174
1424	18/06/2019	25.05	126.34	62.14	0.0036	0.0085	0.0195
1425	19/06/2019	24.89	126.01	61.82	-0.0064	-0.0026	-0.0052
1426	20/06/2019	25.03	126.57	64.45	0.0056	0.0044	0.0417
1427	21/06/2019	25.24	126.20	65.2	0.0084	-0.0030	0.0116
1428	24/06/2019	26.31	126.51	64.86	0.0415	0.0025	-0.0052
1429	25/06/2019	26.39	126.78	65.05	0.0030	0.0021	0.0029
1430	26/06/2019	27.37	126.57	66.49	0.0365	-0.0017	0.0219

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1431	27/06/2019	26.87	126.65	66.55	-0.0184	0.0006	0.0009
1432	28/06/2019	26.26	126.75	66.55	-0.0230	0.0008	0.0000
1433	1/07/2019	26.89	127.17	65.06	0.0237	0.0033	-0.0226
1434	2/07/2019	26.69	127.15	62.4	-0.0075	-0.0002	-0.0417
1435	3/07/2019	26.48	127.70	63.82	-0.0079	0.0044	0.0225
1436	4/07/2019	25.98	127.98	63.3	-0.0191	0.0022	-0.0082
1437	5/07/2019	26.35	127.64	64.23	0.0141	-0.0027	0.0146
1438	8/07/2019	26.78	127.66	64.11	0.0162	0.0002	-0.0019
1439	9/07/2019	26.53	127.37	64.16	-0.0094	-0.0023	0.0008
1440	10/07/2019	28.16	126.96	67.01	0.0596	-0.0032	0.0435
1441	11/07/2019	28.26	126.50	66.52	0.0035	-0.0036	-0.0073
1442	12/07/2019	28.76	126.29	66.72	0.0175	-0.0017	0.0030
1443	15/07/2019	29.02	126.76	66.48	0.0090	0.0037	-0.0036
1444	16/07/2019	28.44	126.92	64.35	-0.0202	0.0013	-0.0326
1445	17/07/2019	28.43	127.29	63.66	-0.0004	0.0029	-0.0108
1446	18/07/2019	27.74	127.46	61.93	-0.0246	0.0014	-0.0276
1447	19/07/2019	28.85	127.55	62.47	0.0392	0.0007	0.0087
1448	22/07/2019	28.96	127.74	63.26	0.0038	0.0015	0.0126
1449	23/07/2019	29.78	127.84	63.83	0.0279	0.0007	0.0090
1450	24/07/2019	29.16	128.21	63.18	-0.0210	0.0029	-0.0102
1451	25/07/2019	28.99	128.16	63.39	-0.0058	-0.0004	0.0033
1452	26/07/2019	28.26	128.34	63.46	-0.0255	0.0014	0.0011
1453	29/07/2019	28.39	128.55	63.71	0.0046	0.0016	0.0039
1454	30/07/2019	27.87	128.57	64.72	-0.0185	0.0002	0.0157
1455	31/07/2019	27.95	129.01	65.17	0.0029	0.0034	0.0069
1456	1/08/2019	29.42	129.29	60.5	0.0513	0.0022	-0.0744
1457	2/08/2019	29.23	129.60	61.89	-0.0065	0.0024	0.0227
1458	5/08/2019	28.67	129.73	59.81	-0.0193	0.0010	-0.0342
1459	6/08/2019	28.38	129.98	58.94	-0.0102	0.0019	-0.0147
1460	7/08/2019	28.25	130.68	56.23	-0.0046	0.0054	-0.0471
1461	8/08/2019	28.51	130.23	57.38	0.0092	-0.0034	0.0202
1462	9/08/2019	28.1	130.18	58.53	-0.0145	-0.0003	0.0198
1463	12/08/2019	26.68	130.39	58.57	-0.0519	0.0015	0.0007
1464	13/08/2019	27.08	130.73	61.3	0.0149	0.0026	0.0456
1465	14/08/2019	26.89	131.28	59.48	-0.0070	0.0042	-0.0301
1466	15/08/2019	25.97	132.01	58.23	-0.0348	0.0055	-0.0212
1467	16/08/2019	25.95	131.71	58.64	-0.0008	-0.0022	0.0070
1468	19/08/2019	26.55	131.17	59.74	0.0229	-0.0042	0.0186
1469	20/08/2019	26.24	131.60	60.03	-0.0117	0.0033	0.0048
1470	21/08/2019	26.01	131.49	60.3	-0.0088	-0.0008	0.0045

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1471	22/08/2019	25.65	130.98	59.92	-0.0139	-0.0039	-0.0063
1472	23/08/2019	25.08	131.22	59.34	-0.0225	0.0018	-0.0097
1473	26/08/2019	25.82	131.22	58.7	0.0291	0.0000	-0.0108
1474	27/08/2019	25.4	131.75	59.51	-0.0164	0.0040	0.0137
1475	28/08/2019	26	132.17	60.49	0.0233	0.0032	0.0163
1476	29/08/2019	26.45	131.87	61.08	0.0172	-0.0023	0.0097
1477	30/08/2019	26.31	131.82	60.43	-0.0053	-0.0003	-0.0107
1478	2/09/2019	25.18	131.59	58.66	-0.0439	-0.0017	-0.0297
1479	3/09/2019	25.22	131.87	58.26	0.0016	0.0021	-0.0068
1480	4/09/2019	25.52	131.35	60.7	0.0118	-0.0039	0.0410
1481	5/09/2019	25.53	130.36	60.95	0.0004	-0.0076	0.0041
1482	6/09/2019	25.08	130.91	61.54	-0.0178	0.0042	0.0096
1483	9/09/2019	25.01	130.02	62.59	-0.0028	-0.0068	0.0169
1484	10/09/2019	26.72	129.74	62.38	0.0661	-0.0021	-0.0034
1485	11/09/2019	26.27	129.87	60.81	-0.0170	0.0010	-0.0255
1486	12/09/2019	26.43	129.86	60.38	0.0061	-0.0001	-0.0071
1487	13/09/2019	26.37	128.90	60.22	-0.0023	-0.0074	-0.0027
1488	16/09/2019	27.02	129.30	69.02	0.0244	0.0031	0.1364
1489	17/09/2019	26.2	129.14	64.55	-0.0308	-0.0012	-0.0670
1490	18/09/2019	25.44	129.59	63.6	-0.0294	0.0035	-0.0148
1491	19/09/2019	25.94	129.54	64.4	0.0195	-0.0004	0.0125
1492	20/09/2019	26.51	129.68	64.28	0.0217	0.0011	-0.0019
1493	23/09/2019	25.78	130.48	64.77	-0.0279	0.0062	0.0076
1494	24/09/2019	25.52	130.68	63.1	-0.0101	0.0015	-0.0261
1495	25/09/2019	25.19	130.49	62.39	-0.0130	-0.0014	-0.0113
1496	26/09/2019	25.62	130.54	62.74	0.0169	0.0004	0.0056
1497	27/09/2019	25.29	130.45	61.91	-0.0130	-0.0007	-0.0133
1498	30/09/2019	24.72	130.45	60.78	-0.0228	0.0000	-0.0184
1499	1/10/2019	25.04	130.33	58.89	0.0129	-0.0010	-0.0316
1500	2/10/2019	24.19	130.01	57.69	-0.0345	-0.0024	-0.0206
1501	3/10/2019	23.24	130.42	57.71	-0.0401	0.0032	0.0003
1502	4/10/2019	22.94	130.40	58.37	-0.0130	-0.0002	0.0114
1503	7/10/2019	23.41	130.26	58.35	0.0203	-0.0011	-0.0003
1504	8/10/2019	22.53	130.47	58.24	-0.0383	0.0016	-0.0019
1505	9/10/2019	22.65	130.06	58.32	0.0053	-0.0031	0.0014
1506	10/10/2019	23.26	129.42	59.1	0.0266	-0.0049	0.0133
1507	11/10/2019	24.44	129.12	60.51	0.0495	-0.0023	0.0236
1508	14/10/2019	24.15	129.28	59.35	-0.0119	0.0012	-0.0194
1509	15/10/2019	25.71	128.89	58.74	0.0626	-0.0030	-0.0103
1510	16/10/2019	26.3	128.75	59.42	0.0227	-0.0010	0.0115

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1511	17/10/2019	26.06	128.82	59.91	-0.0092	0.0006	0.0082
1512	18/10/2019	25.88	128.62	59.42	-0.0069	-0.0016	-0.0082
1513	21/10/2019	25.93	128.22	58.96	0.0019	-0.0031	-0.0078
1514	22/10/2019	25.66	128.59	59.7	-0.0105	0.0029	0.0125
1515	23/10/2019	24.75	128.88	61.17	-0.0361	0.0022	0.0243
1516	24/10/2019	25.44	128.98	61.67	0.0275	0.0008	0.0081
1517	25/10/2019	24.97	128.64	62.02	-0.0186	-0.0026	0.0057
1518	28/10/2019	25.12	128.23	61.57	0.0060	-0.0032	-0.0073
1519	29/10/2019	25.45	128.45	61.59	0.0131	0.0017	0.0003
1520	30/10/2019	26	128.45	60.61	0.0214	0.0000	-0.0160
1521	31/10/2019	25.61	128.93	60.23	-0.0151	0.0037	-0.0063
1522	1/11/2019	25.29	128.65	61.69	-0.0126	-0.0022	0.0240
1523	4/11/2019	25.63	128.41	62.13	0.0134	-0.0019	0.0071
1524	5/11/2019	25.51	128.26	62.96	-0.0047	-0.0011	0.0133
1525	6/11/2019	24.79	128.33	61.74	-0.0286	0.0006	-0.0196
1526	7/11/2019	24.94	127.64	62.29	0.0060	-0.0055	0.0089
1527	8/11/2019	24.84	127.73	62.51	-0.0040	0.0008	0.0035
1528	11/11/2019	24.93	127.57	62.18	0.0036	-0.0013	-0.0053
1529	12/11/2019	24.12	127.54	62.06	-0.0330	-0.0002	-0.0019
1530	13/11/2019	24.39	128.01	62.37	0.0111	0.0037	0.0050
1531	14/11/2019	23.96	128.30	62.28	-0.0178	0.0023	-0.0014
1532	15/11/2019	23.85	128.24	63.3	-0.0046	-0.0005	0.0162
1533	18/11/2019	23.39	128.24	62.44	-0.0195	0.0000	-0.0137
1534	19/11/2019	23.44	128.21	60.91	0.0021	-0.0002	-0.0248
1535	20/11/2019	24.03	128.25	62.4	0.0249	0.0003	0.0242
1536	21/11/2019	23.94	127.98	63.97	-0.0038	-0.0021	0.0248
1537	22/11/2019	24.58	128.28	63.39	0.0264	0.0023	-0.0091
1538	25/11/2019	24.44	128.24	63.65	-0.0057	-0.0003	0.0041
1539	26/11/2019	24.38	128.50	64.27	-0.0025	0.0020	0.0097
1540	27/11/2019	25.11	128.50	64.06	0.0295	0.0000	-0.0033
1541	28/11/2019	25.01	128.46	63.87	-0.0040	-0.0004	-0.0030
1542	29/11/2019	25.22	128.42	62.43	0.0084	-0.0003	-0.0228
1543	2/12/2019	24.33	127.66	60.92	-0.0359	-0.0059	-0.0245
1544	3/12/2019	24	128.42	60.82	-0.0137	0.0059	-0.0016
1545	4/12/2019	24.74	128.15	63	0.0304	-0.0021	0.0352
1546	5/12/2019	24.69	127.88	63.39	-0.0020	-0.0021	0.0062
1547	6/12/2019	24.94	127.81	64.39	0.0101	-0.0006	0.0157
1548	9/12/2019	25.13	127.98	64.25	0.0076	0.0014	-0.0022
1549	10/12/2019	24.94	127.96	64.34	-0.0076	-0.0001	0.0014
1550	11/12/2019	24.48	128.18	63.72	-0.0186	0.0017	-0.0097

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1551	12/12/2019	25.07	127.70	64.2	0.0238	-0.0038	0.0075
1552	13/12/2019	24.02	128.08	65.22	-0.0428	0.0030	0.0158
1553	16/12/2019	24.86	127.98	65.34	0.0344	-0.0008	0.0018
1554	17/12/2019	25.95	128.14	66.1	0.0429	0.0012	0.0116
1555	18/12/2019	26.47	127.72	66.17	0.0198	-0.0033	0.0011
1556	19/12/2019	26.74	127.61	66.54	0.0101	-0.0009	0.0056
1557	20/12/2019	26.56	127.73	66.14	-0.0068	0.0010	-0.0060
1558	23/12/2019	26.43	127.65	66.39	-0.0049	-0.0007	0.0038
1559	24/12/2019	25.97	127.65	67.2	-0.0176	0.0000	0.0121
1560	25/12/2019	25.97	127.65	67.2	0.0000	0.0000	0.0000
1561	26/12/2019	25.97	127.65	67.92	0.0000	0.0000	0.0107
1562	27/12/2019	26.59	127.74	68.16	0.0236	0.0007	0.0035
1563	30/12/2019	24.97	127.07	68.44	-0.0629	-0.0052	0.0041
1564	31/12/2019	24.52	127.07	66	-0.0182	0.0000	-0.0363
1565	1/01/2020	24.52	127.07	66	0.0000	0.0000	0.0000
1566	2/01/2020	24.28	127.53	66.25	-0.0098	0.0036	0.0038
1567	3/01/2020	24.9	128.04	68.6	0.0252	0.0040	0.0349
1568	6/01/2020	24.15	128.09	68.91	-0.0306	0.0004	0.0045
1569	7/01/2020	24.47	128.02	68.27	0.0132	-0.0006	-0.0093
1570	8/01/2020	23.97	127.82	65.44	-0.0206	-0.0016	-0.0423
1571	9/01/2020	24.58	127.49	65.37	0.0251	-0.0026	-0.0011
1572	10/01/2020	24.12	127.64	64.98	-0.0189	0.0012	-0.0060
1573	13/01/2020	24.06	127.21	64.2	-0.0025	-0.0034	-0.0121
1574	14/01/2020	23.77	127.40	64.49	-0.0121	0.0015	0.0045
1575	15/01/2020	24.43	127.68	64	0.0274	0.0022	-0.0076
1576	16/01/2020	24.77	127.81	64.62	0.0138	0.0010	0.0096
1577	17/01/2020	25.36	127.77	64.85	0.0235	-0.0003	0.0036
1578	20/01/2020	25.11	127.86	65.2	-0.0099	0.0006	0.0054
1579	21/01/2020	24.85	128.24	64.59	-0.0104	0.0030	-0.0094
1580	22/01/2020	24.94	128.36	63.21	0.0036	0.0009	-0.0216
1581	23/01/2020	24.63	128.80	62.04	-0.0125	0.0035	-0.0187
1582	24/01/2020	24.3	128.97	60.69	-0.0135	0.0013	-0.0220
1583	27/01/2020	24.52	129.59	59.32	0.0090	0.0048	-0.0228
1584	28/01/2020	24.58	129.29	59.51	0.0024	-0.0023	0.0032
1585	29/01/2020	23.92	129.55	59.81	-0.0272	0.0020	0.0050
1586	30/01/2020	23.67	129.84	58.29	-0.0105	0.0023	-0.0257
1587	31/01/2020	23.82	130.17	58.16	0.0063	0.0025	-0.0022
1588	3/02/2020	23.15	130.03	54.45	-0.0285	-0.0010	-0.0659
1589	4/02/2020	23.3	129.84	53.96	0.0065	-0.0015	-0.0090
1590	5/02/2020	23.71	129.49	55.28	0.0174	-0.0027	0.0242

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1591	6/02/2020	23.5	129.43	54.93	-0.0089	-0.0005	-0.0064
1592	7/02/2020	23.26	129.72	54.47	-0.0103	0.0022	-0.0084
1593	10/02/2020	23.11	130.00	53.27	-0.0065	0.0021	-0.0223
1594	11/02/2020	23.25	129.80	54.01	0.0060	-0.0015	0.0138
1595	12/02/2020	23.83	129.77	55.79	0.0246	-0.0003	0.0324
1596	13/02/2020	24.35	129.95	56.34	0.0216	0.0014	0.0098
1597	14/02/2020	24.24	130.09	57.32	-0.0045	0.0011	0.0172
1598	17/02/2020	25	130.13	57.67	0.0309	0.0003	0.0061
1599	18/02/2020	25.09	130.17	57.75	0.0036	0.0003	0.0014
1600	19/02/2020	25.66	130.32	59.12	0.0225	0.0012	0.0234
1601	20/02/2020	25.59	130.64	59.31	-0.0027	0.0024	0.0032
1602	21/02/2020	25.56	130.74	58.5	-0.0012	0.0008	-0.0138
1603	24/02/2020	24.53	131.01	56.3	-0.0411	0.0020	-0.0383
1604	25/02/2020	24.14	131.14	54.95	-0.0160	0.0010	-0.0243
1605	26/02/2020	24.22	130.83	53.43	0.0033	-0.0024	-0.0281
1606	27/02/2020	23.56	131.00	52.18	-0.0276	0.0013	-0.0237
1607	28/02/2020	23.57	131.22	50.52	0.0004	0.0016	-0.0323
1608	2/03/2020	23.49	131.34	51.9	-0.0034	0.0009	0.0269
1609	3/03/2020	23.33	131.54	51.86	-0.0068	0.0015	-0.0008
1610	4/03/2020	23.8	131.69	51.13	0.0199	0.0011	-0.0142
1611	5/03/2020	23.77	131.82	49.99	-0.0013	0.0010	-0.0225
1612	6/03/2020	23.39	132.03	45.27	-0.0161	0.0017	-0.0992
1613	9/03/2020	23.25	131.96	34.36	-0.0060	-0.0005	-0.2758
1614	10/03/2020	24.07	131.52	37.22	0.0347	-0.0034	0.0800
1615	11/03/2020	23.89	131.42	35.79	-0.0075	-0.0007	-0.0392
1616	12/03/2020	22.49	129.77	33.22	-0.0604	-0.0127	-0.0745
1617	13/03/2020	21.89	128.26	33.85	-0.0270	-0.0116	0.0188
1618	16/03/2020	19.41	126.17	30.05	-0.1202	-0.0165	-0.1191
1619	17/03/2020	18.25	125.42	28.73	-0.0616	-0.0060	-0.0449
1620	18/03/2020	15.24	122.98	24.88	-0.1802	-0.0196	-0.1439
1621	19/03/2020	16.31	122.83	28.47	0.0679	-0.0013	0.1348
1622	20/03/2020	16.04	124.21	26.98	-0.0167	0.0112	-0.0538
1623	23/03/2020	15.45	124.00	27.03	-0.0375	-0.0017	0.0019
1624	24/03/2020	16.7	123.09	27.15	0.0778	-0.0074	0.0044
1625	25/03/2020	17.41	122.56	27.39	0.0416	-0.0043	0.0088
1626	26/03/2020	17.22	123.79	26.34	-0.0110	0.0100	-0.0391
1627	27/03/2020	16.26	124.85	24.93	-0.0574	0.0085	-0.0550
1628	30/03/2020	16.93	125.27	22.76	0.0404	0.0033	-0.0911
1629	31/03/2020	17.59	124.56	22.74	0.0382	-0.0057	-0.0009
1630	1/04/2020	17	124.61	24.74	-0.0341	0.0005	0.0843

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1631	2/04/2020	17.99	124.46	29.94	0.0566	-0.0012	0.1908
1632	3/04/2020	17.89	124.42	34.11	-0.0056	-0.0003	0.1304
1633	6/04/2020	20.33	124.31	33.05	0.1279	-0.0009	-0.0316
1634	7/04/2020	20.44	123.73	31.87	0.0054	-0.0047	-0.0364
1635	8/04/2020	21.06	123.92	32.84	0.0299	0.0015	0.0300
1636	9/04/2020	21.01	124.78	31.48	-0.0024	0.0069	-0.0423
1637	10/04/2020	21.01	124.78	31.48	0.0000	0.0000	0.0000
1638	13/04/2020	21.01	124.78	31.74	0.0000	0.0000	0.0082
1639	14/04/2020	19.76	125.38	29.6	-0.0613	0.0048	-0.0698
1640	15/04/2020	19.2	125.98	27.69	-0.0287	0.0048	-0.0667
1641	16/04/2020	20.89	125.94	27.82	0.0844	-0.0003	0.0047
1642	17/04/2020	21.64	126.03	28.08	0.0353	0.0007	0.0093
1643	20/04/2020	21.32	125.55	25.57	-0.0149	-0.0038	-0.0936
1644	21/04/2020	19.79	125.60	19.33	-0.0745	0.0003	-0.2798
1645	22/04/2020	20.59	125.12	20.37	0.0396	-0.0038	0.0524
1646	23/04/2020	20.97	125.61	21.33	0.0183	0.0039	0.0461
1647	24/04/2020	20.68	126.17	21.44	-0.0139	0.0045	0.0051
1648	27/04/2020	20.22	126.25	19.99	-0.0225	0.0006	-0.0700
1649	28/04/2020	20.15	126.44	20.46	-0.0035	0.0015	0.0232
1650	29/04/2020	20.13	126.73	22.54	-0.0010	0.0022	0.0968
1651	30/04/2020	19.51	127.56	25.27	-0.0313	0.0066	0.1143
1652	1/05/2020	18.91	127.56	26.44	-0.0312	0.0000	0.0453
1653	4/05/2020	19.29	126.96	27.2	0.0199	-0.0048	0.0283
1654	5/05/2020	19.03	127.09	30.97	-0.0136	0.0010	0.1298
1655	6/05/2020	18.94	126.36	29.72	-0.0047	-0.0058	-0.0412
1656	7/05/2020	19.48	126.66	29.46	0.0281	0.0024	-0.0088
1657	8/05/2020	19.29	126.66	30.97	-0.0098	0.0000	0.0500
1658	11/05/2020	19	126.51	29.63	-0.0151	-0.0012	-0.0442
1659	12/05/2020	18.46	126.61	29.98	-0.0288	0.0008	0.0117
1660	13/05/2020	18.6	126.82	29.19	0.0076	0.0017	-0.0267
1661	14/05/2020	18.77	126.62	31.13	0.0091	-0.0016	0.0643
1662	15/05/2020	19.11	126.62	32.5	0.0180	0.0000	0.0431
1663	18/05/2020	20.28	126.32	34.81	0.0594	-0.0023	0.0687
1664	19/05/2020	19.9	126.41	34.65	-0.0189	0.0007	-0.0046
1665	20/05/2020	21.19	126.64	35.75	0.0628	0.0018	0.0313
1666	21/05/2020	21.12	126.89	36.06	-0.0033	0.0020	0.0086
1667	22/05/2020	21.33	126.87	35.13	0.0099	-0.0002	-0.0261
1668	25/05/2020	21.54	126.87	35.53	0.0098	0.0000	0.0113
1669	26/05/2020	21.53	126.56	36.17	-0.0005	-0.0025	0.0179
1670	27/05/2020	21.26	126.93	34.74	-0.0126	0.0029	-0.0403

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1671	28/05/2020	21.19	127.18	35.29	-0.0033	0.0020	0.0157
1672	29/05/2020	21.33	127.47	35.33	0.0066	0.0023	0.0011
1673	1/06/2020	20.9	126.93	38.32	-0.0204	-0.0042	0.0812
1674	2/06/2020	22	127.25	39.57	0.0513	0.0025	0.0321
1675	3/06/2020	22.01	126.98	39.79	0.0005	-0.0021	0.0055
1676	4/06/2020	22.14	127.14	39.99	0.0059	0.0012	0.0050
1677	5/06/2020	23.17	127.13	42.3	0.0455	-0.0001	0.0562
1678	8/06/2020	22.65	127.72	40.8	-0.0227	0.0047	-0.0361
1679	9/06/2020	22.42	127.62	41.18	-0.0102	-0.0009	0.0093
1680	10/06/2020	22.85	127.55	41.73	0.0190	-0.0005	0.0133
1681	11/06/2020	22.21	128.22	38.55	-0.0284	0.0052	-0.0793
1682	12/06/2020	21.93	128.34	38.73	-0.0127	0.0009	0.0047
1683	15/06/2020	22.1	128.25	39.72	0.0077	-0.0007	0.0252
1684	16/06/2020	22.72	128.55	40.96	0.0277	0.0023	0.0307
1685	17/06/2020	22.69	128.55	40.71	-0.0013	0.0000	-0.0061
1686	18/06/2020	24.4	128.75	41.51	0.0727	0.0015	0.0195
1687	19/06/2020	24.09	128.85	42.19	-0.0128	0.0008	0.0162
1688	22/06/2020	24.46	129.08	43.08	0.0152	0.0018	0.0209
1689	23/06/2020	25.35	128.71	42.63	0.0357	-0.0029	-0.0105
1690	24/06/2020	25.33	128.94	40.31	-0.0008	0.0018	-0.0560
1691	25/06/2020	25.11	129.13	41.05	-0.0087	0.0015	0.0182
1692	26/06/2020	24.66	129.17	41.02	-0.0181	0.0003	-0.0007
1693	29/06/2020	26.55	129.13	41.71	0.0738	-0.0003	0.0167
1694	30/06/2020	26.95	129.11	41.15	0.0150	-0.0002	-0.0135
1695	1/07/2020	27.69	128.37	42.03	0.0271	-0.0058	0.0212
1696	2/07/2020	27.35	128.95	43.14	-0.0124	0.0045	0.0261
1697	3/07/2020	27.89	128.93	42.8	0.0196	-0.0001	-0.0079
1698	6/07/2020	29.68	129.01	43.1	0.0622	0.0006	0.0070
1699	7/07/2020	29.36	129.07	43.08	-0.0108	0.0004	-0.0005
1700	8/07/2020	29.29	129.24	43.29	-0.0024	0.0014	0.0049
1701	9/07/2020	28.58	129.50	42.35	-0.0245	0.0020	-0.0220
1702	10/07/2020	28.98	129.57	43.24	0.0139	0.0006	0.0208
1703	13/07/2020	29.31	128.98	42.72	0.0113	-0.0046	-0.0121
1704	14/07/2020	29.6	129.44	42.9	0.0098	0.0035	0.0042
1705	15/07/2020	28.81	129.44	43.79	-0.0271	0.0000	0.0205
1706	16/07/2020	26.54	129.69	43.37	-0.0821	0.0019	-0.0096
1707	17/07/2020	27.75	129.56	43.14	0.0446	-0.0010	-0.0053
1708	20/07/2020	26.1	129.88	43.28	-0.0613	0.0024	0.0032
1709	21/07/2020	26.55	129.99	44.32	0.0171	0.0008	0.0237
1710	22/07/2020	26.57	130.34	44.29	0.0008	0.0027	-0.0007

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1711	23/07/2020	27.27	130.36	43.31	0.0260	0.0002	-0.0224
1712	24/07/2020	26.31	129.96	43.34	-0.0358	-0.0031	0.0007
1713	27/07/2020	24.95	130.44	43.41	-0.0531	0.0037	0.0016
1714	28/07/2020	25.69	130.62	43.22	0.0292	0.0014	-0.0044
1715	29/07/2020	26.14	130.43	43.75	0.0174	-0.0014	0.0122
1716	30/07/2020	25.5	130.83	42.94	-0.0248	0.0030	-0.0187
1717	31/07/2020	26.23	130.67	43.3	0.0282	-0.0012	0.0083
1718	3/08/2020	26.07	130.59	44.15	-0.0061	-0.0006	0.0194
1719	4/08/2020	26.78	131.04	44.43	0.0269	0.0035	0.0063
1720	5/08/2020	26.73	130.67	45.17	-0.0019	-0.0028	0.0165
1721	6/08/2020	26.35	131.04	45.09	-0.0143	0.0028	-0.0018
1722	7/08/2020	26.38	130.91	44.4	0.0011	-0.0009	-0.0154
1723	10/08/2020	26.68	131.19	44.99	0.0113	0.0021	0.0132
1724	11/08/2020	26.16	130.76	44.5	-0.0197	-0.0033	-0.0110
1725	12/08/2020	25.94	130.59	45.43	-0.0084	-0.0013	0.0207
1726	13/08/2020	25.4	130.12	44.96	-0.0210	-0.0036	-0.0104
1727	14/08/2020	25.44	130.18	44.8	0.0016	0.0005	-0.0036
1728	17/08/2020	26.26	130.48	45.37	0.0317	0.0023	0.0126
1729	18/08/2020	26.51	130.63	45.46	0.0095	0.0011	0.0020
1730	19/08/2020	26.2	130.74	45.37	-0.0118	0.0009	-0.0020
1731	20/08/2020	25.88	130.96	44.9	-0.0123	0.0016	-0.0104
1732	21/08/2020	25.63	130.96	44.35	-0.0097	0.0000	-0.0123
1733	24/08/2020	27.46	130.95	45.13	0.0690	-0.0001	0.0174
1734	25/08/2020	28.59	130.23	45.86	0.0403	-0.0055	0.0160
1735	26/08/2020	28.6	130.15	45.64	0.0003	-0.0006	-0.0048
1736	27/08/2020	28.35	129.91	45.09	-0.0088	-0.0018	-0.0121
1737	28/08/2020	29.5	129.97	45.05	0.0398	0.0005	-0.0009
1738	31/08/2020	28.64	129.92	45.28	-0.0296	-0.0004	0.0051
1739	1/09/2020	27.72	130.04	45.58	-0.0327	0.0009	0.0066
1740	2/09/2020	28.21	130.76	44.43	0.0175	0.0055	-0.0256
1741	3/09/2020	28.72	131.01	44.07	0.0179	0.0019	-0.0081
1742	4/09/2020	27.34	130.77	42.66	-0.0492	-0.0018	-0.0325
1743	7/09/2020	27.04	130.61	42.01	-0.0110	-0.0012	-0.0154
1744	8/09/2020	26.78	130.95	39.78	-0.0097	0.0026	-0.0545
1745	9/09/2020	27.19	130.59	40.79	0.0152	-0.0028	0.0251
1746	10/09/2020	28.4	130.31	40.06	0.0435	-0.0021	-0.0181
1747	11/09/2020	28.24	130.85	39.83	-0.0056	0.0041	-0.0058
1748	14/09/2020	30.44	130.94	39.61	0.0750	0.0007	-0.0055
1749	15/09/2020	29.76	130.99	40.53	-0.0226	0.0004	0.0230
1750	16/09/2020	29.96	131.06	42.22	0.0067	0.0005	0.0409

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1751	17/09/2020	28.41	131.30	43.3	-0.0531	0.0018	0.0253
1752	18/09/2020	27.97	131.21	43.15	-0.0156	-0.0007	-0.0035
1753	21/09/2020	26.38	131.57	41.44	-0.0585	0.0027	-0.0404
1754	22/09/2020	27.83	131.33	41.72	0.0535	-0.0018	0.0067
1755	23/09/2020	26.48	131.25	41.77	-0.0497	-0.0006	0.0012
1756	24/09/2020	26.77	131.26	41.94	0.0109	0.0001	0.0041
1757	25/09/2020	26.15	131.40	41.92	-0.0234	0.0011	-0.0005
1758	28/09/2020	27.69	131.41	42.43	0.0572	0.0001	0.0121
1759	29/09/2020	26.79	131.63	41.03	-0.0330	0.0016	-0.0336
1760	30/09/2020	26.93	131.40	40.95	0.0052	-0.0017	-0.0020
1761	1/10/2020	26.51	131.55	40.93	-0.0157	0.0011	-0.0005
1762	2/10/2020	27.03	131.57	39.27	0.0194	0.0001	-0.0414
1763	5/10/2020	26.94	131.52	41.29	-0.0033	-0.0004	0.0502
1764	6/10/2020	26.79	131.51	42.65	-0.0056	-0.0001	0.0324
1765	7/10/2020	26.9	131.41	41.99	0.0041	-0.0007	-0.0156
1766	8/10/2020	26.34	131.68	43.34	-0.0210	0.0020	0.0316
1767	9/10/2020	25.71	131.86	42.85	-0.0242	0.0014	-0.0114
1768	12/10/2020	25.87	131.97	41.72	0.0062	0.0008	-0.0267
1769	13/10/2020	25.22	132.15	42.45	-0.0254	0.0014	0.0173
1770	14/10/2020	25.75	132.30	43.32	0.0208	0.0011	0.0203
1771	15/10/2020	24.96	132.60	43.16	-0.0312	0.0023	-0.0037
1772	16/10/2020	24.89	132.72	42.93	-0.0028	0.0009	-0.0053
1773	19/10/2020	24.98	132.65	42.62	0.0036	-0.0005	-0.0072
1774	20/10/2020	24.41	132.50	43.16	-0.0231	-0.0011	0.0126
1775	21/10/2020	23.56	132.46	41.73	-0.0354	-0.0003	-0.0337
1776	22/10/2020	24.18	132.07	42.46	0.0260	-0.0030	0.0173
1777	23/10/2020	25.49	132.17	41.77	0.0528	0.0008	-0.0164
1778	26/10/2020	23.85	132.21	40.46	-0.0665	0.0003	-0.0319
1779	27/10/2020	24.07	132.60	41.2	0.0092	0.0029	0.0181
1780	28/10/2020	23.03	132.50	39.12	-0.0442	-0.0007	-0.0518
1781	29/10/2020	23.67	132.69	37.65	0.0274	0.0014	-0.0383
1782	30/10/2020	23.71	132.57	37.46	0.0017	-0.0009	-0.0051
1783	2/11/2020	23.67	132.59	38.97	-0.0017	0.0002	0.0395
1784	3/11/2020	24.39	132.61	39.71	0.0300	0.0001	0.0188
1785	4/11/2020	25.11	132.88	41.23	0.0291	0.0021	0.0376
1786	5/11/2020	25.98	132.96	40.93	0.0341	0.0006	-0.0073
1787	6/11/2020	25.42	132.80	39.45	-0.0218	-0.0012	-0.0368
1788	9/11/2020	26.55	131.95	42.4	0.0435	-0.0064	0.0721
1789	10/11/2020	26.23	131.82	43.61	-0.0121	-0.0010	0.0281
1790	11/11/2020	26.13	132.08	43.8	-0.0038	0.0020	0.0043

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1791	12/11/2020	25.92	132.37	43.53	-0.0081	0.0022	-0.0062
1792	13/11/2020	26.28	132.54	42.78	0.0138	0.0013	-0.0174
1793	16/11/2020	27.39	132.67	43.82	0.0414	0.0010	0.0240
1794	17/11/2020	26.64	132.90	43.75	-0.0278	0.0017	-0.0016
1795	18/11/2020	27.19	132.87	44.34	0.0204	-0.0002	0.0134
1796	19/11/2020	26.35	133.03	44.2	-0.0314	0.0012	-0.0032
1797	20/11/2020	26.74	133.12	44.96	0.0147	0.0007	0.0170
1798	23/11/2020	27.25	132.98	46.06	0.0189	-0.0010	0.0242
1799	24/11/2020	27.63	132.98	47.86	0.0138	0.0000	0.0383
1800	25/11/2020	27.62	133.04	48.61	-0.0004	0.0004	0.0155
1801	26/11/2020	28.1	133.18	47.8	0.0172	0.0010	-0.0168
1802	27/11/2020	28.13	133.15	48.18	0.0011	-0.0002	0.0079
1803	30/11/2020	29.14	133.02	47.59	0.0353	-0.0010	-0.0123
1804	1/12/2020	28.86	132.57	47.42	-0.0097	-0.0034	-0.0036
1805	2/12/2020	29.55	132.56	48.25	0.0236	0.0000	0.0174
1806	3/12/2020	29	132.88	48.71	-0.0188	0.0024	0.0095
1807	4/12/2020	30.11	132.79	49.25	0.0376	-0.0007	0.0110
1808	7/12/2020	29.62	133.18	48.79	-0.0164	0.0029	-0.0094
1809	8/12/2020	29.57	133.48	48.84	-0.0017	0.0023	0.0010
1810	9/12/2020	29.7	133.43	48.86	0.0044	-0.0004	0.0004
1811	10/12/2020	30.9	133.38	50.25	0.0396	-0.0004	0.0281
1812	11/12/2020	30.52	133.78	49.97	-0.0124	0.0030	-0.0056
1813	14/12/2020	30.81	133.61	50.29	0.0095	-0.0013	0.0064
1814	15/12/2020	32.05	133.53	50.76	0.0395	-0.0006	0.0093
1815	16/12/2020	31.66	133.08	51.08	-0.0122	-0.0033	0.0063
1816	17/12/2020	31.83	133.19	51.5	0.0054	0.0008	0.0082
1817	18/12/2020	30.96	133.16	52.26	-0.0277	-0.0002	0.0146
1818	21/12/2020	30.77	133.24	50.91	-0.0062	0.0005	-0.0262
1819	22/12/2020	31.03	133.29	50.08	0.0084	0.0004	-0.0164
1820	23/12/2020	31.79	132.77	51.2	0.0242	-0.0039	0.0221
1821	24/12/2020	32.06	132.77	51.29	0.0085	0.0000	0.0018
1822	25/12/2020	32.06	132.77	51.29	0.0000	0.0000	0.0000
1823	28/12/2020	33.29	132.77	50.86	0.0376	0.0000	-0.0084
1824	29/12/2020	32.89	133.22	51.09	-0.0121	0.0034	0.0045
1825	30/12/2020	32.08	133.19	51.34	-0.0249	-0.0002	0.0049
1826	31/12/2020	32.59	133.20	51.8	0.0158	0.0000	0.0089
1827	1/01/2021	32.59	133.20	51.8	0.0000	0.0000	0.0000
1828	4/01/2021	33.58	133.47	51.09	0.0299	0.0020	-0.0138
1829	5/01/2021	32.87	133.38	53.6	-0.0214	-0.0007	0.0480
1830	6/01/2021	33.53	133.13	54.3	0.0199	-0.0019	0.0130

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1831	7/01/2021	34.66	133.07	54.38	0.0331	-0.0004	0.0015
1832	8/01/2021	34.82	133.16	55.99	0.0046	0.0007	0.0292
1833	11/01/2021	34.43	132.87	55.66	-0.0113	-0.0022	-0.0059
1834	12/01/2021	34.56	132.46	56.58	0.0038	-0.0031	0.0164
1835	13/01/2021	33.55	133.04	56.06	-0.0297	0.0044	-0.0092
1836	14/01/2021	33.43	133.24	56.42	-0.0036	0.0015	0.0064
1837	15/01/2021	31.65	133.07	55.1	-0.0547	-0.0013	-0.0237
1838	18/01/2021	31.54	132.85	54.75	-0.0035	-0.0017	-0.0064
1839	19/01/2021	33	132.90	55.9	0.0453	0.0004	0.0208
1840	20/01/2021	32.82	132.92	56.08	-0.0055	0.0001	0.0032
1841	21/01/2021	34.03	132.46	56.1	0.0362	-0.0034	0.0004
1842	22/01/2021	34.17	132.67	55.41	0.0041	0.0016	-0.0124
1843	25/01/2021	33.1	133.08	55.88	-0.0318	0.0031	0.0084
1844	26/01/2021	33.29	132.85	55.91	0.0057	-0.0017	0.0005
1845	27/01/2021	33.22	132.91	55.81	-0.0021	0.0005	-0.0018
1846	28/01/2021	33.89	132.83	55.53	0.0200	-0.0007	-0.0050
1847	29/01/2021	32.89	132.50	55.88	-0.0300	-0.0025	0.0063
1848	1/02/2021	32.81	132.50	56.35	-0.0024	0.0000	0.0084
1849	2/02/2021	34.93	132.24	57.46	0.0626	-0.0019	0.0195
1850	3/02/2021	37.39	132.10	58.46	0.0681	-0.0011	0.0173
1851	4/02/2021	37.23	132.03	58.84	-0.0043	-0.0006	0.0065
1852	5/02/2021	38.15	131.95	59.34	0.0244	-0.0006	0.0085
1853	8/02/2021	38.56	131.88	60.56	0.0107	-0.0005	0.0204
1854	9/02/2021	38.21	131.92	61.09	-0.0091	0.0004	0.0087
1855	10/02/2021	39.28	131.81	61.47	0.0276	-0.0008	0.0062
1856	11/02/2021	38.71	131.99	61.14	-0.0146	0.0013	-0.0054
1857	12/02/2021	39.97	131.59	62.43	0.0320	-0.0030	0.0209
1858	15/02/2021	39.47	131.15	63.3	-0.0126	-0.0033	0.0138
1859	16/02/2021	38.81	130.85	63.35	-0.0169	-0.0023	0.0008
1860	17/02/2021	38.04	130.90	64.34	-0.0200	0.0004	0.0155
1861	18/02/2021	38.27	130.58	63.93	0.0060	-0.0025	-0.0064
1862	19/02/2021	37.36	130.31	62.91	-0.0241	-0.0020	-0.0161
1863	22/02/2021	37.91	130.65	65.24	0.0146	0.0026	0.0364
1864	23/02/2021	38.61	130.38	65.37	0.0183	-0.0021	0.0020
1865	24/02/2021	39.09	130.08	67.04	0.0124	-0.0023	0.0252
1866	25/02/2021	38.2	129.53	66.88	-0.0230	-0.0043	-0.0024
1867	26/02/2021	37.23	129.87	66.13	-0.0257	0.0026	-0.0113
1868	1/03/2021	37.07	130.64	63.69	-0.0043	0.0059	-0.0376
1869	2/03/2021	38.29	130.66	62.7	0.0324	0.0002	-0.0157
1870	3/03/2021	37.41	130.16	64.07	-0.0233	-0.0038	0.0216

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1871	4/03/2021	38.1	130.24	66.74	0.0183	0.0006	0.0408
1872	5/03/2021	38.96	130.03	69.36	0.0223	-0.0017	0.0385
1873	8/03/2021	39.07	129.93	68.24	0.0028	-0.0008	-0.0163
1874	9/03/2021	40.58	130.14	67.52	0.0379	0.0016	-0.0106
1875	10/03/2021	41.47	130.18	67.9	0.0217	0.0003	0.0056
1876	11/03/2021	41.85	130.39	69.63	0.0091	0.0016	0.0252
1877	12/03/2021	42.77	130.00	69.22	0.0217	-0.0030	-0.0059
1878	15/03/2021	42.29	130.35	68.88	-0.0113	0.0027	-0.0049
1879	16/03/2021	41.47	130.34	68.39	-0.0196	-0.0001	-0.0071
1880	17/03/2021	42.86	129.79	68	0.0330	-0.0042	-0.0057
1881	18/03/2021	42.28	129.55	63.28	-0.0136	-0.0018	-0.0719
1882	19/03/2021	41.84	129.80	64.53	-0.0105	0.0019	0.0196
1883	22/03/2021	42.72	129.91	64.62	0.0208	0.0008	0.0014
1884	23/03/2021	41.35	130.16	60.79	-0.0326	0.0019	-0.0611
1885	24/03/2021	41.53	130.34	64.41	0.0043	0.0014	0.0578
1886	25/03/2021	40.29	130.59	61.95	-0.0303	0.0020	-0.0389
1887	26/03/2021	41.66	130.31	64.57	0.0334	-0.0022	0.0414
1888	29/03/2021	41.78	129.95	64.98	0.0029	-0.0027	0.0063
1889	30/03/2021	41.98	129.62	64.14	0.0048	-0.0026	-0.0130
1890	31/03/2021	42.48	129.84	63.54	0.0118	0.0017	-0.0094
1891	1/04/2021	42.4	130.20	64.86	-0.0019	0.0028	0.0206
1892	2/04/2021	42.4	130.20	64.86	0.0000	0.0000	0.0000
1893	5/04/2021	42.4	130.20	62.15	0.0000	0.0000	-0.0427
1894	6/04/2021	44.17	130.14	62.74	0.0409	-0.0005	0.0094
1895	7/04/2021	43.79	130.17	63.16	-0.0086	0.0002	0.0067
1896	8/04/2021	43.41	130.30	63.2	-0.0087	0.0010	0.0006
1897	9/04/2021	43.58	129.98	62.95	0.0039	-0.0025	-0.0040
1898	12/04/2021	44.42	129.91	63.28	0.0191	-0.0005	0.0052
1899	13/04/2021	43.79	129.87	63.67	-0.0143	-0.0003	0.0061
1900	14/04/2021	43.76	129.63	66.58	-0.0007	-0.0018	0.0447
1901	15/04/2021	44.1	129.96	66.94	0.0077	0.0025	0.0054
1902	16/04/2021	44.35	129.74	66.77	0.0057	-0.0017	-0.0025
1903	19/04/2021	44.28	129.55	67.05	-0.0016	-0.0015	0.0042
1904	20/04/2021	44.82	129.69	66.57	0.0121	0.0011	-0.0072
1905	21/04/2021	45.83	129.80	65.32	0.0223	0.0009	-0.0190
1906	22/04/2021	47.02	129.83	65.4	0.0256	0.0003	0.0012
1907	23/04/2021	46.88	129.73	66.11	-0.0030	-0.0008	0.0108
1908	26/04/2021	47.13	129.72	65.65	0.0053	-0.0001	-0.0070
1909	27/04/2021	47.21	129.65	66.42	0.0017	-0.0005	0.0117
1910	28/04/2021	47.7	129.45	67.27	0.0103	-0.0015	0.0127

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1911	29/04/2021	47.93	129.00	68.56	0.0048	-0.0035	0.0190
1912	30/04/2021	48.75	128.98	67.25	0.0170	-0.0001	-0.0193
1913	3/05/2021	49.33	129.09	67.56	0.0118	0.0009	0.0046
1914	4/05/2021	48.52	129.41	68.88	-0.0166	0.0024	0.0193
1915	5/05/2021	49.35	129.26	68.96	0.0170	-0.0012	0.0012
1916	6/05/2021	49.84	129.25	68.09	0.0099	0.0000	-0.0127
1917	7/05/2021	50.35	129.07	68.28	0.0102	-0.0014	0.0028
1918	10/05/2021	52.12	129.03	68.32	0.0346	-0.0003	0.0006
1919	11/05/2021	52.92	128.47	68.55	0.0152	-0.0044	0.0034
1920	12/05/2021	55.17	128.11	69.32	0.0416	-0.0028	0.0112
1921	13/05/2021	54.35	128.01	67.05	-0.0150	-0.0007	-0.0333
1922	14/05/2021	56.49	128.03	68.71	0.0386	0.0001	0.0245
1923	17/05/2021	56.17	127.86	69.46	-0.0057	-0.0013	0.0109
1924	18/05/2021	52.92	127.82	68.71	-0.0596	-0.0003	-0.0109
1925	19/05/2021	49.57	127.81	66.66	-0.0654	-0.0001	-0.0303
1926	20/05/2021	52.59	127.91	65.11	0.0591	0.0008	-0.0235
1927	21/05/2021	51.66	128.15	66.44	-0.0178	0.0019	0.0202
1928	24/05/2021	52.69	128.26	68.46	0.0197	0.0008	0.0300
1929	25/05/2021	53.24	128.59	68.65	0.0104	0.0026	0.0028
1930	26/05/2021	53.59	129.01	68.87	0.0066	0.0033	0.0032
1931	27/05/2021	51.76	128.66	69.46	-0.0347	-0.0027	0.0085
1932	28/05/2021	50.95	128.75	69.63	-0.0158	0.0006	0.0024
1933	31/05/2021	51.62	128.79	69.32	0.0131	0.0003	-0.0045
1934	1/06/2021	52.32	128.75	70.25	0.0135	-0.0003	0.0133
1935	2/06/2021	51.32	128.96	71.35	-0.0193	0.0016	0.0155
1936	3/06/2021	50.17	128.82	71.31	-0.0227	-0.0011	-0.0006
1937	4/06/2021	49.9	129.05	71.89	-0.0054	0.0018	0.0081
1938	7/06/2021	51.39	128.94	71.49	0.0294	-0.0008	-0.0056
1939	8/06/2021	52.09	129.19	72.22	0.0135	0.0019	0.0102
1940	9/06/2021	53.43	129.52	72.22	0.0254	0.0026	0.0000
1941	10/06/2021	53.7	129.39	72.52	0.0050	-0.0010	0.0041
1942	11/06/2021	52.59	129.69	72.69	-0.0209	0.0023	0.0023
1943	14/06/2021	52.81	129.49	72.86	0.0042	-0.0015	0.0023
1944	15/06/2021	51.31	129.30	73.99	-0.0288	-0.0014	0.0154
1945	16/06/2021	51.25	129.39	74.39	-0.0012	0.0006	0.0054
1946	17/06/2021	50.82	129.26	73.08	-0.0084	-0.0010	-0.0178
1947	18/06/2021	51.81	129.39	73.51	0.0193	0.0010	0.0059
1948	21/06/2021	52.33	129.15	74.9	0.0100	-0.0018	0.0187
1949	22/06/2021	53.31	129.04	74.81	0.0186	-0.0009	-0.0012
1950	23/06/2021	54.57	129.14	75.19	0.0234	0.0008	0.0051

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1951	24/06/2021	54.99	129.21	75.56	0.0077	0.0005	0.0049
1952	25/06/2021	54.95	128.72	76.18	-0.0007	-0.0038	0.0082
1953	28/06/2021	55.4	129.07	74.68	0.0082	0.0027	-0.0199
1954	29/06/2021	55.58	129.01	74.76	0.0032	-0.0005	0.0011
1955	30/06/2021	56.31	129.40	75.13	0.0130	0.0030	0.0049
1956	1/07/2021	57.58	129.38	75.84	0.0223	-0.0001	0.0094
1957	2/07/2021	57.29	129.72	76.17	-0.0050	0.0026	0.0043
1958	5/07/2021	57.81	129.49	77.16	0.0090	-0.0018	0.0129
1959	6/07/2021	53.96	130.15	74.53	-0.0689	0.0051	-0.0347
1960	7/07/2021	52.56	130.48	73.43	-0.0263	0.0025	-0.0149
1961	8/07/2021	52.29	130.59	74.12	-0.0052	0.0009	0.0094
1962	9/07/2021	54.2	130.27	75.55	0.0359	-0.0025	0.0191
1963	12/07/2021	51.65	130.37	75.16	-0.0482	0.0008	-0.0052
1964	13/07/2021	52.79	130.46	76.49	0.0218	0.0007	0.0175
1965	14/07/2021	53.3	130.61	74.76	0.0096	0.0012	-0.0229
1966	15/07/2021	52.91	130.78	73.47	-0.0073	0.0013	-0.0174
1967	16/07/2021	52.82	131.01	73.59	-0.0017	0.0017	0.0016
1968	19/07/2021	52.34	131.42	68.62	-0.0091	0.0031	-0.0699
1969	20/07/2021	51.15	131.65	69.35	-0.0230	0.0018	0.0106
1970	21/07/2021	52.08	131.36	72.23	0.0180	-0.0022	0.0407
1971	22/07/2021	50.74	131.67	73.79	-0.0261	0.0023	0.0214
1972	23/07/2021	50.84	131.68	74.1	0.0020	0.0001	0.0042
1973	26/07/2021	53.15	131.65	74.5	0.0444	-0.0002	0.0054
1974	27/07/2021	52.85	131.83	74.48	-0.0057	0.0013	-0.0003
1975	28/07/2021	53.78	131.81	74.74	0.0174	-0.0001	0.0035
1976	29/07/2021	54	131.90	76.05	0.0041	0.0007	0.0174
1977	30/07/2021	53.28	132.02	76.33	-0.0134	0.0009	0.0037
1978	2/08/2021	54.38	132.28	72.89	0.0204	0.0020	-0.0461
1979	3/08/2021	54.14	132.39	72.41	-0.0044	0.0009	-0.0066
1980	4/08/2021	55.41	132.41	70.38	0.0232	0.0001	-0.0284
1981	5/08/2021	55.93	132.70	71.29	0.0093	0.0022	0.0128
1982	6/08/2021	56.61	132.17	70.7	0.0121	-0.0040	-0.0083
1983	9/08/2021	56.57	132.23	69.04	-0.0007	0.0005	-0.0238
1984	10/08/2021	57.36	132.37	70.63	0.0139	0.0010	0.0228
1985	11/08/2021	57.73	132.27	71.44	0.0064	-0.0008	0.0114
1986	12/08/2021	56.21	132.30	71.31	-0.0267	0.0002	-0.0018
1987	13/08/2021	55.33	132.34	70.59	-0.0158	0.0003	-0.0101
1988	16/08/2021	58.11	132.39	69.51	0.0490	0.0004	-0.0154
1989	17/08/2021	57.18	132.34	69.03	-0.0161	-0.0004	-0.0069
1990	18/08/2021	57.08	132.44	68.23	-0.0018	0.0008	-0.0117

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
1991	19/08/2021	53.45	132.55	66.45	-0.0657	0.0008	-0.0264
1992	20/08/2021	54.33	132.63	65.18	0.0163	0.0006	-0.0193
1993	23/08/2021	55.3	132.46	68.75	0.0177	-0.0013	0.0533
1994	24/08/2021	56.6	132.42	71.05	0.0232	-0.0003	0.0329
1995	25/08/2021	56.5	131.71	72.25	-0.0018	-0.0054	0.0167
1996	26/08/2021	56.82	131.65	71.07	0.0056	-0.0004	-0.0165
1997	27/08/2021	58.96	131.64	72.7	0.0370	-0.0001	0.0227
1998	30/08/2021	60.72	131.64	73.41	0.0294	0.0000	0.0097
1999	31/08/2021	60.72	131.28	72.99	0.0000	-0.0027	-0.0057
2000	1/09/2021	60.07	131.15	71.59	-0.0108	-0.0010	-0.0194
2001	2/09/2021	61.48	131.29	73.03	0.0232	0.0011	0.0199
2002	3/09/2021	61.28	131.09	72.61	-0.0033	-0.0015	-0.0058
2003	6/09/2021	62.27	131.18	72.22	0.0160	0.0006	-0.0054
2004	7/09/2021	61.95	130.65	71.69	-0.0052	-0.0040	-0.0074
2005	8/09/2021	62.41	130.75	72.6	0.0074	0.0007	0.0126
2006	9/09/2021	62.69	131.22	71.45	0.0045	0.0036	-0.0160
2007	10/09/2021	60.86	130.94	72.92	-0.0296	-0.0021	0.0204
2008	13/09/2021	61.01	130.87	73.51	0.0025	-0.0005	0.0081
2009	14/09/2021	59.8	131.00	73.6	-0.0200	0.0010	0.0012
2010	15/09/2021	59.8	130.74	75.46	0.0000	-0.0020	0.0250
2011	16/09/2021	59.26	130.63	75.67	-0.0091	-0.0008	0.0028
2012	17/09/2021	59.43	130.35	75.34	0.0029	-0.0022	-0.0044
2013	20/09/2021	60.63	130.63	73.92	0.0200	0.0021	-0.0190
2014	21/09/2021	60.11	130.78	74.36	-0.0086	0.0012	0.0059
2015	22/09/2021	60.54	130.81	76.19	0.0071	0.0002	0.0243
2016	23/09/2021	60.48	130.14	77.25	-0.0010	-0.0051	0.0138
2017	24/09/2021	62.88	129.79	78.09	0.0389	-0.0027	0.0108
2018	27/09/2021	64.31	129.71	79.53	0.0225	-0.0006	0.0183
2019	28/09/2021	61.92	129.49	79.09	-0.0379	-0.0017	-0.0055
2020	29/09/2021	62.88	129.68	78.64	0.0154	0.0015	-0.0057
2021	30/09/2021	61.74	129.43	78.52	-0.0183	-0.0020	-0.0015
2022	1/10/2021	62.04	129.67	79.28	0.0048	0.0019	0.0096
2023	4/10/2021	63.4	129.57	81.26	0.0217	-0.0008	0.0247
2024	5/10/2021	64.72	129.28	82.56	0.0206	-0.0023	0.0159
2025	6/10/2021	59.12	129.20	81.08	-0.0905	-0.0006	-0.0181
2026	7/10/2021	60.37	129.26	81.95	0.0209	0.0005	0.0107
2027	8/10/2021	58.33	128.94	82.39	-0.0344	-0.0025	0.0054
2028	11/10/2021	59.15	128.62	83.65	0.0140	-0.0025	0.0152
2029	12/10/2021	58.93	128.38	83.42	-0.0037	-0.0018	-0.0028
2030	13/10/2021	59.07	128.87	83.18	0.0024	0.0038	-0.0029

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
2031	14/10/2021	61.44	129.42	84	0.0393	0.0043	0.0098
2032	15/10/2021	59.44	129.33	84.86	-0.0331	-0.0007	0.0102
2033	18/10/2021	58.56	129.16	84.33	-0.0149	-0.0014	-0.0063
2034	19/10/2021	54.55	128.75	85.08	-0.0709	-0.0032	0.0089
2035	20/10/2021	57.78	128.87	85.82	0.0575	0.0009	0.0087
2036	21/10/2021	57.98	128.63	84.61	0.0035	-0.0019	-0.0142
2037	22/10/2021	58.27	128.70	85.53	0.0050	0.0005	0.0108
2038	25/10/2021	58.99	128.88	85.99	0.0123	0.0014	0.0054
2039	26/10/2021	59.81	128.90	86.4	0.0138	0.0001	0.0048
2040	27/10/2021	59.9	129.57	84.58	0.0015	0.0052	-0.0213
2041	28/10/2021	58.57	129.32	84.32	-0.0225	-0.0020	-0.0031
2042	29/10/2021	58.71	128.65	84.38	0.0024	-0.0052	0.0007
2043	1/11/2021	56.94	128.63	84.71	-0.0306	-0.0002	0.0039
2044	2/11/2021	59.46	129.46	84.72	0.0433	0.0064	0.0001
2045	3/11/2021	59.82	129.53	81.99	0.0060	0.0005	-0.0328
2046	4/11/2021	59.86	130.00	80.54	0.0007	0.0037	-0.0178
2047	5/11/2021	59.39	130.71	82.74	-0.0079	0.0054	0.0269
2048	8/11/2021	60.63	130.36	83.43	0.0207	-0.0026	0.0083
2049	9/11/2021	60.41	130.91	84.78	-0.0036	0.0042	0.0161
2050	10/11/2021	63.16	130.34	82.64	0.0445	-0.0044	-0.0256
2051	11/11/2021	63.7	130.05	82.87	0.0085	-0.0022	0.0028
2052	12/11/2021	63.27	130.21	82.17	-0.0068	0.0013	-0.0085
2053	15/11/2021	65.93	130.04	82.05	0.0412	-0.0014	-0.0015
2054	16/11/2021	67.55	129.90	82.43	0.0243	-0.0010	0.0046
2055	17/11/2021	67.16	129.76	80.28	-0.0058	-0.0011	-0.0264
2056	18/11/2021	69.1	130.19	81.24	0.0285	0.0033	0.0119
2057	19/11/2021	69.36	130.84	78.89	0.0038	0.0049	-0.0294
2058	22/11/2021	69.91	130.39	79.7	0.0079	-0.0034	0.0102
2059	23/11/2021	69.17	129.55	82.31	-0.0106	-0.0065	0.0322
2060	24/11/2021	72.91	129.21	82.25	0.0527	-0.0027	-0.0007
2061	25/11/2021	74.46	129.51	82.22	0.0210	0.0023	-0.0004
2062	26/11/2021	72.78	130.21	72.72	-0.0228	0.0054	-0.1228
2063	29/11/2021	74.21	130.06	73.44	0.0195	-0.0012	0.0099
2064	30/11/2021	75.37	130.51	70.57	0.0155	0.0035	-0.0399
2065	1/12/2021	76.81	130.44	68.87	0.0189	-0.0006	-0.0244
2066	2/12/2021	79.86	130.98	69.67	0.0389	0.0042	0.0115
2067	3/12/2021	78.25	131.04	69.88	-0.0204	0.0004	0.0030
2068	6/12/2021	81.25	131.23	73.08	0.0376	0.0015	0.0448
2069	7/12/2021	84.91	131.26	75.44	0.0441	0.0002	0.0318
2070	8/12/2021	88.88	130.58	75.82	0.0457	-0.0052	0.0050

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
2071	9/12/2021	80.2	130.99	74.42	-0.1028	0.0031	-0.0186
2072	10/12/2021	83.73	131.09	75.15	0.0431	0.0008	0.0098
2073	13/12/2021	82.12	131.45	74.39	-0.0194	0.0027	-0.0102
2074	14/12/2021	79.48	131.31	73.7	-0.0327	-0.0011	-0.0093
2075	15/12/2021	80.5	131.19	73.88	0.0128	-0.0009	0.0024
2076	16/12/2021	84.77	130.90	75.02	0.0517	-0.0022	0.0153
2077	17/12/2021	73.28	131.20	73.52	-0.1457	0.0023	-0.0202
2078	20/12/2021	79.38	131.10	71.52	0.0800	-0.0008	-0.0276
2079	21/12/2021	80.49	130.19	73.98	0.0139	-0.0069	0.0338
2080	22/12/2021	76.37	130.02	75.29	-0.0525	-0.0013	0.0176
2081	23/12/2021	74.04	129.45	76.85	-0.0310	-0.0044	0.0205
2082	24/12/2021	75.91	129.45	76.14	0.0249	0.0000	-0.0093
2083	27/12/2021	76.55	129.41	78.6	0.0084	-0.0003	0.0318
2084	28/12/2021	78.86	129.43	78.94	0.0297	0.0002	0.0043
2085	29/12/2021	79.97	128.81	79.23	0.0140	-0.0048	0.0037
2086	30/12/2021	79.77	128.71	79.32	-0.0025	-0.0007	0.0011
2087	31/12/2021	80.22	128.72	77.78	0.0056	0.0000	-0.0196
2088	3/01/2022	83.63	128.34	78.98	0.0416	-0.0029	0.0153
2089	4/01/2022	84.55	128.40	80	0.0109	0.0004	0.0128
2090	5/01/2022	87.24	128.37	80.8	0.0313	-0.0002	0.0100
2091	6/01/2022	86.4	128.04	81.99	-0.0097	-0.0026	0.0146
2092	7/01/2022	85.09	127.82	81.75	-0.0153	-0.0017	-0.0029
2093	10/01/2022	79.8	127.81	80.87	-0.0642	-0.0001	-0.0108
2094	11/01/2022	81.03	127.64	83.72	0.0153	-0.0013	0.0346
2095	12/01/2022	79.75	127.98	84.67	-0.0159	0.0027	0.0113
2096	13/01/2022	80.3	128.35	84.47	0.0069	0.0029	-0.0024
2097	14/01/2022	81.82	127.84	86.06	0.0188	-0.0039	0.0186
2098	17/01/2022	80.32	127.52	86.48	-0.0185	-0.0025	0.0049
2099	18/01/2022	82.38	127.42	87.51	0.0253	-0.0008	0.0118
2100	19/01/2022	81.82	127.25	88.44	-0.0068	-0.0014	0.0106
2101	20/01/2022	85.32	127.54	88.38	0.0419	0.0023	-0.0007
2102	21/01/2022	84.17	127.85	87.89	-0.0136	0.0025	-0.0056
2103	24/01/2022	83.72	128.04	86.27	-0.0054	0.0014	-0.0186
2104	25/01/2022	87.15	127.84	88.2	0.0402	-0.0016	0.0221
2105	26/01/2022	88.36	127.53	89.96	0.0138	-0.0024	0.0198
2106	27/01/2022	89.46	127.51	89.34	0.0124	-0.0001	-0.0069
2107	28/01/2022	88.9	127.29	90.03	-0.0063	-0.0017	0.0077
2108	31/01/2022	88.89	126.70	91.21	-0.0001	-0.0047	0.0130
2109	1/02/2022	89.18	126.41	89.16	0.0033	-0.0022	-0.0227
2110	2/02/2022	93.76	126.45	89.47	0.0501	0.0003	0.0035

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
2111	3/02/2022	94.38	125.21	91.11	0.0066	-0.0099	0.0182
2112	4/02/2022	96.03	124.41	93.27	0.0173	-0.0064	0.0234
2113	7/02/2022	96.28	123.70	92.69	0.0026	-0.0057	-0.0062
2114	8/02/2022	96.48	123.31	90.78	0.0021	-0.0032	-0.0208
2115	9/02/2022	90.4	123.80	91.55	-0.0651	0.0040	0.0084
2116	10/02/2022	90.41	123.09	91.41	0.0001	-0.0058	-0.0015
2117	11/02/2022	92.5	122.88	94.44	0.0229	-0.0017	0.0326
2118	14/02/2022	91.33	122.79	96.48	-0.0127	-0.0008	0.0214
2119	15/02/2022	90.71	122.31	93.28	-0.0068	-0.0039	-0.0337
2120	16/02/2022	89.38	122.75	94.81	-0.0148	0.0036	0.0163
2121	17/02/2022	85.98	123.13	92.97	-0.0388	0.0031	-0.0196
2122	18/02/2022	89.05	123.27	93.54	0.0351	0.0011	0.0061
2123	21/02/2022	89.29	123.02	95.39	0.0027	-0.0021	0.0196
2124	22/02/2022	89.39	122.54	96.84	0.0011	-0.0039	0.0151
2125	23/02/2022	94.69	122.67	96.84	0.0576	0.0011	0.0000
2126	24/02/2022	86.66	122.96	99.08	-0.0886	0.0023	0.0229
2127	25/02/2022	87.74	122.54	97.93	0.0124	-0.0034	-0.0117
2128	28/02/2022	81.82	122.94	100.99	-0.0699	0.0033	0.0308
2129	1/03/2022	68.53	125.10	104.97	-0.1773	0.0174	0.0387
2130	2/03/2022	68.26	124.41	112.93	-0.0039	-0.0055	0.0731
2131	3/03/2022	67.09	124.20	110.46	-0.0173	-0.0017	-0.0221
2132	4/03/2022	64.79	125.06	118.11	-0.0349	0.0069	0.0670
2133	7/03/2022	57.93	124.44	123.21	-0.1119	-0.0050	0.0423
2134	8/03/2022	68.12	123.24	127.98	0.1620	-0.0097	0.0380
2135	9/03/2022	72.78	122.36	111.14	0.0662	-0.0071	-0.1411
2136	10/03/2022	76.03	121.53	109.33	0.0437	-0.0068	-0.0164
2137	11/03/2022	76.39	121.39	112.67	0.0047	-0.0012	0.0301
2138	14/03/2022	77.89	120.51	106.9	0.0194	-0.0073	-0.0526
2139	15/03/2022	77.04	120.88	99.91	-0.0110	0.0030	-0.0676
2140	16/03/2022	77.77	120.57	98.02	0.0094	-0.0025	-0.0191
2141	17/03/2022	79.53	120.69	106.64	0.0224	0.0010	0.0843
2142	18/03/2022	78.52	120.94	107.93	-0.0128	0.0021	0.0120
2143	21/03/2022	78.01	120.24	115.62	-0.0065	-0.0058	0.0688
2144	22/03/2022	80.29	119.69	115.48	0.0288	-0.0046	-0.0012
2145	23/03/2022	76.25	119.92	121.6	-0.0516	0.0019	0.0516
2146	24/03/2022	77.94	119.62	119.03	0.0219	-0.0025	-0.0214
2147	25/03/2022	78.31	119.34	120.65	0.0047	-0.0023	0.0135
2148	28/03/2022	80.54	119.23	112.48	0.0281	-0.0010	-0.0701
2149	29/03/2022	81.54	118.78	110.23	0.0123	-0.0037	-0.0202
2150	30/03/2022	78.12	118.63	113.45	-0.0428	-0.0013	0.0288

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
2151	31/03/2022	76.32	119.57	107.91	-0.0233	0.0079	-0.0501
2152	1/04/2022	78.35	119.16	104.39	0.0263	-0.0034	-0.0332
2153	4/04/2022	78.34	119.54	107.53	-0.0001	0.0031	0.0296
2154	5/04/2022	77.89	118.35	106.64	-0.0058	-0.0099	-0.0083
2155	6/04/2022	77.02	117.94	101.07	-0.0112	-0.0035	-0.0536
2156	7/04/2022	79.78	117.70	100.58	0.0352	-0.0020	-0.0049
2157	8/04/2022	79.93	117.51	102.78	0.0019	-0.0016	0.0216
2158	11/04/2022	77.79	116.68	98.48	-0.0271	-0.0071	-0.0427
2159	12/04/2022	78.84	116.75	104.64	0.0134	0.0005	0.0607
2160	13/04/2022	77.26	117.03	108.78	-0.0202	0.0024	0.0388
2161	14/04/2022	79.78	116.28	111.7	0.0321	-0.0064	0.0265
2162	15/04/2022	79.78	116.28	111.7	0.0000	0.0000	0.0000
2163	18/04/2022	79.78	116.28	113.16	0.0000	0.0000	0.0130
2164	19/04/2022	79.98	115.54	107.25	0.0025	-0.0063	-0.0536
2165	20/04/2022	87.6	116.11	106.8	0.0910	0.0049	-0.0042
2166	21/04/2022	86.19	115.56	108.33	-0.0162	-0.0047	0.0142
2167	22/04/2022	88.68	115.12	106.65	0.0285	-0.0038	-0.0156
2168	25/04/2022	83.13	115.82	102.32	-0.0646	0.0061	-0.0414
2169	26/04/2022	82.35	116.14	104.99	-0.0094	0.0028	0.0258
2170	27/04/2022	80.66	115.81	105.32	-0.0207	-0.0029	0.0031
2171	28/04/2022	82.31	114.86	107.59	0.0202	-0.0083	0.0213
2172	29/04/2022	84.04	114.45	109.34	0.0208	-0.0036	0.0161
2173	2/05/2022	82.65	114.24	107.58	-0.0167	-0.0018	-0.0162
2174	3/05/2022	87.78	114.34	104.97	0.0602	0.0009	-0.0246
2175	4/05/2022	87.9	113.97	110.14	0.0014	-0.0033	0.0481
2176	5/05/2022	88.53	113.55	110.9	0.0071	-0.0036	0.0069
2177	6/05/2022	91.14	112.30	112.39	0.0291	-0.0111	0.0133
2178	9/05/2022	86.62	112.44	105.94	-0.0509	0.0012	-0.0591
2179	10/05/2022	86.93	113.24	102.46	0.0036	0.0071	-0.0334
2180	11/05/2022	88.45	113.36	107.51	0.0173	0.0010	0.0481
2181	12/05/2022	87.87	114.58	107.45	-0.0066	0.0108	-0.0006
2182	13/05/2022	88.09	113.99	111.55	0.0025	-0.0052	0.0374
2183	16/05/2022	89.18	114.18	114.24	0.0123	0.0016	0.0238
2184	17/05/2022	91.33	113.38	111.93	0.0238	-0.0071	-0.0204
2185	18/05/2022	84.27	113.65	109.11	-0.0805	0.0024	-0.0255
2186	19/05/2022	82.82	113.98	112.04	-0.0174	0.0029	0.0265
2187	20/05/2022	80.05	113.79	112.55	-0.0340	-0.0017	0.0045
2188	23/05/2022	77.81	113.23	113.42	-0.0284	-0.0049	0.0077
2189	24/05/2022	80.98	113.56	113.56	0.0399	0.0029	0.0012
2190	25/05/2022	81.04	113.49	114.03	0.0007	-0.0006	0.0041

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
2191	26/05/2022	84.4	113.02	117.4	0.0406	-0.0042	0.0291
2192	27/05/2022	83.84	113.43	119.43	-0.0067	0.0037	0.0171
2193	30/05/2022	83.61	112.88	121.67	-0.0027	-0.0049	0.0186
2194	31/05/2022	83.66	112.13	122.84	0.0006	-0.0067	0.0096
2195	1/06/2022	85.72	111.65	116.29	0.0243	-0.0043	-0.0548
2196	2/06/2022	85.98	111.65	117.61	0.0030	0.0000	0.0113
2197	3/06/2022	86.5	111.65	119.72	0.0060	0.0000	0.0178
2198	6/06/2022	81.08	110.29	119.51	-0.0647	-0.0123	-0.0018
2199	7/06/2022	80.98	110.72	120.57	-0.0012	0.0039	0.0088
2200	8/06/2022	79.49	110.18	123.58	-0.0186	-0.0049	0.0247
2201	9/06/2022	80.68	109.31	123.07	0.0149	-0.0079	-0.0041
2202	10/06/2022	81.53	108.48	122.01	0.0105	-0.0076	-0.0087
2203	13/06/2022	81.2	106.86	122.27	-0.0041	-0.0150	0.0021
2204	14/06/2022	83.78	105.69	121.17	0.0313	-0.0110	-0.0090
2205	15/06/2022	85.83	106.58	118.51	0.0242	0.0084	-0.0222
2206	16/06/2022	82.61	106.10	119.81	-0.0382	-0.0045	0.0109
2207	17/06/2022	81.99	106.37	113.12	-0.0075	0.0025	-0.0575
2208	20/06/2022	83.59	105.73	114.13	0.0193	-0.0060	0.0089
2209	21/06/2022	84.27	105.45	114.65	0.0081	-0.0026	0.0045
2210	22/06/2022	81.42	106.64	111.74	-0.0344	0.0112	-0.0257
2211	23/06/2022	83.67	108.24	110.05	0.0273	0.0150	-0.0152
2212	24/06/2022	82.98	108.15	113.12	-0.0083	-0.0009	0.0275
2213	27/06/2022	84.59	107.32	115.09	0.0192	-0.0077	0.0173
2214	28/06/2022	87.12	106.47	117.98	0.0295	-0.0080	0.0248
2215	29/06/2022	88.07	107.36	116.26	0.0108	0.0083	-0.0147
2216	30/06/2022	89.88	108.12	114.81	0.0203	0.0071	-0.0126
2217	1/07/2022	85.3	109.47	111.63	-0.0523	0.0124	-0.0281
2218	4/07/2022	84.29	108.23	113.5	-0.0119	-0.0113	0.0166
2219	5/07/2022	82.99	109.49	102.77	-0.0155	0.0116	-0.0993
2220	6/07/2022	82.94	109.89	100.69	-0.0006	0.0036	-0.0204
2221	7/07/2022	84.64	109.16	104.65	0.0203	-0.0067	0.0386
2222	8/07/2022	82.51	108.97	107.02	-0.0255	-0.0017	0.0224
2223	11/07/2022	84.07	109.70	107.1	0.0187	0.0067	0.0007
2224	12/07/2022	85.37	110.87	99.49	0.0153	0.0106	-0.0737
2225	13/07/2022	83.59	110.65	99.57	-0.0211	-0.0019	0.0008
2226	14/07/2022	83.7	110.25	99.1	0.0013	-0.0036	-0.0047
2227	15/07/2022	85.09	110.71	101.16	0.0165	0.0041	0.0206
2228	18/07/2022	84.66	110.06	106.27	-0.0051	-0.0059	0.0493
2229	19/07/2022	83.37	109.69	107.35	-0.0154	-0.0033	0.0101
2230	20/07/2022	78.58	110.03	106.92	-0.0592	0.0031	-0.0040

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
2231	21/07/2022	77.85	110.45	103.86	-0.0093	0.0038	-0.0290
2232	22/07/2022	76.03	111.91	103.2	-0.0237	0.0132	-0.0064
2233	25/07/2022	76.08	112.21	105.15	0.0007	0.0027	0.0187
2234	26/07/2022	76.39	112.87	104.4	0.0041	0.0058	-0.0072
2235	27/07/2022	75.85	112.91	106.62	-0.0071	0.0003	0.0210
2236	28/07/2022	78.68	114.17	107.14	0.0366	0.0112	0.0049
2237	29/07/2022	78.27	114.37	110.01	-0.0052	0.0017	0.0264
2238	1/08/2022	80.28	114.85	100.03	0.0254	0.0042	-0.0951
2239	2/08/2022	81.66	114.66	100.54	0.0170	-0.0017	0.0051
2240	3/08/2022	83.71	114.11	96.78	0.0248	-0.0048	-0.0381
2241	4/08/2022	83.9	114.70	94.12	0.0023	0.0051	-0.0279
2242	5/08/2022	84.48	113.50	94.92	0.0069	-0.0105	0.0085
2243	8/08/2022	83.53	113.87	96.65	-0.0113	0.0033	0.0181
2244	9/08/2022	85.65	113.43	96.31	0.0251	-0.0039	-0.0035
2245	10/08/2022	85.63	113.86	97.4	-0.0002	0.0037	0.0113
2246	11/08/2022	87.27	113.05	99.6	0.0190	-0.0072	0.0223
2247	12/08/2022	88.58	112.94	98.15	0.0149	-0.0009	-0.0147
2248	15/08/2022	90.48	113.86	95.1	0.0212	0.0081	-0.0316
2249	16/08/2022	91.77	113.08	92.34	0.0142	-0.0069	-0.0295
2250	17/08/2022	95.5	112.09	93.65	0.0398	-0.0088	0.0141
2251	18/08/2022	95.72	112.09	96.59	0.0023	0.0000	0.0309
2252	19/08/2022	97.67	110.70	96.72	0.0202	-0.0125	0.0013
2253	22/08/2022	91.83	109.98	96.48	-0.0617	-0.0065	-0.0025
2254	23/08/2022	88.94	109.57	100.22	-0.0320	-0.0037	0.0380
2255	24/08/2022	88.86	109.14	101.22	-0.0009	-0.0039	0.0099
2256	25/08/2022	88.95	109.56	99.34	0.0010	0.0038	-0.0187
2257	26/08/2022	89.94	108.87	100.99	0.0111	-0.0063	0.0165
2258	29/08/2022	86.24	108.87	105.09	-0.0420	0.0000	0.0398
2259	30/08/2022	80.34	107.74	99.31	-0.0709	-0.0105	-0.0566
2260	31/08/2022	79.61	107.50	96.49	-0.0091	-0.0022	-0.0288
2261	1/09/2022	80.33	106.98	92.36	0.0090	-0.0049	-0.0437
2262	2/09/2022	77.45	107.55	93.02	-0.0365	0.0053	0.0071
2263	5/09/2022	74.05	107.01	95.74	-0.0449	-0.0051	0.0288
2264	6/09/2022	69.57	106.99	92.83	-0.0624	-0.0002	-0.0309
2265	7/09/2022	68.71	107.39	88	-0.0124	0.0037	-0.0534
2266	8/09/2022	66.93	106.63	89.15	-0.0262	-0.0070	0.0130
2267	9/09/2022	65.72	106.49	92.84	-0.0182	-0.0014	0.0406
2268	12/09/2022	71.44	107.14	94	0.0835	0.0062	0.0124
2269	13/09/2022	69.36	106.44	93.17	-0.0295	-0.0066	-0.0089
2270	14/09/2022	72.14	106.65	94.1	0.0393	0.0020	0.0099

	Date	MO1	GBEUTREU	CO1	RMO1	RGBEUTREU	RCO1
2271	15/09/2022	71.45	106.52	90.84	-0.0096	-0.0013	-0.0353
2272	16/09/2022	72.87	106.13	91.35	0.0197	-0.0037	0.0056
2273	19/09/2022	70.71	106.13	92	-0.0301	0.0000	0.0071
2274	20/09/2022	70.74	104.80	90.62	0.0004	-0.0125	-0.0151
2275	21/09/2022	69.4	105.11	89.83	-0.0191	0.0029	-0.0088
2276	22/09/2022	70.05	104.45	90.46	0.0093	-0.0064	0.0070
2277	23/09/2022	65.41	104.10	86.15	-0.0685	-0.0033	-0.0488
2278	26/09/2022	69.97	103.57	84.06	0.0674	-0.0051	-0.0246
2279	27/09/2022	67.96	102.32	86.27	-0.0291	-0.0121	0.0260
2280	28/09/2022	65.15	102.39	89.32	-0.0422	0.0007	0.0347
2281	29/09/2022	65.73	101.91	88.49	0.0089	-0.0047	-0.0093
2282	30/09/2022	66.73	102.38	87.96	0.0151	0.0045	-0.0060
2283	3/10/2022	65.94	104.05	88.86	-0.0119	0.0162	0.0102
2284	4/10/2022	66.92	104.48	91.8	0.0148	0.0041	0.0326
2285	5/10/2022	67.07	103.23	93.37	0.0022	-0.0120	0.0170
2286	6/10/2022	68.96	102.73	94.42	0.0278	-0.0048	0.0112
2287	7/10/2022	69.85	101.79	97.92	0.0128	-0.0092	0.0364
2288	10/10/2022	66.77	100.85	96	-0.0451	-0.0093	-0.0198

Appendix B. Delays with the most significant impact (category - High) on the forecast of CO2-E returns

RMO1_k-3	RMO1_k-169	RGBEUTREU_k-21	RGBEUTREU_k-61	RGBEUTREU_k-101	RGBEUTREU_k-141	RGBEUTREU_k-181	RGBEUTREU_k-221	RCO1_k-29	RCO1_k-179
RMO1_k-5	RMO1_k-170	RGBEUTREU_k-22	RGBEUTREU_k-62	RGBEUTREU_k-102	RGBEUTREU_k-142	RGBEUTREU_k-182	RGBEUTREU_k-222	RCO1_k-33	RCO1_k-184
RMO1_k-6	RMO1_k-179	RGBEUTREU_k-23	RGBEUTREU_k-63	RGBEUTREU_k-103	RGBEUTREU_k-143	RGBEUTREU_k-183	RGBEUTREU_k-223	RCO1_k-35	RCO1_k-185
RMO1_k-9	RMO1_k-190	RGBEUTREU_k-24	RGBEUTREU_k-64	RGBEUTREU_k-104	RGBEUTREU_k-144	RGBEUTREU_k-184	RGBEUTREU_k-224	RCO1_k-39	RCO1_k-197
RMO1_k-10	RMO1_k-196	RGBEUTREU_k-25	RGBEUTREU_k-65	RGBEUTREU_k-105	RGBEUTREU_k-145	RGBEUTREU_k-185	RGBEUTREU_k-225	RCO1_k-40	RCO1_k-198
RMO1_k-15	RMO1_k-197	RGBEUTREU_k-26	RGBEUTREU_k-66	RGBEUTREU_k-106	RGBEUTREU_k-146	RGBEUTREU_k-186	RGBEUTREU_k-226	RCO1_k-41	RCO1_k-200
RMO1_k-16	RMO1_k-198	RGBEUTREU_k-27	RGBEUTREU_k-67	RGBEUTREU_k-107	RGBEUTREU_k-147	RGBEUTREU_k-187	RGBEUTREU_k-227	RCO1_k-47	RCO1_k-202
RMO1_k-29	RMO1_k-200	RGBEUTREU_k-28	RGBEUTREU_k-68	RGBEUTREU_k-108	RGBEUTREU_k-148	RGBEUTREU_k-188	RGBEUTREU_k-228	RCO1_k-48	RCO1_k-204
RMO1_k-34	RMO1_k-202	RGBEUTREU_k-29	RGBEUTREU_k-69	RGBEUTREU_k-109	RGBEUTREU_k-149	RGBEUTREU_k-189	RGBEUTREU_k-229	RCO1_k-49	RCO1_k-206
RMO1_k-41	RMO1_k-211	RGBEUTREU_k-30	RGBEUTREU_k-70	RGBEUTREU_k-110	RGBEUTREU_k-150	RGBEUTREU_k-190	RGBEUTREU_k-230	RCO1_k-53	RCO1_k-208
RMO1_k-45	RMO1_k-214	RGBEUTREU_k-31	RGBEUTREU_k-71	RGBEUTREU_k-111	RGBEUTREU_k-151	RGBEUTREU_k-191	RGBEUTREU_k-231	RCO1_k-55	RCO1_k-209
RMO1_k-46	RMO1_k-220	RGBEUTREU_k-32	RGBEUTREU_k-72	RGBEUTREU_k-112	RGBEUTREU_k-152	RGBEUTREU_k-192	RGBEUTREU_k-232	RCO1_k-71	RCO1_k-218
RMO1_k-49	RMO1_k-225	RGBEUTREU_k-33	RGBEUTREU_k-73	RGBEUTREU_k-113	RGBEUTREU_k-153	RGBEUTREU_k-193	RGBEUTREU_k-233	RCO1_k-72	RCO1_k-222
RMO1_k-58	RMO1_k-231	RGBEUTREU_k-34	RGBEUTREU_k-74	RGBEUTREU_k-114	RGBEUTREU_k-154	RGBEUTREU_k-194	RGBEUTREU_k-234	RCO1_k-74	RCO1_k-225
RMO1_k-72	RMO1_k-232	RGBEUTREU_k-35	RGBEUTREU_k-75	RGBEUTREU_k-115	RGBEUTREU_k-155	RGBEUTREU_k-195	RGBEUTREU_k-235	RCO1_k-77	RCO1_k-226
RMO1_k-76	RMO1_k-238	RGBEUTREU_k-36	RGBEUTREU_k-76	RGBEUTREU_k-116	RGBEUTREU_k-156	RGBEUTREU_k-196	RGBEUTREU_k-236	RCO1_k-79	RCO1_k-228
RMO1_k-77	RMO1_k-239	RGBEUTREU_k-37	RGBEUTREU_k-77	RGBEUTREU_k-117	RGBEUTREU_k-157	RGBEUTREU_k-197	RGBEUTREU_k-237	RCO1_k-80	RCO1_k-230
RMO1_k-80	RMO1_k-241	RGBEUTREU_k-38	RGBEUTREU_k-78	RGBEUTREU_k-118	RGBEUTREU_k-158	RGBEUTREU_k-198	RGBEUTREU_k-238	RCO1_k-84	RCO1_k-231
RMO1_k-87	RMO1_k-243	RGBEUTREU_k-39	RGBEUTREU_k-79	RGBEUTREU_k-119	RGBEUTREU_k-159	RGBEUTREU_k-199	RGBEUTREU_k-239	RCO1_k-86	RCO1_k-237
RMO1_k-91	RGBEUTREU_k	RGBEUTREU_k-40	RGBEUTREU_k-80	RGBEUTREU_k-120	RGBEUTREU_k-160	RGBEUTREU_k-200	RGBEUTREU_k-240	RCO1_k-87	RCO1_k-238
RMO1_k-93	RGBEUTREU_k-1	RGBEUTREU_k-41	RGBEUTREU_k-81	RGBEUTREU_k-121	RGBEUTREU_k-161	RGBEUTREU_k-201	RGBEUTREU_k-241	RCO1_k-92	RCO1_k-241
RMO1_k-96	RGBEUTREU_k-2	RGBEUTREU_k-42	RGBEUTREU_k-82	RGBEUTREU_k-122	RGBEUTREU_k-162	RGBEUTREU_k-202	RGBEUTREU_k-242	RCO1_k-98	RCO1_k-249
RMO1_k-98	RGBEUTREU_k-3	RGBEUTREU_k-43	RGBEUTREU_k-83	RGBEUTREU_k-123	RGBEUTREU_k-163	RGBEUTREU_k-203	RGBEUTREU_k-243	RCO1_k-103	
RMO1_k-99	RGBEUTREU_k-4	RGBEUTREU_k-44	RGBEUTREU_k-84	RGBEUTREU_k-124	RGBEUTREU_k-164	RGBEUTREU_k-204	RGBEUTREU_k-244	RCO1_k-113	
RMO1_k-106	RGBEUTREU_k-5	RGBEUTREU_k-45	RGBEUTREU_k-85	RGBEUTREU_k-125	RGBEUTREU_k-165	RGBEUTREU_k-205	RGBEUTREU_k-245	RCO1_k-114	
RMO1_k-107	RGBEUTREU_k-6	RGBEUTREU_k-46	RGBEUTREU_k-86	RGBEUTREU_k-126	RGBEUTREU_k-166	RGBEUTREU_k-206	RGBEUTREU_k-246	RCO1_k-115	
RMO1_k-108	RGBEUTREU_k-7	RGBEUTREU_k-47	RGBEUTREU_k-87	RGBEUTREU_k-127	RGBEUTREU_k-167	RGBEUTREU_k-207	RGBEUTREU_k-247	RCO1_k-118	
RMO1_k-110	RGBEUTREU_k-8	RGBEUTREU_k-48	RGBEUTREU_k-88	RGBEUTREU_k-128	RGBEUTREU_k-168	RGBEUTREU_k-208	RGBEUTREU_k-248	RCO1_k-133	
RMO1_k-118	RGBEUTREU_k-9	RGBEUTREU_k-49	RGBEUTREU_k-89	RGBEUTREU_k-129	RGBEUTREU_k-169	RGBEUTREU_k-209	RGBEUTREU_k-249	RCO1_k-136	
RMO1_k-123	RGBEUTREU_k-10	RGBEUTREU_k-50	RGBEUTREU_k-90	RGBEUTREU_k-130	RGBEUTREU_k-170	RGBEUTREU_k-210	RGBEUTREU_k-250	RCO1_k-145	
RMO1_k-129	RGBEUTREU_k-11	RGBEUTREU_k-51	RGBEUTREU_k-91	RGBEUTREU_k-131	RGBEUTREU_k-171	RGBEUTREU_k-211	RGBEUTREU_k-251	RCO1_k-148	
RMO1_k-134	RGBEUTREU_k-12	RGBEUTREU_k-52	RGBEUTREU_k-92	RGBEUTREU_k-132	RGBEUTREU_k-172	RGBEUTREU_k-212	RCO1_k-2	RCO1_k-151	
RMO1_k-138	RGBEUTREU_k-13	RGBEUTREU_k-53	RGBEUTREU_k-93	RGBEUTREU_k-133	RGBEUTREU_k-173	RGBEUTREU_k-213	RCO1_k-6	RCO1_k-166	
RMO1_k-146	RGBEUTREU_k-14	RGBEUTREU_k-54	RGBEUTREU_k-94	RGBEUTREU_k-134	RGBEUTREU_k-174	RGBEUTREU_k-214	RCO1_k-10	RCO1_k-167	
RMO1_k-149	RGBEUTREU_k-15	RGBEUTREU_k-55	RGBEUTREU_k-95	RGBEUTREU_k-135	RGBEUTREU_k-175	RGBEUTREU_k-215	RCO1_k-16	RCO1_k-169	
RMO1_k-151	RGBEUTREU_k-16	RGBEUTREU_k-56	RGBEUTREU_k-96	RGBEUTREU_k-136	RGBEUTREU_k-176	RGBEUTREU_k-216	RCO1_k-17	RCO1_k-171	
RMO1_k-161	RGBEUTREU_k-17	RGBEUTREU_k-57	RGBEUTREU_k-97	RGBEUTREU_k-137	RGBEUTREU_k-177	RGBEUTREU_k-217	RCO1_k-21	RCO1_k-173	
RMO1_k-165	RGBEUTREU_k-18	RGBEUTREU_k-58	RGBEUTREU_k-98	RGBEUTREU_k-138	RGBEUTREU_k-178	RGBEUTREU_k-218	RCO1_k-22	RCO1_k-175	
RMO1_k-167	RGBEUTREU_k-19	RGBEUTREU_k-59	RGBEUTREU_k-99	RGBEUTREU_k-139	RGBEUTREU_k-179	RGBEUTREU_k-219	RCO1_k-25	RCO1_k-177	
RMO1_k-168	RGBEUTREU_k-20	RGBEUTREU_k-60	RGBEUTREU_k-100	RGBEUTREU_k-140	RGBEUTREU_k-180	RGBEUTREU_k-220	RCO1_k-27	RCO1_k-178	

Appendix C. Delays with the most significant impact (category – Positive High) on the forecast of CO2-E returns

RMO1_k-4	RMO1_k-137	RCO1_k-31	RCO1_k-112	RCO1_k-227
RMO1_k-7	RMO1_k-139	RCO1_k-34	RCO1_k-119	RCO1_k-229
RMO1_k-12	RMO1_k-141	RCO1_k-36	RCO1_k-120	RCO1_k-234
RMO1_k-14	RMO1_k-142	RCO1_k-37	RCO1_k-122	RCO1_k-236
RMO1_k-19	RMO1_k-148	RCO1_k-38	RCO1_k-123	RCO1_k-239
RMO1_k-21	RMO1_k-150	RCO1_k-43	RCO1_k-124	RCO1_k-246
RMO1_k-22	RMO1_k-152	RCO1_k-46	RCO1_k-130	RCO1_k-248
RMO1_k-25	RMO1_k-155	RCO1_k-50	RCO1_k-131	RCO1_k-250
RMO1_k-33	RMO1_k-158	RCO1_k-56	RCO1_k-134	
RMO1_k-37	RMO1_k-160	RCO1_k-57	RCO1_k-140	
RMO1_k-47	RMO1_k-171	RCO1_k-58	RCO1_k-141	
RMO1_k-50	RMO1_k-176	RCO1_k-59	RCO1_k-142	
RMO1_k-55	RMO1_k-181	RCO1_k-60	RCO1_k-144	
RMO1_k-57	RMO1_k-203	RCO1_k-62	RCO1_k-146	
RMO1_k-59	RMO1_k-207	RCO1_k-65	RCO1_k-150	
RMO1_k-60	RMO1_k-222	RCO1_k-67	RCO1_k-152	
RMO1_k-62	RMO1_k-226	RCO1_k-68	RCO1_k-155	
RMO1_k-65	RMO1_k-227	RCO1_k-69	RCO1_k-164	
RMO1_k-67	RMO1_k-229	RCO1_k-78	RCO1_k-165	
RMO1_k-69	RMO1_k-234	RCO1_k-81	RCO1_k-172	
RMO1_k-100	RMO1_k-250	RCO1_k-88	RCO1_k-181	
RMO1_k-102	RCO1_k-3	RCO1_k-89	RCO1_k-186	
RMO1_k-105	RCO1_k-4	RCO1_k-91	RCO1_k-193	
RMO1_k-111	RCO1_k-5	RCO1_k-93	RCO1_k-195	
RMO1_k-115	RCO1_k-9	RCO1_k-99	RCO1_k-196	
RMO1_k-117	RCO1_k-12	RCO1_k-100	RCO1_k-203	
RMO1_k-127	RCO1_k-14	RCO1_k-102	RCO1_k-207	
RMO1_k-130	RCO1_k-15	RCO1_k-109	RCO1_k-215	
RMO1_k-133	RCO1_k-19	RCO1_k-110	RCO1_k-217	
RMO1_k-136	RCO1_k-24	RCO1_k-111	RCO1_k-224	

Appendix D. Delays with the most significant impact (category –High) on the forecast of GB-V returns

RMO1_k	RMO1_k-199	RCO1_k-89	RCO1_k-212
RMO1_k-1	RMO1_k-202	RCO1_k-93	RCO1_k-215
RMO1_k-5	RMO1_k-205	RCO1_k-97	RCO1_k-220
RMO1_k-36	RMO1_k-206	RCO1_k-103	RCO1_k-230
RMO1_k-54	RMO1_k-210	RCO1_k-106	RCO1_k-235
RMO1_k-55	RMO1_k-212	RCO1_k-112	RCO1_k-237
RMO1_k-56	RMO1_k-217	RCO1_k-113	RCO1_k-241
RMO1_k-58	RMO1_k-224	RCO1_k-117	RCO1_k-244
RMO1_k-62	RMO1_k-243	RCO1_k-118	
RMO1_k-88	RMO1_k-246	RCO1_k-122	
RMO1_k-89	RMO1_k-249	RCO1_k-125	
RMO1_k-108	RMO1_k-251	RCO1_k-143	
RMO1_k-118	RCO1_k-1	RCO1_k-144	
RMO1_k-125	RCO1_k-5	RCO1_k-146	
RMO1_k-136	RCO1_k-7	RCO1_k-148	
RMO1_k-137	RCO1_k-13	RCO1_k-149	
RMO1_k-138	RCO1_k-17	RCO1_k-150	
RMO1_k-140	RCO1_k-19	RCO1_k-153	
RMO1_k-144	RCO1_k-20	RCO1_k-168	
RMO1_k-147	RCO1_k-38	RCO1_k-169	
RMO1_k-162	RCO1_k-44	RCO1_k-170	
RMO1_k-170	RCO1_k-48	RCO1_k-174	
RMO1_k-171	RCO1_k-50	RCO1_k-175	
RMO1_k-175	RCO1_k-51	RCO1_k-178	
RMO1_k-181	RCO1_k-58	RCO1_k-182	
RMO1_k-186	RCO1_k-66	RCO1_k-184	
RMO1_k-188	RCO1_k-69	RCO1_k-189	
RMO1_k-189	RCO1_k-85	RCO1_k-194	
RMO1_k-190	RCO1_k-86	RCO1_k-199	
RMO1_k-193	RCO1_k-88	RCO1_k-202	

Appendix E. Delays with the most significant impact (category – Positive High) on the forecast of GB-V returns

RMO1_k-8	RMO1_k-166	RGBEUTREU_k-23	RGBEUTREU_k-64	RGBEUTREU_k-105	RGBEUTREU_k-146	RGBEUTREU_k-187	RGBEUTREU_k-228	RCO1_k-55	RCO1_k-151
RMO1_k-12	RMO1_k-178	RGBEUTREU_k-24	RGBEUTREU_k-65	RGBEUTREU_k-106	RGBEUTREU_k-147	RGBEUTREU_k-188	RGBEUTREU_k-229	RCO1_k-57	RCO1_k-155
RMO1_k-13	RMO1_k-179	RGBEUTREU_k-25	RGBEUTREU_k-66	RGBEUTREU_k-107	RGBEUTREU_k-148	RGBEUTREU_k-189	RGBEUTREU_k-230	RCO1_k-59	RCO1_k-156
RMO1_k-27	RMO1_k-187	RGBEUTREU_k-26	RGBEUTREU_k-67	RGBEUTREU_k-108	RGBEUTREU_k-149	RGBEUTREU_k-190	RGBEUTREU_k-231	RCO1_k-61	RCO1_k-157
RMO1_k-28	RMO1_k-192	RGBEUTREU_k-27	RGBEUTREU_k-68	RGBEUTREU_k-109	RGBEUTREU_k-150	RGBEUTREU_k-191	RGBEUTREU_k-232	RCO1_k-64	RCO1_k-158
RMO1_k-30	RMO1_k-201	RGBEUTREU_k-28	RGBEUTREU_k-69	RGBEUTREU_k-110	RGBEUTREU_k-151	RGBEUTREU_k-192	RGBEUTREU_k-233	RCO1_k-67	RCO1_k-159
RMO1_k-44	RMO1_k-209	RGBEUTREU_k-29	RGBEUTREU_k-70	RGBEUTREU_k-111	RGBEUTREU_k-152	RGBEUTREU_k-193	RGBEUTREU_k-234	RCO1_k-68	RCO1_k-160
RMO1_k-52	RMO1_k-213	RGBEUTREU_k-30	RGBEUTREU_k-71	RGBEUTREU_k-112	RGBEUTREU_k-153	RGBEUTREU_k-194	RGBEUTREU_k-235	RCO1_k-70	RCO1_k-163
RMO1_k-59	RMO1_k-218	RGBEUTREU_k-31	RGBEUTREU_k-72	RGBEUTREU_k-113	RGBEUTREU_k-154	RGBEUTREU_k-195	RGBEUTREU_k-236	RCO1_k-73	RCO1_k-165
RMO1_k-61	RMO1_k-219	RGBEUTREU_k-32	RGBEUTREU_k-73	RGBEUTREU_k-114	RGBEUTREU_k-155	RGBEUTREU_k-196	RGBEUTREU_k-237	RCO1_k-74	RCO1_k-167
RMO1_k-67	RMO1_k-221	RGBEUTREU_k-33	RGBEUTREU_k-74	RGBEUTREU_k-115	RGBEUTREU_k-156	RGBEUTREU_k-197	RGBEUTREU_k-238	RCO1_k-77	RCO1_k-171
RMO1_k-73	RMO1_k-223	RGBEUTREU_k-34	RGBEUTREU_k-75	RGBEUTREU_k-116	RGBEUTREU_k-157	RGBEUTREU_k-198	RGBEUTREU_k-239	RCO1_k-79	RCO1_k-176
RMO1_k-76	RMO1_k-230	RGBEUTREU_k-35	RGBEUTREU_k-76	RGBEUTREU_k-117	RGBEUTREU_k-158	RGBEUTREU_k-199	RGBEUTREU_k-240	RCO1_k-81	RCO1_k-180
RMO1_k-77	RMO1_k-232	RGBEUTREU_k-36	RGBEUTREU_k-77	RGBEUTREU_k-118	RGBEUTREU_k-159	RGBEUTREU_k-200	RGBEUTREU_k-241	RCO1_k-83	RCO1_k-186
RMO1_k-83	RMO1_k-233	RGBEUTREU_k-37	RGBEUTREU_k-78	RGBEUTREU_k-119	RGBEUTREU_k-160	RGBEUTREU_k-201	RGBEUTREU_k-242	RCO1_k-90	RCO1_k-187
RMO1_k-86	RMO1_k-244	RGBEUTREU_k-38	RGBEUTREU_k-79	RGBEUTREU_k-120	RGBEUTREU_k-161	RGBEUTREU_k-202	RGBEUTREU_k-243	RCO1_k-92	RCO1_k-188
RMO1_k-93	RMO1_k-248	RGBEUTREU_k-39	RGBEUTREU_k-80	RGBEUTREU_k-121	RGBEUTREU_k-162	RGBEUTREU_k-203	RGBEUTREU_k-244	RCO1_k-95	RCO1_k-193
RMO1_k-96	RMO1_k-250	RGBEUTREU_k-40	RGBEUTREU_k-81	RGBEUTREU_k-122	RGBEUTREU_k-163	RGBEUTREU_k-204	RGBEUTREU_k-245	RCO1_k-98	RCO1_k-204
RMO1_k-97	RGBEUTREU_k	RGBEUTREU_k-41	RGBEUTREU_k-82	RGBEUTREU_k-123	RGBEUTREU_k-164	RGBEUTREU_k-205	RGBEUTREU_k-246	RCO1_k-100	RCO1_k-207
RMO1_k-100	RGBEUTREU_k-1	RGBEUTREU_k-42	RGBEUTREU_k-83	RGBEUTREU_k-124	RGBEUTREU_k-165	RGBEUTREU_k-206	RGBEUTREU_k-247	RCO1_k-101	RCO1_k-209
RMO1_k-101	RGBEUTREU_k-2	RGBEUTREU_k-43	RGBEUTREU_k-84	RGBEUTREU_k-125	RGBEUTREU_k-166	RGBEUTREU_k-207	RGBEUTREU_k-248	RCO1_k-104	RCO1_k-211
RMO1_k-104	RGBEUTREU_k-3	RGBEUTREU_k-44	RGBEUTREU_k-85	RGBEUTREU_k-126	RGBEUTREU_k-167	RGBEUTREU_k-208	RGBEUTREU_k-249	RCO1_k-105	RCO1_k-217
RMO1_k-107	RGBEUTREU_k-4	RGBEUTREU_k-45	RGBEUTREU_k-86	RGBEUTREU_k-127	RGBEUTREU_k-168	RGBEUTREU_k-209	RGBEUTREU_k-250	RCO1_k-107	RCO1_k-219
RMO1_k-114	RGBEUTREU_k-5	RGBEUTREU_k-46	RGBEUTREU_k-87	RGBEUTREU_k-128	RGBEUTREU_k-169	RGBEUTREU_k-210	RGBEUTREU_k-251	RCO1_k-108	RCO1_k-223
RMO1_k-117	RGBEUTREU_k-6	RGBEUTREU_k-47	RGBEUTREU_k-88	RGBEUTREU_k-129	RGBEUTREU_k-170	RGBEUTREU_k-211	RCO1_k-2	RCO1_k-110	RCO1_k-224
RMO1_k-119	RGBEUTREU_k-7	RGBEUTREU_k-48	RGBEUTREU_k-89	RGBEUTREU_k-130	RGBEUTREU_k-171	RGBEUTREU_k-212	RCO1_k-4	RCO1_k-114	RCO1_k-226
RMO1_k-124	RGBEUTREU_k-8	RGBEUTREU_k-49	RGBEUTREU_k-90	RGBEUTREU_k-131	RGBEUTREU_k-172	RGBEUTREU_k-213	RCO1_k-8	RCO1_k-120	RCO1_k-228
RMO1_k-128	RGBEUTREU_k-9	RGBEUTREU_k-50	RGBEUTREU_k-91	RGBEUTREU_k-132	RGBEUTREU_k-173	RGBEUTREU_k-214	RCO1_k-12	RCO1_k-121	RCO1_k-233
RMO1_k-131	RGBEUTREU_k-10	RGBEUTREU_k-51	RGBEUTREU_k-92	RGBEUTREU_k-133	RGBEUTREU_k-174	RGBEUTREU_k-215	RCO1_k-15	RCO1_k-124	RCO1_k-236
RMO1_k-132	RGBEUTREU_k-11	RGBEUTREU_k-52	RGBEUTREU_k-93	RGBEUTREU_k-134	RGBEUTREU_k-175	RGBEUTREU_k-216	RCO1_k-24	RCO1_k-126	RCO1_k-239
RMO1_k-135	RGBEUTREU_k-12	RGBEUTREU_k-53	RGBEUTREU_k-94	RGBEUTREU_k-135	RGBEUTREU_k-176	RGBEUTREU_k-217	RCO1_k-25	RCO1_k-127	RCO1_k-242
RMO1_k-139	RGBEUTREU_k-13	RGBEUTREU_k-54	RGBEUTREU_k-95	RGBEUTREU_k-136	RGBEUTREU_k-177	RGBEUTREU_k-218	RCO1_k-26	RCO1_k-128	RCO1_k-243
RMO1_k-145	RGBEUTREU_k-14	RGBEUTREU_k-55	RGBEUTREU_k-96	RGBEUTREU_k-137	RGBEUTREU_k-178	RGBEUTREU_k-219	RCO1_k-27	RCO1_k-129	RCO1_k-246
RMO1_k-149	RGBEUTREU_k-15	RGBEUTREU_k-56	RGBEUTREU_k-97	RGBEUTREU_k-138	RGBEUTREU_k-179	RGBEUTREU_k-220	RCO1_k-28	RCO1_k-134	RCO1_k-251
RMO1_k-150	RGBEUTREU_k-16	RGBEUTREU_k-57	RGBEUTREU_k-98	RGBEUTREU_k-139	RGBEUTREU_k-180	RGBEUTREU_k-221	RCO1_k-33	RCO1_k-136	
RMO1_k-155	RGBEUTREU_k-17	RGBEUTREU_k-58	RGBEUTREU_k-99	RGBEUTREU_k-140	RGBEUTREU_k-181	RGBEUTREU_k-222	RCO1_k-35	RCO1_k-137	
RMO1_k-156	RGBEUTREU_k-18	RGBEUTREU_k-59	RGBEUTREU_k-100	RGBEUTREU_k-141	RGBEUTREU_k-182	RGBEUTREU_k-223	RCO1_k-36	RCO1_k-138	
RMO1_k-157	RGBEUTREU_k-19	RGBEUTREU_k-60	RGBEUTREU_k-101	RGBEUTREU_k-142	RGBEUTREU_k-183	RGBEUTREU_k-224	RCO1_k-39	RCO1_k-139	
RMO1_k-159	RGBEUTREU_k-20	RGBEUTREU_k-61	RGBEUTREU_k-102	RGBEUTREU_k-143	RGBEUTREU_k-184	RGBEUTREU_k-225	RCO1_k-43	RCO1_k-140	
RMO1_k-160	RGBEUTREU_k-21	RGBEUTREU_k-62	RGBEUTREU_k-103	RGBEUTREU_k-144	RGBEUTREU_k-185	RGBEUTREU_k-226	RCO1_k-46	RCO1_k-141	
RMO1_k-163	RGBEUTREU_k-22	RGBEUTREU_k-63	RGBEUTREU_k-104	RGBEUTREU_k-145	RGBEUTREU_k-186	RGBEUTREU_k-227	RCO1_k-54	RCO1_k-145	

Appendix F. Delays with the most significant impact (category –High) on the forecast of BB-P returns

RMO1_k-2	RMO1_k-157	RGBEUTREU_k-20	RGBEUTREU_k-60	RGBEUTREU_k-100	RGBEUTREU_k-140	RGBEUTREU_k-180	RGBEUTREU_k-220	RCO1_k-33	RCO1_k-131	RCO1_k-233
RMO1_k-10	RMO1_k-158	RGBEUTREU_k-21	RGBEUTREU_k-61	RGBEUTREU_k-101	RGBEUTREU_k-141	RGBEUTREU_k-181	RGBEUTREU_k-221	RCO1_k-36	RCO1_k-133	RCO1_k-236
RMO1_k-12	RMO1_k-161	RGBEUTREU_k-22	RGBEUTREU_k-62	RGBEUTREU_k-102	RGBEUTREU_k-142	RGBEUTREU_k-182	RGBEUTREU_k-222	RCO1_k-37	RCO1_k-134	RCO1_k-243
RMO1_k-13	RMO1_k-168	RGBEUTREU_k-23	RGBEUTREU_k-63	RGBEUTREU_k-103	RGBEUTREU_k-143	RGBEUTREU_k-183	RGBEUTREU_k-223	RCO1_k-38	RCO1_k-138	RCO1_k-244
RMO1_k-15	RMO1_k-169	RGBEUTREU_k-24	RGBEUTREU_k-64	RGBEUTREU_k-104	RGBEUTREU_k-144	RGBEUTREU_k-184	RGBEUTREU_k-224	RCO1_k-40	RCO1_k-139	RCO1_k-248
RMO1_k-22	RMO1_k-189	RGBEUTREU_k-25	RGBEUTREU_k-65	RGBEUTREU_k-105	RGBEUTREU_k-145	RGBEUTREU_k-185	RGBEUTREU_k-225	RCO1_k-46	RCO1_k-141	RCO1_k-249
RMO1_k-34	RMO1_k-190	RGBEUTREU_k-26	RGBEUTREU_k-66	RGBEUTREU_k-106	RGBEUTREU_k-146	RGBEUTREU_k-186	RGBEUTREU_k-226	RCO1_k-48	RCO1_k-142	RCO1_k-250
RMO1_k-35	RMO1_k-192	RGBEUTREU_k-27	RGBEUTREU_k-67	RGBEUTREU_k-107	RGBEUTREU_k-147	RGBEUTREU_k-187	RGBEUTREU_k-227	RCO1_k-55	RCO1_k-145	RCO1_k-251
RMO1_k-40	RMO1_k-207	RGBEUTREU_k-28	RGBEUTREU_k-68	RGBEUTREU_k-108	RGBEUTREU_k-148	RGBEUTREU_k-188	RGBEUTREU_k-228	RCO1_k-58	RCO1_k-148	
RMO1_k-41	RMO1_k-208	RGBEUTREU_k-29	RGBEUTREU_k-69	RGBEUTREU_k-109	RGBEUTREU_k-149	RGBEUTREU_k-189	RGBEUTREU_k-229	RCO1_k-63	RCO1_k-149	
RMO1_k-43	RMO1_k-218	RGBEUTREU_k-30	RGBEUTREU_k-70	RGBEUTREU_k-110	RGBEUTREU_k-150	RGBEUTREU_k-190	RGBEUTREU_k-230	RCO1_k-67	RCO1_k-152	
RMO1_k-44	RMO1_k-226	RGBEUTREU_k-31	RGBEUTREU_k-71	RGBEUTREU_k-111	RGBEUTREU_k-151	RGBEUTREU_k-191	RGBEUTREU_k-231	RCO1_k-69	RCO1_k-157	
RMO1_k-46	RMO1_k-230	RGBEUTREU_k-32	RGBEUTREU_k-72	RGBEUTREU_k-112	RGBEUTREU_k-152	RGBEUTREU_k-192	RGBEUTREU_k-232	RCO1_k-71	RCO1_k-164	
RMO1_k-47	RMO1_k-233	RGBEUTREU_k-33	RGBEUTREU_k-73	RGBEUTREU_k-113	RGBEUTREU_k-153	RGBEUTREU_k-193	RGBEUTREU_k-233	RCO1_k-72	RCO1_k-168	
RMO1_k-54	RMO1_k-234	RGBEUTREU_k-34	RGBEUTREU_k-74	RGBEUTREU_k-114	RGBEUTREU_k-154	RGBEUTREU_k-194	RGBEUTREU_k-234	RCO1_k-77	RCO1_k-169	
RMO1_k-55	RMO1_k-236	RGBEUTREU_k-35	RGBEUTREU_k-75	RGBEUTREU_k-115	RGBEUTREU_k-155	RGBEUTREU_k-195	RGBEUTREU_k-235	RCO1_k-80	RCO1_k-176	
RMO1_k-58	RMO1_k-237	RGBEUTREU_k-36	RGBEUTREU_k-76	RGBEUTREU_k-116	RGBEUTREU_k-156	RGBEUTREU_k-196	RGBEUTREU_k-236	RCO1_k-83	RCO1_k-177	
RMO1_k-75	RMO1_k-245	RGBEUTREU_k-37	RGBEUTREU_k-77	RGBEUTREU_k-117	RGBEUTREU_k-157	RGBEUTREU_k-197	RGBEUTREU_k-237	RCO1_k-88	RCO1_k-178	
RMO1_k-78	RMO1_k-249	RGBEUTREU_k-38	RGBEUTREU_k-78	RGBEUTREU_k-118	RGBEUTREU_k-158	RGBEUTREU_k-198	RGBEUTREU_k-238	RCO1_k-89	RCO1_k-183	
RMO1_k-86	RMO1_k-250	RGBEUTREU_k-39	RGBEUTREU_k-79	RGBEUTREU_k-119	RGBEUTREU_k-159	RGBEUTREU_k-199	RGBEUTREU_k-239	RCO1_k-94	RCO1_k-186	
RMO1_k-88	RGBEUTREU_k	RGBEUTREU_k-40	RGBEUTREU_k-80	RGBEUTREU_k-120	RGBEUTREU_k-160	RGBEUTREU_k-200	RGBEUTREU_k-240	RCO1_k-95	RCO1_k-188	
RMO1_k-90	RGBEUTREU_k-1	RGBEUTREU_k-41	RGBEUTREU_k-81	RGBEUTREU_k-121	RGBEUTREU_k-161	RGBEUTREU_k-201	RGBEUTREU_k-241	RCO1_k-96	RCO1_k-195	
RMO1_k-97	RGBEUTREU_k-2	RGBEUTREU_k-42	RGBEUTREU_k-82	RGBEUTREU_k-122	RGBEUTREU_k-162	RGBEUTREU_k-202	RGBEUTREU_k-242	RCO1_k-97	RCO1_k-199	
RMO1_k-106	RGBEUTREU_k-3	RGBEUTREU_k-43	RGBEUTREU_k-83	RGBEUTREU_k-123	RGBEUTREU_k-163	RGBEUTREU_k-203	RGBEUTREU_k-243	RCO1_k-98	RCO1_k-206	
RMO1_k-107	RGBEUTREU_k-4	RGBEUTREU_k-44	RGBEUTREU_k-84	RGBEUTREU_k-124	RGBEUTREU_k-164	RGBEUTREU_k-204	RGBEUTREU_k-244	RCO1_k-100	RCO1_k-207	
RMO1_k-110	RGBEUTREU_k-5	RGBEUTREU_k-45	RGBEUTREU_k-85	RGBEUTREU_k-125	RGBEUTREU_k-165	RGBEUTREU_k-205	RGBEUTREU_k-245	RCO1_k-102	RCO1_k-208	
RMO1_k-111	RGBEUTREU_k-6	RGBEUTREU_k-46	RGBEUTREU_k-86	RGBEUTREU_k-126	RGBEUTREU_k-166	RGBEUTREU_k-206	RGBEUTREU_k-246	RCO1_k-103	RCO1_k-209	
RMO1_k-116	RGBEUTREU_k-7	RGBEUTREU_k-47	RGBEUTREU_k-87	RGBEUTREU_k-127	RGBEUTREU_k-167	RGBEUTREU_k-207	RGBEUTREU_k-247	RCO1_k-106	RCO1_k-210	
RMO1_k-119	RGBEUTREU_k-8	RGBEUTREU_k-48	RGBEUTREU_k-88	RGBEUTREU_k-128	RGBEUTREU_k-168	RGBEUTREU_k-208	RGBEUTREU_k-248	RCO1_k-108	RCO1_k-212	
RMO1_k-122	RGBEUTREU_k-9	RGBEUTREU_k-49	RGBEUTREU_k-89	RGBEUTREU_k-129	RGBEUTREU_k-169	RGBEUTREU_k-209	RGBEUTREU_k-249	RCO1_k-110	RCO1_k-215	
RMO1_k-126	RGBEUTREU_k-10	RGBEUTREU_k-50	RGBEUTREU_k-90	RGBEUTREU_k-130	RGBEUTREU_k-170	RGBEUTREU_k-210	RGBEUTREU_k-250	RCO1_k-111	RCO1_k-217	
RMO1_k-128	RGBEUTREU_k-11	RGBEUTREU_k-51	RGBEUTREU_k-91	RGBEUTREU_k-131	RGBEUTREU_k-171	RGBEUTREU_k-211	RGBEUTREU_k-251	RCO1_k-113	RCO1_k-219	
RMO1_k-131	RGBEUTREU_k-12	RGBEUTREU_k-52	RGBEUTREU_k-92	RGBEUTREU_k-132	RGBEUTREU_k-172	RGBEUTREU_k-212	RCO1_k-6	RCO1_k-117	RCO1_k-220	
RMO1_k-137	RGBEUTREU_k-13	RGBEUTREU_k-53	RGBEUTREU_k-93	RGBEUTREU_k-133	RGBEUTREU_k-173	RGBEUTREU_k-213	RCO1_k-14	RCO1_k-122	RCO1_k-221	
RMO1_k-138	RGBEUTREU_k-14	RGBEUTREU_k-54	RGBEUTREU_k-94	RGBEUTREU_k-134	RGBEUTREU_k-174	RGBEUTREU_k-214	RCO1_k-15	RCO1_k-123	RCO1_k-222	
RMO1_k-139	RGBEUTREU_k-15	RGBEUTREU_k-55	RGBEUTREU_k-95	RGBEUTREU_k-135	RGBEUTREU_k-175	RGBEUTREU_k-215	RCO1_k-17	RCO1_k-125	RCO1_k-225	
RMO1_k-145	RGBEUTREU_k-16	RGBEUTREU_k-56	RGBEUTREU_k-96	RGBEUTREU_k-136	RGBEUTREU_k-176	RGBEUTREU_k-216	RCO1_k-25	RCO1_k-126	RCO1_k-226	
RMO1_k-149	RGBEUTREU_k-17	RGBEUTREU_k-57	RGBEUTREU_k-97	RGBEUTREU_k-137	RGBEUTREU_k-177	RGBEUTREU_k-217	RCO1_k-26	RCO1_k-127	RCO1_k-228	
RMO1_k-152	RGBEUTREU_k-18	RGBEUTREU_k-58	RGBEUTREU_k-98	RGBEUTREU_k-138	RGBEUTREU_k-178	RGBEUTREU_k-218	RCO1_k-27	RCO1_k-128	RCO1_k-230	
RMO1_k-153	RGBEUTREU_k-19	RGBEUTREU_k-59	RGBEUTREU_k-99	RGBEUTREU_k-139	RGBEUTREU_k-179	RGBEUTREU_k-219	RCO1_k-29	RCO1_k-130	RCO1_k-232	

Appendix G. Delays with the most significant impact (category – Positive High) on the forecast of BB-P returns

RMO1_k-3	RMO1_k-142	RCO1_k-2	RCO1_k-114	RCO1_k-224
RMO1_k-5	RMO1_k-146	RCO1_k-3	RCO1_k-115	RCO1_k-227
RMO1_k-17	RMO1_k-155	RCO1_k-5	RCO1_k-116	RCO1_k-229
RMO1_k-21	RMO1_k-162	RCO1_k-7	RCO1_k-118	RCO1_k-231
RMO1_k-26	RMO1_k-164	RCO1_k-9	RCO1_k-119	RCO1_k-234
RMO1_k-38	RMO1_k-165	RCO1_k-10	RCO1_k-121	RCO1_k-237
RMO1_k-48	RMO1_k-177	RCO1_k-12	RCO1_k-124	RCO1_k-239
RMO1_k-53	RMO1_k-179	RCO1_k-19	RCO1_k-136	RCO1_k-241
RMO1_k-59	RMO1_k-181	RCO1_k-21	RCO1_k-137	RCO1_k-246
RMO1_k-60	RMO1_k-183	RCO1_k-22	RCO1_k-143	
RMO1_k-65	RMO1_k-188	RCO1_k-24	RCO1_k-144	
RMO1_k-69	RMO1_k-193	RCO1_k-28	RCO1_k-146	
RMO1_k-72	RMO1_k-195	RCO1_k-34	RCO1_k-147	
RMO1_k-74	RMO1_k-200	RCO1_k-41	RCO1_k-150	
RMO1_k-77	RMO1_k-202	RCO1_k-43	RCO1_k-153	
RMO1_k-79	RMO1_k-205	RCO1_k-50	RCO1_k-155	
RMO1_k-83	RMO1_k-210	RCO1_k-52	RCO1_k-162	
RMO1_k-100	RMO1_k-212	RCO1_k-53	RCO1_k-165	
RMO1_k-102	RMO1_k-214	RCO1_k-56	RCO1_k-167	
RMO1_k-103	RMO1_k-217	RCO1_k-59	RCO1_k-171	
RMO1_k-108	RMO1_k-220	RCO1_k-60	RCO1_k-172	
RMO1_k-109	RMO1_k-222	RCO1_k-65	RCO1_k-179	
RMO1_k-114	RMO1_k-229	RCO1_k-74	RCO1_k-181	
RMO1_k-115	RMO1_k-231	RCO1_k-81	RCO1_k-193	
RMO1_k-118	RMO1_k-239	RCO1_k-86	RCO1_k-196	
RMO1_k-121	RMO1_k-241	RCO1_k-87	RCO1_k-198	
RMO1_k-124	RMO1_k-243	RCO1_k-90	RCO1_k-200	
RMO1_k-130	RMO1_k-246	RCO1_k-91	RCO1_k-202	
RMO1_k-133	RMO1_k-248	RCO1_k-105	RCO1_k-203	
RMO1_k-134	RMO1_k-251	RCO1_k-109	RCO1_k-205	

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