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From climate risk to the returns and volatility of energy assets and green bonds: A predictability analysis under various conditions

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Abstract

The importance of climate risk as a source of systemic risk for financial markets and the decisions of investors, portfolio managers, and regulators is growing. We examine the directional predictability from two climate risk measures, transition risk and physical risk, to the returns and volatility of European brown and green energy stocks, European carbon emission allowances, and global green bonds. Using daily data, we apply a cross-quantilogram approach in a time-varying setting to measure potential differences in the predictability across quantiles and over various crisis periods. The return predictability results are more pronounced for transition risk than physical risk, especially for brown energy stocks and carbon emission allowances, and they generally vary across periods and markets conditions. The predictability of volatility is also significant at specific time periods and volatility states, especially from transition risk, and the sign of the predictability is positive for brown energy and carbon emission allowances whereas it is negative for green bonds. We show that a lower-than-expected level of discussion about the transition process leads to a heightened volatility of brown energy markets. These findings have important implications regarding climate risks assessment on return and volatility predictability and climate risk and portfolio decarbonization under COP26.

Keywords: Quantile dependency and predictability; cross-quantilogram; physical and transition risk; green and brown energy; carbon emission allowances; green bonds; European markets

1. Introduction

Increasing changes in climate and the consequent risks posed to societies and ecosystems have attracted a great deal of attention from regulators, financial participants, and academics (Sinha et al., 2020). The world needs to re-shape the entire economy toward a greener and climate-neutral society to fight rising temperatures and reduce the frequency and severity of physical hazards (e.g. storms, floods, wildfires) and their impact on economic activities.[1] Several climate summits have taken place in recent years, the latest being the 26th United Nation Climate Change Conference (COP26) where parties discussed ways to accelerate action towards the Paris Agreement temperature goals. Central banks and financial institutions are keen to incorporate climate, as well as environmental, social, and governance (ESG), considerations in their policies, and investors want to manage climate risks and find procedures to decarbonize their portfolios. Climate-related risks raise the stress of the financial system (Flori et al., 2021), systematically drive the cross-section of both stock returns (e.g. Bolton & Kacperczyk, 2021; Bua et al., 2021; Hsu et al., 2023; Faccini et al., 2021) and bond returns (e.g. Painter, 2020; Huynh & Xia, 2021), and impact the price dynamics of green and brown energy stocks (Bouri et al., 2022) and other asset classes, including real estate (e.g. Baldauf et al., 2020; Murfin & Spiegel, 2020; Bernstein et al., 2019), currencies (Bonato et al., 2022), gold (Cepni et al., 2022), and fixed-income securities, as well as financial institutions (e.g. Battiston et al., 2021a; Giglio et al., 2021)[2].

Climate-related risks are complex by nature and can affect the financial system, notably financial markets, through physical and transition risks (Bua et al., 2022), suggesting the relevance of considering the financial implications of these two risks separately.[3] Using a textual-analysis approach in line with Engle et al. (2020), Bua et al. (2022) exploit scientific texts on climate and

[1] https://news.climate.columbia.edu/2019/06/20/climate-change-economy-impacts/
[2] Polat et al. (2023) consider the impact of COVID-19 media coverage index on the return and volatility spillovers across several climate changes indices.
[3] Among the mechanisms of climate-related risk transmission to the real economy, are concerns that physical and transition risk can lead to sudden and unexpected adjustments in the value of financial assets, impairing financial stability and threatening asset managers, institutional investors, banks, insurance companies, and other economic agents (Battiston et al., 2021a). Physical risk's economic consequences include, among others, business interruptions, damage to assets and firm productivity, and decreases in firms' collateral value, whereas, depending on how fast and orderly the decarbonization process is, examples of transition risk's negative consequences include large swings in asset prices, stranded assets, and the downgrading of firms' credit ratings. For asset returns, according to the equilibrium model of Pastor et al. (2021), the expected returns of green assets are lower than brown assets, but the realized returns are higher when climate change concerns take agents by surprise.

a wide range of news and press articles from Reuters News to construct the Physical Risk Index (PRI) and Transition Risk Index (TRI), two comprehensive climate risk indicators which capture innovations in the two facets of climate change risk. In short, physical risk includes a loss of value or increased costs due to the disruptive impact of chronic hazards such as sea level rise or drought, or acute hazards such as floods or heat waves. Conversely, transition risk involves risks and costs due to the adjustment process towards a climate-neutral economy, typically triggered by climate mitigation policies, technological advances, and shifts in public preferences. Interestingly, using both types of climate change risk gives an advantage over previous studies capturing sub-dimensions of physical and transition risks only (e.g. Faccini et al., 2021; Ardia et al., 2023) or climate change as a single risk factor (Engle et al., 2020). By considering the nexus between climate risks and financial assets, we acknowledge that this can be dependent on several factors including market conditions, type of asset, and time period, as well as the source of climate risk, physical or transition. A deeper understanding of the risk-return characteristics of various asset classes in relation to types of climate risk under bull, normal, and bear market conditions, as well as low, moderate, and high volatility states is therefore an essential tool for, among others, investors making climate-informed investment decisions, and policy-makers and regulators implementing effective climate mitigation policies, taking into consideration market return and volatility conditions. Nonetheless, the academic literature lacks a comprehensive analysis of the impact of the two facets of climate risk on the returns and volatility of various financial markets under various return conditions and volatility states.

In light of this discussion, this paper investigates whether climate-related risks, physical and transition, have predictive ability for the returns and volatility of European brown and green energy stocks, European carbon emission allowances, and global green bonds, under various return and volatility conditions, considering various crisis periods. In doing so, the paper offers a multi-level study revealing new mechanisms underlying the financial implications of climate change. Notably, it highlights an aspect often overlooked in the literature, that is investors, policy makers, and regulators want to gain an understanding of the implications of climate risks, physical and transition, at a higher than monthly frequency. Investors may need to make prompt investment decisions, e.g., rapid adjustments to their portfolio compositions, in response to climate risk shocks, whereas policy makers, regulators, and supervisors, in the long-term, are concerned about short-term climate-related risk effects on, e.g., financial price stability and the consequent obstacles to achieving climate goals. However, many studies adopt monthly climate risk measures, e.g. the climate policy uncertainty (CPU) measure of Gavriilidis (2021) or the climate change news index of Engle et al. (2020), rather than climate risk proxies at higher frequencies (see, Bouri et al., 2022; Sarker et al., 2023). Thanks to the availability of daily TRI and PRI data, we instead examine the dynamics of climate risk impacts on financial assets in a timelier manner which helps the formulation of prompter investment decisions and the planning of better climate policies. While an abrupt transition can cause dramatic effects in financial markets, an orderly transition is expected to limit financial risks (Carney, 2015). Therefore, knowing the effects of daily climate shocks can inform us whether actual climate policies are fostering an orderly or disorderly transition process.[4]

For the purpose of this analysis, the cross-quantilogram approach of Han et al. (2016) is a suitable methodology, as it enables us to capture the direction, duration, and strength of the predictability from climate risk to the return and volatility of assets, while considering a large number of lags and various quantiles of the return and volatility distributions. Using daily data and applying this cross-quantilogram method, we can study how different levels of climate risk (from high to low), not simply average levels, impact the return and volatility of assets over a wide spectrum of market conditions, from bullish to bearish states and from heightened to low volatility, allowing us to show a potential asymmetry in the predictability between low and high climate risk quantiles. Furthermore, we extend the analysis to a time-varying setting to document any evolution of the predictability of climate risk over time and during crisis periods. Our sample includes data for STOXX EUROPE 600 OIL & GAS, EUROSTOXX OIL & GAS, European Renewable Energy, and EEX-EU CO2 Emissions EUA from September 20, 2010 to June 30, 2022, and data for the global green bond index from June 1, 2012 to June 1, 2022. For the climate data, we extend the Bua et al. (2022) PRI and TRI to June 30, 2022, applying a computational improvement to the text-based algorithm as explained further in the methodology section.

The results of the static analysis suggest that it is transition risk, rather than physical climate change risk, that has a stronger returns predictive ability, especially for energy stocks and carbon emission

[4] For the energy transition process, Cook (2012) highlights the importance of governments promoting a balanced energy mix, in light of the inability of renewable energies to meet global demand.

allowances. From the time-varying analysis, the results for the predictability of assets returns are more complex, possibly reflecting structural changes in the impact of PRI and TRI due to events in financial markets. However, while the results are heterogeneous across periods and market conditions, we document a common short-term significance effect of climate risk on the asset returns studied, such that the impact of climate-related shocks appears to dissipate after one trading day. This finding might either imply that the market incorporates the new information into asset prices quickly, or be a signal of myopic investment behaviour. The static analysis of the effects of climate risks on assets volatility, shows that climate risk affects the volatility of stocks and green bonds in the span of a trading day to a trading week, with heterogeneous effects for both transition risk and physical risk. We show that a lack of information or discussion about the decarbonization process when market agents expect it (i.e. low quantile TRI), causes an increase in brown energy asset volatility. Finally, in a time-varying setting, we find that the significance of the predictability of volatility depends on the time period and volatility state, such that, typically, climate risks increase the volatility of brown energy stocks and carbon emission allowances whereas the volatility of green bonds is dampened, especially by the effect of transition climate risk.

The remainder of the paper is organised as follows. Section 2 provides a review of the related literature. Section 3 describes the cross-quantilogram methodology. Section 4 reports the data used in the analysis. Section 5 presents the empirical findings on the directional predictability from climate risks to the returns and volatilities of the assets under study, both in a static and a time-varying setting. Section 6 concludes the paper and proposes directions for future research.

2. Related literature and contribution

This paper contributes to both the growing literature on green finance, which explores the role of climate-related risks in financial markets, and the literature on the return and volatility predictability of energy stocks, carbon allowances, and green bonds. Climate risks pose economic challenges (see e.g. Stern & Stern, 2007; Pankratz et al., 2019) and previous research finds that investors care about climate risks in their investment decisions and are already demanding extra-returns to compensate for climate risk exposure (e.g. Bolton & Kacperczyk, 2021; Bua et al., 2022). Some studies, such as Andersson et al. (2016) and Engle et al. (2020), propose decarbonized portfolio procedures, while others explore green-labelled investments' hedging abilities against climate risks (e.g. Dutta et al., 2021; Yousaf et al., 2022; Cepni et al., 2022)[5].

Many studies focus on understanding the financial implications of a specific sub-dimension of climate change risks, so-called climate policy uncertainty. This refers to the uncertainty stemming from the unsure response of financial markets, and the economy more broadly, to climate or environmental policies aimed at slowing the rate of changes in the hope of mitigating adverse environmental and socio-economic impacts introduced by national authorities or international bodies (e.g. global emission reduction goals from international negotiations in climate summits such as COP26 and the Paris Agreement, or country-specific policies such as the European Green Deal). Some studies examine the effects CPU has on firm profitability or demand for renewable versus non-renewable energy. For instance, Shang et al. (2022) document that CPU promotes long-run renewable energy demand and reduces non-renewable energy demand, whereas Ren et al. (2022), using a Chinese sample, find that CPU reduces firm-level total factor productivity. Other studies, closer to the current paper, investigate the role of CPU in predicting asset volatility. For example, Bouri et al. (2022) find that CPU is relevant to predicting green and brown energy equity price dynamics. Climate change risk, however, has a broader definition than that captured by climate policy uncertainty, related to the transition risk component. Climate change risk includes both physical and transition risk, and encapsulates the uncertainty stemming from climate policies. Therefore, in this paper, we aim to provide a broader analysis of climate change risk than only CPU.

This paper and its findings have implications for the recent COP26 climate conference. As climate change can compromise sustainable development (see e.g. Jiang et al., 2021), the COP26 international climate negotiations highlight the importance of fostering a green energy transition to achieve the Paris Agreement net zero emissions goals by 2050. Governments need to promote green energy while considering the necessities of companies (Lu et al., 2022; Dogan et al., 2022). Under COP26, the demand for renewable energy is expected to increase (Dogan et al., 2022) as

[5] Wei et al. (2023) consider the linkages between crude oil decomposed shocks and green bond markets while accounting for the role of the pandemic. There are also studies on central banks and environmental policy objectives (e.g. Hilmi et al., 2021) and banking policies under a changing financial conditions (Shahin and El Achkar, 2017). Furthermore, Djoundourian et al. (2022) find evidence that receiving adaptation funding negatively affects CO2 emissions.

clean energies become central to decarbonizing economies (Przychodzen & Przychodzen, 2020). Lang et al. (2013) provide evidence on the interaction of climate risk and bank liquidity[6]. Recent studies explore the role of climate-related risks under evolving regulatory challenges due to the more stringent climate and environmental policies of COP26. Khalfaoui et al. (2022) study the connectedness of US stock markets and find it to be sensitive to climate-related risks, especially under bust and boom markets. In the current paper, we contribute to the literature by studying the effects of physical and transition risk, separately, on the risk-return of various assets under various conditions in relation to the recent COP26 negotiations. In particular, by considering quantiles of the climate risk distribution our findings inform regulators and policy-makers of the heterogenous effects climate states have on financial assets, helping the formulation of climate policies. Our finding that low-quantiles of transition risk generate an increase in brown energy asset volatility serves to warn central banks and supervisors, as it implies that a lower than expected level of discussion about the transition process causes price instability.

Overall, despite the growing climate finance literature, the Granger causal relationship between climate risks and financial assets considering various market conditions and crisis periods remains largely unexplored, leaving many unanswered questions about asset return and volatility predictability which we address in this paper. Unlike most previous studies, we: i) consider both aspects of climate risks, physical and transition, in full, while the existent literature, with few exceptions (e.g. Bua et al., 2022), considers climate change as a unique risk factor (Engle et al., 2020) or focuses solely on the transition risk aspect (Batten et al., 2016; Meinerding et al., 2020), physical risk (e.g. Alok et al., 2020; Choi et al., 2020), or sub-categories of both (Faccini et al., 2021; Ardia et al., 2023), meanwhile we expand and enhance through computational improvement the text-based PRI and TRI of Bua et al. (2022) using European news sourced from Reuters News, updating the daily climate risk series to June 2022 which allows us to incorporate recent developments such as the COVID-19 Omicron wave and the Russo-Ukraine war; ii) study multiple asset classes and focus on Europe rather than the US, proposing a relevant analysis for, but not limited to, European investors and institutions; iii) consider various market conditions,

[6] Other related studies consider sustainability practices (Nader et al., 2022), digital transformation for sustainable societies (Tarhini et al. 2022), policy insights on carbon capture (Gowd et al., 2023), energy transition in OECD economies (Hu et al., 2022). On a different front, Qin et al. (2023) consider the role of blockchain as a carbon-neutral facilitator.

differentiating between bear and bull markets and low and high volatility states; iv) look at both the static and time-varying effects of climate risks; and v) perform a daily analysis documenting the short-term effects of climate risks of particular interest for short-horizon investors and policymakers looking to make timely decisions at a higher frequency, such as daily, unlike studies that consider lower frequencies (e.g. monthly) or the long-run effects of climate change (e.g. Engle et al., 2020; Bansal et al., 2017; Bouri et al., 2022).

3. Methodology

We apply the cross-quantilogram approach of Han et al. (2016) to capture the direction, duration, and strength of the predictability from PRI and TRI to the return and volatility of the indices under study, while considering a large number of lags and the quantiles of the distributions of the time series. Notably, this approach can be applied in a time-varying setting, allowing us to make inferences regarding the time evolution of predictability from one variable to another, on a quantile-on-quantile basis (Bouri et al., 2020). This reveals potential evidence of asymmetry in the predictability between low and high quantiles. We consider both the returns and volatility of the indices and thus, through low and high quantiles, we differentiate between bear and bull market conditions and low and high volatility states.

According to Han et al. (2016), the cross-quantilogram approach can be presented as follows. Assume y_t and x_t to be two stationary time series, where $y_t = (y_{1t}, y_{2t})^{\mathrm{T}} \in \mathbb{R}^2$ and $x_t = (x_{1t}, x_{2t})^{\mathrm{T}} \in \mathbb{R}^{d_1} \times \mathbb{R}^{d_2}$. The conditional distribution function of y_{it} given x_{it} can be defined as $F_{(y_i|x_i)}(\cdot\,|x_{it})$, whereas the corresponding quantile function is defined as $q_{i,t}(\alpha_{\mathrm{i}}) = \inf\{v : F_{(y_i|x_i)}(v|x_{it}) \geq \alpha_i\}$ for $\alpha_i \in (0,1)$, for *i* = 1, 2.

We represent the cross-quantilogram of α quantiles for *k* lags as:

$$\rho_\alpha(k) = \frac{E\left[\psi_{\alpha_1}\left(y_{1,t} - q_{1,t}(\alpha_1)\right)\psi_{\tau_2}\left(y_{2,t-k} - q_{2,t-k}(\alpha_2)\right)\right]}{\sqrt{E\left[\psi^2_{\alpha_1}\left(y_{1,t} - q_{1,t}(\alpha_1)\right)\right]}\sqrt{E\left[\psi^2_{\alpha_2}\left(y_{2,t-k} - q_{2,t-k}(\alpha_2)\right)\right]}} \tag{1}$$

where, $\psi_\alpha(\mu) = 1[u < 0] - a$ denotes the quantile-hit process.

We test the null-hypothesis of no directional predictability (H_0: $\rho_\alpha(1) = \cdots = \rho_\alpha(p) = 0$) against H_1 $\rho_\alpha(k) \neq 0$ for some $(k, \alpha) \in \{1 \dots \dots \dots p\}$ using the portmanteau test statistic:

$$\widehat{\rho_\alpha}^{(p)} = T(T+2)\sum_{k=1}^{p}\frac{\widehat{\rho_\alpha}^{2}(k)}{T-k} \qquad (2)$$

The stationary bootstrap (Politis and Romano, 1994) method is employed to construct the confidence interval.

4. The dataset

Our data comprises two datasets. The first consists of two distinct climate risk measures for transition and physical risks. Following Bua et al. (2022), we extend both the Transition Risk Index (TRI) and Physical Risk Index (PRI) to the period November 2021 to June 2022 inclusive, and apply a computational improvement to the novelty filter calculation, delivering enhanced climate risk series which can contribute to future research. According to the one-day novelty filter, only the first news of the day is kept from a series of similar news published on the same day, removing redundancy within the data (see Dang et al., 2015). We identify the novelty filter parameter as the similarity threshold value, c, such that if news has a similarity higher than c with any prior news in a day, it is left out of the sample because it is considered repetitive. Usually, this parameter is a predefined value which is very sensitive and needs to be calibrated precisely to make sure that the eliminated (kept) news is effectively redundant (novel). We therefore refine and validate the novelty filter parameter by performing various trials on the news dataset, delivering improved climate series. Finally, to update TRI and PRI, we collect (European) news from Reuters News using the Factiva database and apply the term-frequency inverse-document-frequency approach combined with the cosine-similarity technique, in line with Bua et al. (2022) and Engle et al. (2020).

The second dataset involves STOXX EUROPE 600 OIL & GAS (STXOIL) in euro, EUROSTOXX OIL & GAS (EUROOIL) in euro[7], European Renewable Energy (ERIX) in euro[8], and EEX-EU CO2 Emissions (EU Allowance) EUA (EEX) in euro, for the period September 20,

[7] STXOIL and EUROOIL are used as proxies for the performance of brown energy stocks in Europe.
[8] ERIX is used as a proxy for the performance of European firms operating in the following investment segments: solar, water, wind, biofuels, geothermal, and marine energy.

2010 to June 30, 2022, and the global green bond index (GB) for the period June 1, 2012 to June 1, 2022. It is collected from Refinitiv and Bloomberg terminal. The availability of data on each index in the second dataset dictates the sample period used in the empirical analysis. Overall, the sample period is long enough to cover various periods of tranquillity and instability in the energy and carbon emission markets such as the oil price crash of June 2014 to January 2016, the COVID-19 outbreak,[9] and the Russo-Ukrainian war.

Figure 1 plots the levels of climate risk measures and the returns and volatility of the indices under study. It shows heightened levels of volatility around the COVID-19 outbreak around February-March 2020.

We compute log-returns by taking the log difference between two consecutive closing prices in the index multiplied by 100, while volatility is computed as squared returns (see Wang et al., 2022). Table 1 presents the summary statistics of the two climate risk measures and the returns and volatility of the various assets under study. The highest mean of returns (0.058) and highest standard deviation (3.188) are reported for EEX. Conversely, the lowest are for GB. Overall, all series have high kurtosis and non-zero skewness and the Jarque–Bera statistics reject the normality of the return and volatility series. Furthermore, the mean and median are not identical which indicates the suitability of applying a quantile-based approach, while a mean-based approach would lead to partial relationships or an incomplete picture of the relationship across the conditional distribution. The stationarity test of Elliott, Rothenberg, and Stock (1996), which considers potential structural breaks in the data, and that of Phillips and Perron (1988) indicate that all return and volatility series are stationary. The same is true for the two climate risk measures. These results fill the requirements for the application of the cross-quantilogram approach.

5. Results

In this section, we present the results for the directional predictability from TRI (PRI) to the returns and volatility of the indices under study, both in a static and time-varying setting. Overall, our results are heterogeneous indicating that asset returns and volatility predictability from climate risks can depend on multiple factors, including the type of asset, market conditions (bearish or

[9] Brem et al. (2021) highlight the implications of the COVID-19 outbreak for innovation and discuss the technological challenges and their social impacts.

bullish), volatility state (heightened or low), the source of climate risk (physical or transition), and the level of climate risk, along with other major financial events and specific time periods.

5.1. Cross-quantile dependence - static results

The results of the static analysis suggest that transition risk has a generally stronger returns predictive ability than physical risk, especially for energy stocks and carbon emissions. We detect that (daily) climate shocks have predictive power for one-day-ahead stock returns suggesting that the market is significantly sensitive to climate change risks in the short-term. This finding is of particular interest to short-horizon investors because when unexpected climate risks news hits the market it is surprising and they quickly react to it opening investment opportunities for this type of investor. This effect, however, appears not to last long potentially suggesting that the market is able to absorb and digest new information quickly. Alternatively, assuming for instance that daily-frequency climate risk news also incorporates information about the long-term course of changes in climate,[10] this finding might be a signal of myopic investment behaviour or underreaction to climate change risk by financial participants. The static analysis of the predictability of asset volatility shows that climate risks affect the volatility of stocks and green bonds in the span of a trading day to a trading week, with heterogeneous effects for transition risk and physical risk, stressing the role of climate risks in raising market turmoil. We suggest that lower than expected levels of discussion on the transition process causes an increase in brown energy stocks' volatility. Our results further suggest that prediction models for asset returns or volatility could benefit from the inclusion of climate risk, as well as variables measuring the interaction of climate risk with market conditions.

We dedicate the next two sub-sections to a more detailed description of the static analysis results. The heatmaps in Figures 2-5 show the results at various quantiles (0.1, 0.2, …, 0.8, 0.9) and lags of 1, 5, and 22 days, which capture the effects after a trading day, a trading week, and a trading month, respectively. The multicoloured bars below the heatmaps measure the magnitude of the effect (cross dependence), which varies from negative (red) to positive (blue). The white areas indicate no effect and the asterisk (*) indicates a significant effect at the 10% level.

[10] In the asset pricing literature, studies highlight the importance of climate risk as a long-run risk factor (e.g. Bansal et al., 2017).

5.1.1. Climate risk and asset returns

Figure 2 (3) shows the directional predictability from TRI (PRI) to the returns at various quantiles and lags. The vertical axis represents TRI (PRI), and the horizontal axis represents the asset returns. Generally, a change in climate risk measures affects the asset returns during a trading day and no significant effect is shown at higher lags, especially after a trading month.

TRI has a positive impact on the returns of STXOIL in the next trading day, mainly when TRI is in the middle or upper quantiles and the returns of STXOIL are in the lower quantiles. TRI also has a negative impact on the returns of EEX the next trading day, specifically when TRI is in the middle or upper quantiles and the returns of EEX are in the lower or middle quantiles. Considering that TRI is in the upper (middle) quantile when the discussion around transition risk issues is higher than (as high as) expected, the result of a one-day-ahead positive impact on brown energy stock returns may appear controversial. However, we document this effect during bearish brown energy market conditions, possibly indicating a price correction after a contemporaneous (negative) effect. Bua et al. (2022) find that brown energy sector returns are negatively related to contemporaneous TRI, supporting this assumption. There is also some evidence that, when the brown energy market, specifically EUROOIL, is instead in a bullish state a high risk of transition predicts a decrease in returns one-day-ahead, suggesting that a bad (climate) signal during good times is of most surprise to the market pushing the brown energy performance down. This result is in line with Pastor et al. (2021) who argue that brown stocks underperform when agents are surprised by climate risk concerns, and it contributes to Bouri et al. (2022) who investigate the predictive ability of climate risk, specifically from policy uncertainty, for green and brown stock price dynamics. On the other side, acknowledging that the EU Emissions Trading System scheme follows a “cap-and-trade” principle such that a cap on the allowed greenhouse gas emissions over a year is imposed and regulated entities can trade allowances with other entities, the TRI ability to forecast a negative effect on EEX one-day-ahead could indicate a sell-pressure due to, e.g., a switch to clean energies to align with the decarbonization process, or a price correction after a contemporaneous (positive) effect. Finally, a lack of significance one-week and one-month-ahead suggests that the TRI predictability power is higher in the short-term.

Figure 3 indicates that the impact of PRI on the returns of EUROOIL is negative within the next trading day when PRI is at the middle or upper quantiles. Similarly to the case of TRI, a high level of PRI indicates a high level of unexpected discussion of physical climate risk. This represents bad climate news stemming from the verification, or potential verification, of physical hazards that can generate losses and costs. The finding that a high-risk PRI state predicts a decrease in EUROOIL implies therefore that the brown energy stock market is closely linked to risks associated with physical hazards, result of particular relevance in today's environment where changes in climate cause an intensification of physical hazards. From a practical perspective, this result suggests the necessity for brown energy companies to cope with physical risks by building climate resilient strategies to better survive the negative impact of hazards. Furthermore, we document a negative effect of middle-PRI on the returns of GB after a trading day when the returns of GB are in the middle or upper quantiles, suggesting that physical risk has the power to actually decrease green bonds returns during both normal and bullish market states. Our results do not show any notable impact of climate risks on the returns of ERIX.

5.1.2. Climate risks and asset volatility

Figures 4 and 5 show the directional predictability from TRI and PRI, respectively, to the asset volatility at various quantiles and lags. In these figures, the vertical axis represents PRI or TRI, and the horizontal axis represents asset volatility. Generally, a change in climate risk measures affects the volatility of stocks and green bonds within the span of a trading day to a trading week. Our results do not show any significant effect after a trading month. Intuitively, the effect of TRI is more pronounced on the volatility of STXOIL, EUROOIL, EEX, and GB, whereas the effect of PRI is more pronounced on the volatility of EEX. An effective forecasting of energy asset volatility is relevant for climate policy formulation and risk management.

Figure 4 shows that TRI increases the volatility of STXOIL, EUROOIL, and EEX within the next trading day when TRI is at low or average levels. This positive relationship is more significant at the lower quantiles of the volatility of EEX, lower and middle quantiles of the volatility of STXOIL, and almost all quantiles of the volatility of EUROOIL. A positive impact of TRI on the volatility of EUROOIL and EEX is detectable even after a trading week and is more pronounced at lower quantiles of TRI. This result has new and interesting economic implications. Considering that a low level of TRI indicates a lower than expected discussion around transition issues, a general volatility surge effect for brown energy markets and carbon emissions should not be that surprising. To better explain the economic intuition behind this result, we provide an example of a low-quantile TRI scenario. For purely explicative reasons, imagine the period surrounding the COP26. Economic agents expect information on the international climate negotiations, the roadmap to achieve net zero goals, changes to mitigation policies, and much more. However, no news is released. This causes surprise in the market as agents are unsure about the conclusions of the on-going international debate on climate issues. The lack of information generates confusion and increases the stress in the market resulting in asset price swings, as we document a volatility rise. While this finding is very informative for investors, it is certainly of most interest for its policy and regulatory implications. Regulators and policy-makers as well as financial supervisors and central banks learn from this finding that the absence of (clear) climate action plans, where they were expected, threatens price stability. This result contributes to Battiston et al. (2021) who study the relationship between climate risks and financial stability. Additionally, we find that TRI has a negative impact on the volatility of GB, which is significant mainly when both TRI and the volatility of GB are in the middle or upper quantiles. This result shows that an unexpected acceleration of the decarbonization process mitigates the GB volatility during high/normal-volatility states.

The results presented in Figure 5 imply that the impact of PRI on the volatility of EUROOIL is positive within the next trading day when PRI is in the lower quantiles and the volatility of EUROOIL is in the lower or middle quantiles. The impact of PRI on the volatility of EEX is also positive within the span of a trading day to a trading week and is significant mainly at the lower and middle quantiles of both PRI and the volatility of EEX. We do not document any relevant impact of physical risk on the volatility of ERIX.

5.2. Time-varying results of cross dependence

Alongside the static analysis, we examine the effects of climate risks (TRI and PRI) on the returns and volatility of the assets in a time-varying setting. This allows us to check the robustness of the results derived from the entire sample analysis by uncovering possible structural changes due to major events in financial markets.[11] We do this for $\alpha_1 = \alpha_2 = 0.1$, 0.5, and 0.9, reflecting,

[11] To calculate the time-varying cross-quantilograms, each time series is divided into sub-samples from the start to the end of each year (i.e. each sub-sample is equal to around 252 daily observations). Then the cross-quantilogram is calculated for each sub-sample using a rolling window framework for which all trading days in the first year are employed. The cross-quantilogram model is first estimated then re-estimated by shifting the window forward to the next year as many times as needed until the end of the sample period.

respectively, the lower, middle, and upper quantiles of both climate risk measures and returns/volatility series. The results are presented in Figures 6-9, where the upper and lower rows present the cross-quantilograms and results of the portmanteau test obtained for each year. Furthermore, 1000 bootstrapped replicates are used to illustrate 90% bootstrap confidence intervals (dashed lines) in each graph.

5.2.1. Climate risks and asset returns

The results of the time-varying cross-quantilograms from climate risks to asset returns are presented in Figures 6 and 7.

The results of the portmanteau test in Figure 6 indicate a significant impact of TRI on the returns of STXOIL, ERIX, and EEX. The cross-quantilograms obtained in these cases indicate a positive impact of TRI on the returns of STXOIL in 2022, when both TRI and the returns of STXOIL are in the upper quantile, possibly supporting the recent emergence of a transition risk premium so that brown stocks should deliver higher returns to compensate for the higher risk of holding them. The graphs related to the relationship between TRI and the returns of ERIX show both positive and negative impacts of TRI on the returns of ERIX in 2012 and 2021, respectively. Again, these findings may support the emergence of a transition risk premium in the recent period as they show that green stock returns instead decrease due to TRI. Furthermore, these opposite impacts are significant in the upper quantile, and the average impact during the time period of our study could be insignificant. There is also evidence of a negative impact of TRI on the returns of EEX in 2017 when both TRI and the returns of EEX are in the lower quantile. These results, as well as evidence of no significant impact of TRI on EUROOIL and GB provided in Figure 6, confirm the results of the static analysis presented in Figure 2.

Figure 7 shows a significant impact of PRI on the returns of STXOIL, EUROOIL, ERIX, EEX, and GB. The cross-quantilograms obtained in these cases indicate: i) a negative impact of PRI on the returns of STXOIL in 2013 when both variables are in the middle quantile and a positive impact in 2011 when both variables are in the upper quantile; ii) a negative impact of PRI on the returns of EUROOIL in 2013 when both PRI and the returns of EUROOIL are in the lower quantile and in 2014 when both PRI and the returns of EUROOIL are in the upper quantile; and iii) a negative impact of PRI on the returns of ERIX in 2017 when both variables are in the lower quantile. The graphs also show both negative and positive impacts of PRI on the returns of ERIX in 2012 and

2018, respectively. These opposite impacts are significant in the middle quantile. The cross-quantilograms further indicate: iv) negative and positive impacts of PRI on the returns of EEX in 2016 and 2022 when both variables are in the middle quantile, and positive and negative impacts of PRI on the returns of EEX in 2013 and 2017 when both variables are in the upper quantile; and v) a positive impact of PRI on the returns of GB in 2020 when both variables are in the lower quantile and a negative impact in 2013 when both variables are in the middle quantile.

The above results of the dynamic analysis are more comprehensive than those reported in Figure 3 for the static analysis. They reflect possible structural changes in the impact of PRI and TRI due to major events in financial markets, which explain some of the inconsistencies between the results of the static and dynamic analyses. Previous studies demonstrate the time-varying characteristics of climate risks (e.g. Sarhadi et al., 2016) while documenting the return dynamic nature of financial markets (Dutta et al., 2021). Overall, our results are in line with Bouri et al. (2022) who indicate the impact of climate policy uncertainty on the price dynamics of green and brown energy stocks, although our analysis is more comprehensive given its ability to differentiate between market conditions within the quantile-based predictability approach and to consider both transitional climate risk and physical climate risk.

5.2.2. Climate risks and asset volatility

The time-varying cross-quantilograms covering the directional predictability from climate risks to asset volatility are presented in Figures 8 and 9.

The results in Figure 8 confirm the results from the static analysis in Figure 4, indicating a positive impact of TRI on the volatility of STXOIL, EUROOIL, and EEX, and a negative impact of TRI on the volatility of GB, along with non-significant evidence of the impact of TRI on the volatility of ERIX. In particular we find: i) a positive impact of TRI on the volatility of STXOIL in 2017 when both TRI and the volatility of STXOIL are in lower or middle quantiles, suggesting that brown stock volatility increases in the period right after the Paris Agreement and in concomitance with discussions around the EU carbon market reform deal; ii) a positive impact of TRI on the volatility of EUROOIL in 2017 and 2019 when both TRI and the volatility of EUROOIL are in the middle quantile, similarly to STXOIL; iii) a positive impact of TRI on the volatility of EEX in 2021 when both variables are in the lower quantile, in 2013 when both variables are in the middle quantile, and in 2022 when both variables are in the upper quantile; and iv) a negative impact of

TRI on the volatility of GB in 2017 when both variables are in the middle quantile and in 2021 when both variables are in the upper quantile, showing how transition risk dampens the volatility of GB especially in the period after the Paris Agreement.

Figure 9 shows a significant impact of PRI on the volatility of STXOIL, EUROOIL, ERIX, and EEX. The cross-quantilograms obtained in these cases indicate: i) a positive impact of PRI on the volatility of STXOIL in 2017 when both variables are in the lower quantile and a negative impact in 2013 when both variables are in the middle quantile, suggesting a switch in volatility reaction possibly related to the pre- and post-Paris Agreement periods, with brown stock volatility increasing with PRI post-Paris Agreement; ii) a positive impact of PRI on the volatility of EUROOIL in 2017 and 2018 when both variables are in the lower quantile and a negative impact in 2012 and 2014 when both variables are in the upper quantile, similarly to STXOIL; and iii) positive and negative impacts of PRI on the volatility of ERIX in 2012 and 2022 when both PRI and the volatility of ERIX are in the lower quantile and also positive and negative impacts in 2014 and 2021 when both variables are in the middle quantile. Despite the average impact during the time period of our study being potentially insignificant, we observe an opposite reaction of PRI on green stock volatility with respect to brown stocks when making a similar distinction between the pre- and post-Paris Agreement periods. The cross-quantilograms further indicate: iv) a positive impact of PRI on the volatility of EEX in 2013 and 2017 when both PRI and the volatility of EEX are in the lower quantile as well as a positive impact of PRI on the volatility of EEX in 2013 when both variables are in the middle quantile; and v) no significant impact of PRI on the volatility of GB irrespective of the quantiles of either series.

The results of the dynamic analysis presenting the nature of the impact of PRI on the volatility of ERIX, EEX, and GB confirm the results of the static analysis presented in Figure 5. It is worth mentioning that the results of the static analysis provide evidence of positive and negative impacts of PRI on EUROOIL in the lower and upper quantiles of PRI, respectively. This is in line with the dynamic analysis results, but the positive impact in the static analysis is negligible. Overall, our analysis shows the predictive power of climate risks for the volatility of various assets, which is in line with recent studies showing evidence that climate-related risks can increase the stress of the financial system (Flori et al. 2021) and represent a source of systematic risk (e.g. Bolton & Kacperczyk, 2021; Faccini et al., 2021; Bua et al., 2022; Hsu et al., 2023). Our results also concord with Bouri et al. (2022) who point to the importance of climate policy uncertainty on the volatility of green and brown energy stocks.

5.3. Robustness check

We test the robustness of the results of our analysis to the choice of the volatility measure and present them in Appendix A. We estimate 12 GARCH conditional volatility series for each asset return based on 12 models: GARCH(1,1), AR(1) GARCH(1,1), ARMA(1,1) GARCH(1,1), ARMA(1,2) GARCH(1,1), ARMA(2,1) GARCH(1,1), ARMA(2,2) GARCH(1,1), T-GARCH(1,1), AR(1) T-GARCH(1,1), ARMA(1,1) T-GARCH(1,1), ARMA(1,2) T-GARCH(1,1), ARMA(2,1) T-GARCH(1,1), and ARMA(2,2) T-GARCH(1,1), and select the best model based on the Akaike information criterion (AIC).[12] Then we estimate the predictability from TRI and PRI to the new conditional volatility series using static and dynamic cross-quantilogram techniques. The rationale for using conditional volatility instead of squared returns is to reflect stylized facts in asset returns such as volatility clustering and the leverage effect.

The results of the static cross-quantilogram analysis are presented in Appendix Figure A1 (a) for TRI and (b) for PRI. They are consistent with the main results in Figures 4 and 5 in all cases, except for the impact of PRI on STXOIL volatility and the impact of TRI on GB volatility, where we note slight differences. The results of the dynamic cross-quantilogram analysis are presented in Appendix Figures A2 and A3. We note good consistency between these results and the main results in Figures 8 and 9. The only case that shows a difference is GB. For all other cases, similarities are obvious, especially in terms of the overall sign of the impacts.

5.4. Implications for the COP26 and the Climate Glasgow Pact

Our results contribute to and have relevant implications for the COP26 discussion and the resultant Glasgow Climate Pact (GCP), a package of decisions and actions agreed by the nations to limit global temperature rise to 1.5^{o} degrees. The Pact *"underscores the urgency of enhancing understanding and action to make finance flows consistent with a pathway towards low greenhouse gas emission and climate-resilient development in a transparent and inclusive manner in the context of sustainable development"*. It also urges that financial institutions "*scale up investments in climate action and calls for a continued increase in the scale and effectiveness of*

[12] The results of the AIC selection are not presented here but are available from the authors upon request.

climate finance from all sources globally" and, jointly with development banks and the private sector, they should *"enhance finance mobilization in order to deliver the scale of resources needed to achieve climate plans"* (GCP, 2022). The financial sector is therefore recognised to have a crucial role in fostering sustainability and supporting the green transition (e.g., Beltran et al., 2023) by transmitting mitigation policies to the real economy and/or by financing climate actions and the green transition. However, several factors can potentially hinder the achievement of international climate agreement goals, including those enshrined in the CGP, such as the level of integration of sustainable considerations in decision-making processes by economic agents (Ahmed et al., 2023), the recognition that climate risk exposure requires a risk premium (Birindelli et al., 2023), and the actual credibility of climate-policies (Battiston et al., 2021b; Gourdel et al., 2022; Birindelli et al., 2023). We argue that climate risks assessment can be considered as a common element across these factors. Indeed, a good climate risk assessment can improve the quality of climate risk management and its integration into investment decisions, contribute to our understanding of potential heterogeneity of assets reaction to climate risks, and enhance the effectiveness of mitigation policies. In fact, a Paris-aligned response from financial markets is conditioned to a sufficient understanding of how climate risks propagate throughout the economy, including the understanding of how climate-related risks affect assets' returns and volatility.

The findings discussed in this paper therefore highlight the need for a comprehensive assessment of the impact of climate-related risks considering multiple factors. In an ideal scenario with perfect climate risk assessment information, investors would have the complete knowledge they need to make climate-informed investment decisions, fully aware of the risk-return profiles of their investments and whether their decision-making processes adequately account for climate risks, or whether their portfolios are aligned with international agreements' decarbonizations trajectories. However, it is not just climate-informed investments, but also climate-informed policies that are necessary in order to foster a sustainable development and promote the mobilization of net zero capital allocation. In this regard, our results offer a comprehensive study of the effects of different types of climate risks, physical and transition, on the assets under investigation, considering various market conditions and degrees of climate risks severity both in a static and time-varying contexts, improving both climate-informed investments and policy decisions. Our findings are in fact relevant to the COP26 as they contribute to the dissemination of knowledge regarding climate risk assessment. On one hand, policymakers can learn from these results about the diverse effects of climate risks based on, e.g., market return conditions and use this knowledge to formulate more informed and credible policies. On the other hand, our results are informative for investors to better integrate climate considerations within their strategies. Among our set of results, we, for example, show that lower than expected levels of discussion on the transition process leads to heightened volatility in brown energy stocks. This finding highlights the importance of effective communication of climate action plans by governments and serves as a warning to supervisors overseeing financial price stability. Another significant result indicates that transition risk tends to have a greater impact on predicting future returns of assets compared to physical risk. In the context of COP26, this suggests that economic agents may be more focused on regulatory concerns associated with climate change rather than its physical aspects. Consequently, governments may need to enhance investor awareness regarding the financial risks associated with climate hazards.

6. Conclusions

In this paper we study the directional predictability from climate-related risks considering both aspects of climate change, i.e. physical and transition, to the returns and volatility of European brown and green energy stocks, European carbon emission allowances, and global green bonds under various market conditions and crisis periods, both in a static and time-varying setting. We use, extend, and enhance two novel measures of physical and transition climate risks computed from the textual analysis of European news sourced from Reuters News. Using daily data we apply the text-based climate risk factors to the cross-quantilogram approach of Han et al. (2006) to investigate the direction, duration, and strength of their effects to the first and second moments of the distribution of the assets on a quantile-basis considering a large number of lags. Considering low, medium, and high quantiles, we document how the impact of various levels of climate risk, not simply average levels, vary across a spectrum of market conditions from bullish to bearish states and from heightened to low volatility, revealing new underlying financial implications of physical and transition risks. Alongside the static analysis we extend the cross-quantilogram approach to a time-varying setting to provide evidence of any evolution of predictability of climate risks over time.

Our main findings on returns predictability suggest that transition risk has a stronger predictive ability than physical risk, especially for energy and carbon emissions stocks, considering a static analysis, whereas the results for TRI and PRI become more complex in a time-varying setting, possibly due to the impact of other financial events or structural changes in markets. Despite the heterogeneity of the results, we identify a common short-term significance effect of climate risks on the asset returns studied. Daily climate risks, under specific circumstances, can predict one-day-ahead returns only, possibly indicating myopic investment behaviour given the well-known long-run component of climate risk, or indicating the market ability to incorporate the new information as quickly as one trading day ahead. For the predictability of asset volatility, the static analysis provides evidence that the climate risk effect on the volatility of assets and green bonds can last up to one trading week, with heterogeneous results for transition and physical risk. In a time-varying setting, the significance predictability of volatility varies according to time periods and assets volatility states. Generally, climate risks, in particular transition risks, positively relate to the volatility of brown energy and carbon emissions stocks, whereas they negatively relate to the volatility of green bonds.

The analyses conducted in this study and the main findings are relevant for, among others, European policy makers, investors, portfolio managers, and other financial institutions that want to know how to effectively integrate climate-related risks into their policies or investment decisions. For instance, asset managers interested in carbon neutrality procedures, ESG-oriented investments, or climate-hedged strategies can benefit from our results by learning how climate risks, physical and transition, can play a useful role in predicting both asset returns and volatility, as well as how these effects depend on other variables. The European focus makes this paper appealing for, e.g., European regulators, the European Central Bank, and other regulatory bodies interested in international climate development, which need to assess the impact of climate risks within financial markets in preparation for achieving climate goals as, e.g., agreed upon in the European Green Deal or so-called "Fit for 55" scheme. Documenting the different reactions of climate risks under different market conditions and volatility states provides useful insights not only for risk management but also for climate policy formulations and timings. The findings presented in this paper have relevant policy implications as they inform regulators and policy makers of the heterogeneous effects that climate states (high, average, or low) have on the return-risk profile of financial assets helping the formulation of climate regulations. For instance, regulators learn from this paper that the consequent increase in asset volatility due to a lack of information or discussion about the transition process, when this is expected by market agents, has the potential to impair price stability, ultimately warning central banks and supervisors.

In general, this paper relates and contributes to both the green and climate finance literature and the literature on the predictability of asset returns and volatility, as a multi-level study that sheds light on the directional predictive ability of climate-related risks under various market conditions. Future research could, for instance, further explore the role of text-based physical and transition risk measures, as proposed in this paper, in relation to investor behaviour considering various market conditions, or study market efficiency incorporating climate risks and/or propose effective climate hedging strategies according to various scenarios in light of the findings of this paper. Another line of research could involve the use of return and volatility data on financial markets from other regions of the world to see whether the impacts detected in the context of European markets are transferable to other contexts.

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Tables

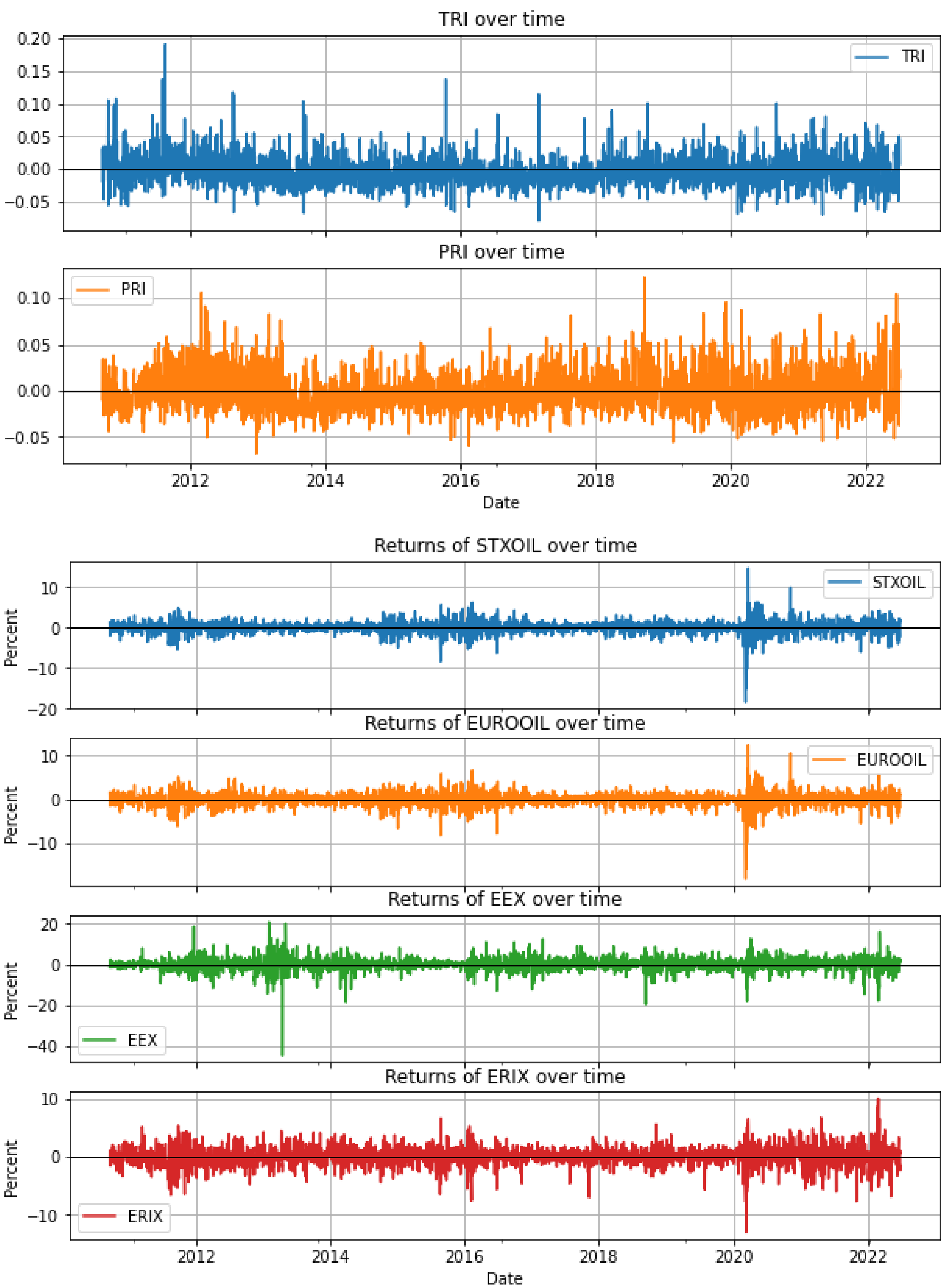
Table 1. Summary statistics of the climate risk measures and returns and volatilities of the assets.

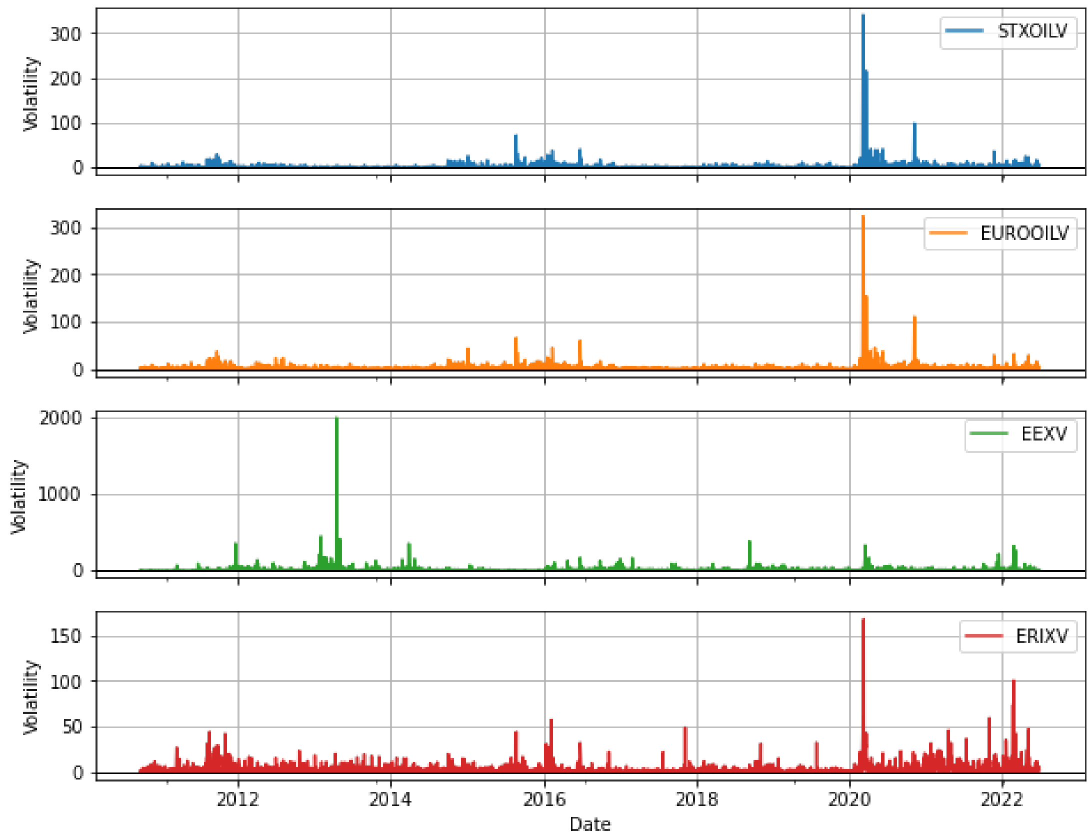
	PRI	TRI	Returns					Volatilities				
			STXOIL	EUROOIL	ERIX	EEX	GB	STXOILV	EUROOILV	ERIXV	EEXV	GBV
Mean	-0.002	-0.003	0.002	0.001	0.039	0.058	0.001	2.256	2.301	2.644	10.164	0.105
Std dev	0.022	0.023	1.502	1.517	1.626	3.188	0.324	9.684	9.307	6.363	43.928	0.288
Min	-0.068	-0.081	-18.432	-17.954	-12.972	-44.655	-2.424	0.000	0.000	0.000	0.000	0.000
25%	-0.017	-0.017	-0.696	-0.739	-0.791	-1.415	-0.170	0.102	0.105	0.164	0.373	0.006
50%	-0.005	-0.005	0.026	0.025	0.089	0.000	0.007	0.504	0.569	0.715	2.281	0.030
75%	0.009	0.009	0.724	0.764	0.900	1.659	0.178	1.833	1.951	2.509	8.450	0.103
Max	0.123	0.191	14.653	12.390	10.030	21.060	2.013	339.733	322.330	168.270	1994.087	5.875
Skewness	0.862	1.032	-0.769	-0.863	-0.290	-0.991	-0.421	22.745	22.139	10.045	31.698	11.895
Kurtosis	1.706	4.234	16.461	14.398	3.831	16.804	5.579	665.819	647.752	187.918	1368.181	200.993
Jarque-Bera	799.7	3083.4	33268	25564.1	1887.2	34936.7	3430.8	54570427	51667911	4494413.6	229913509	4405710.3
ERS	-5.753***	-4.356***	-4.356***	-3.813***	-9.350***	-7.047***	-5.686***	-7.201***	-7.100***	-6.986***	-8.321***	-6.796***
PP	-4632.0***	-4773.7***	-2925.3***	-3034.3***	-2854.9***	-2955.8***	-2544.8***	-4196.7***	-4242.9***	-3761.3***	-3226.3***	-2874.2***
Count	3071	3071	3071	3071	3030	3071	2601	3071	3071	3030	3071	2601

Notes: ERS is the statistic of the unit root test based on Elliott, Rothenberg, and Stock (1996). PP is the statistic of the unit root test based on Phillips and Perron (1988). The null hypothesis of both tests is that the variable has a unit root. The critical values of the ERS test are -3.480, -2.890, and -2.570 and the critical values of Phillips–Perron test are -20.700, -14.100, and -11.300 for 1%, 5%, and 10% significance levels respectively; *** indicates significance at the 1% level. TRI is Transition Risk Index; PRI is Physical Risk Index; STXOIL is STOXX EUROPE 600 OIL & GAS; EUROOIL is EUROSTOXX OIL & GAS in euro; ERIX is European Renewable Energy in euro; EEX is EEX-EU CO2 Emissions EUA; GB is global green bond index.

Figures

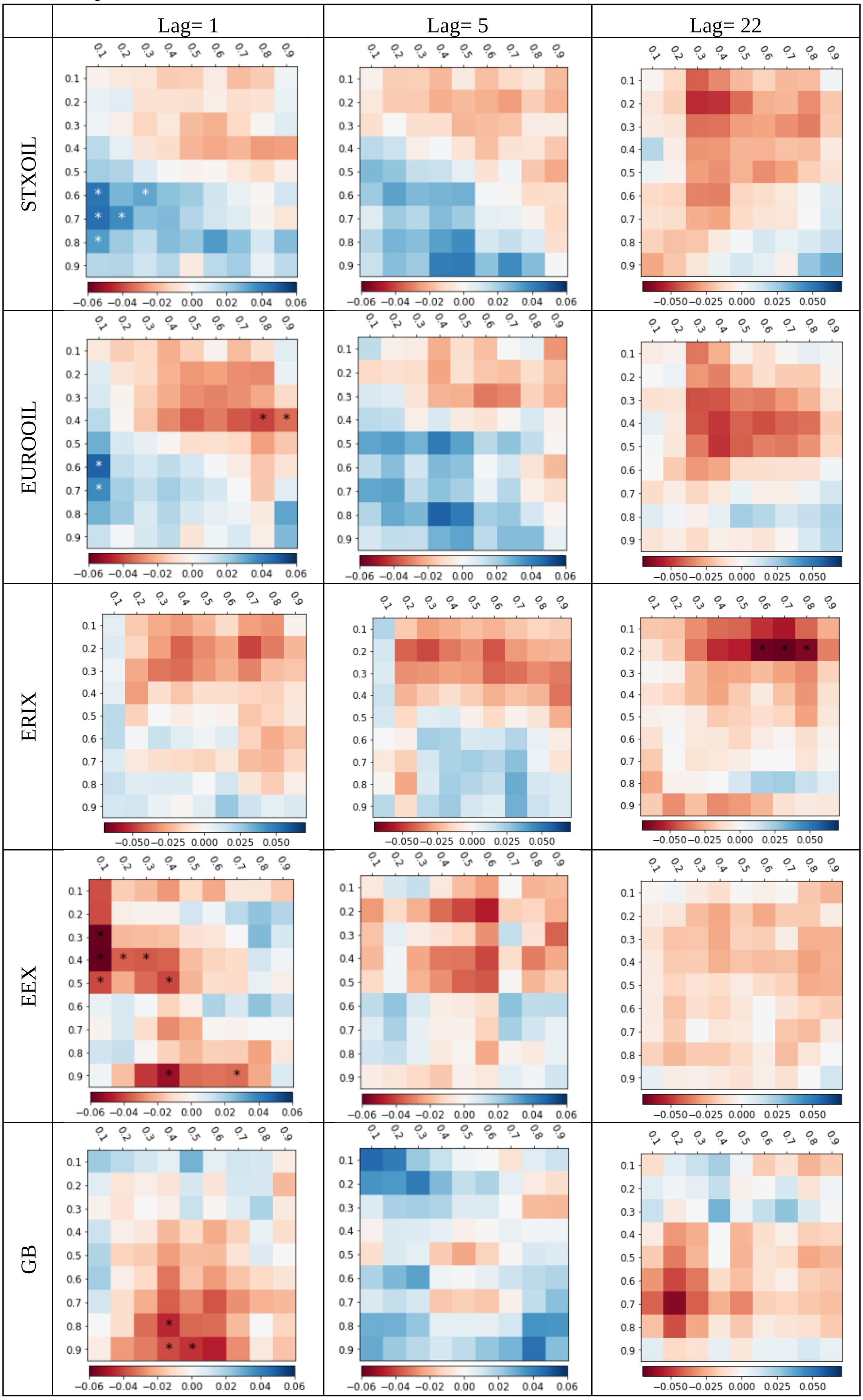
Figure 1. Climate risk measures and the returns and volatility of the indices.





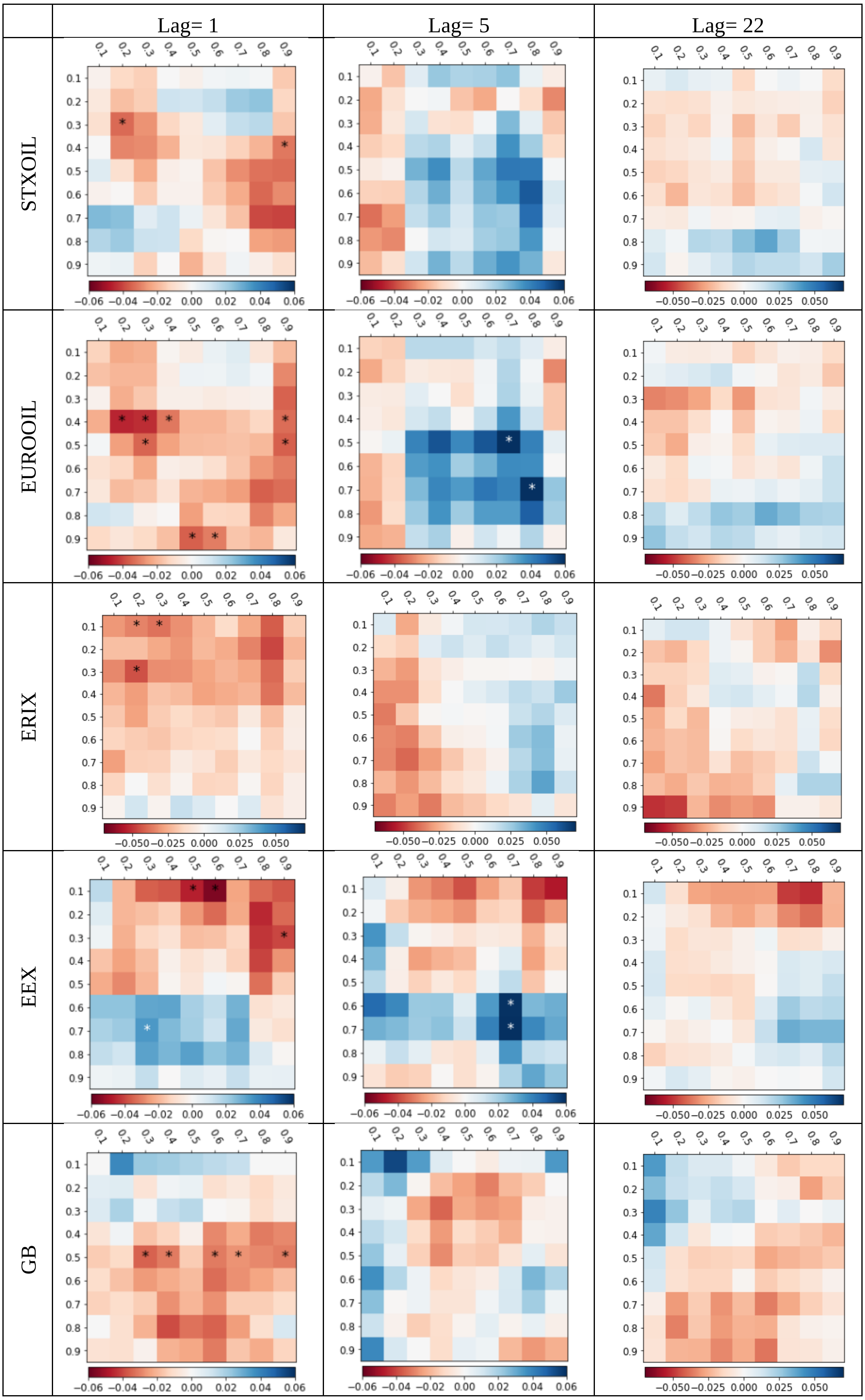
Notes: TRI is Transition Risk Index; PRI is Physical Risk Index; STXOIL is STOXX EUROPE 600 OIL & GAS; EUROOIL is EUROSTOXX OIL & GAS in euro; ERIX is European Renewable Energy in euro; EEX is EEX-EU CO2 Emissions EUA; GB is global green bond index.

Figure 2. Predictability from TRI to return series.



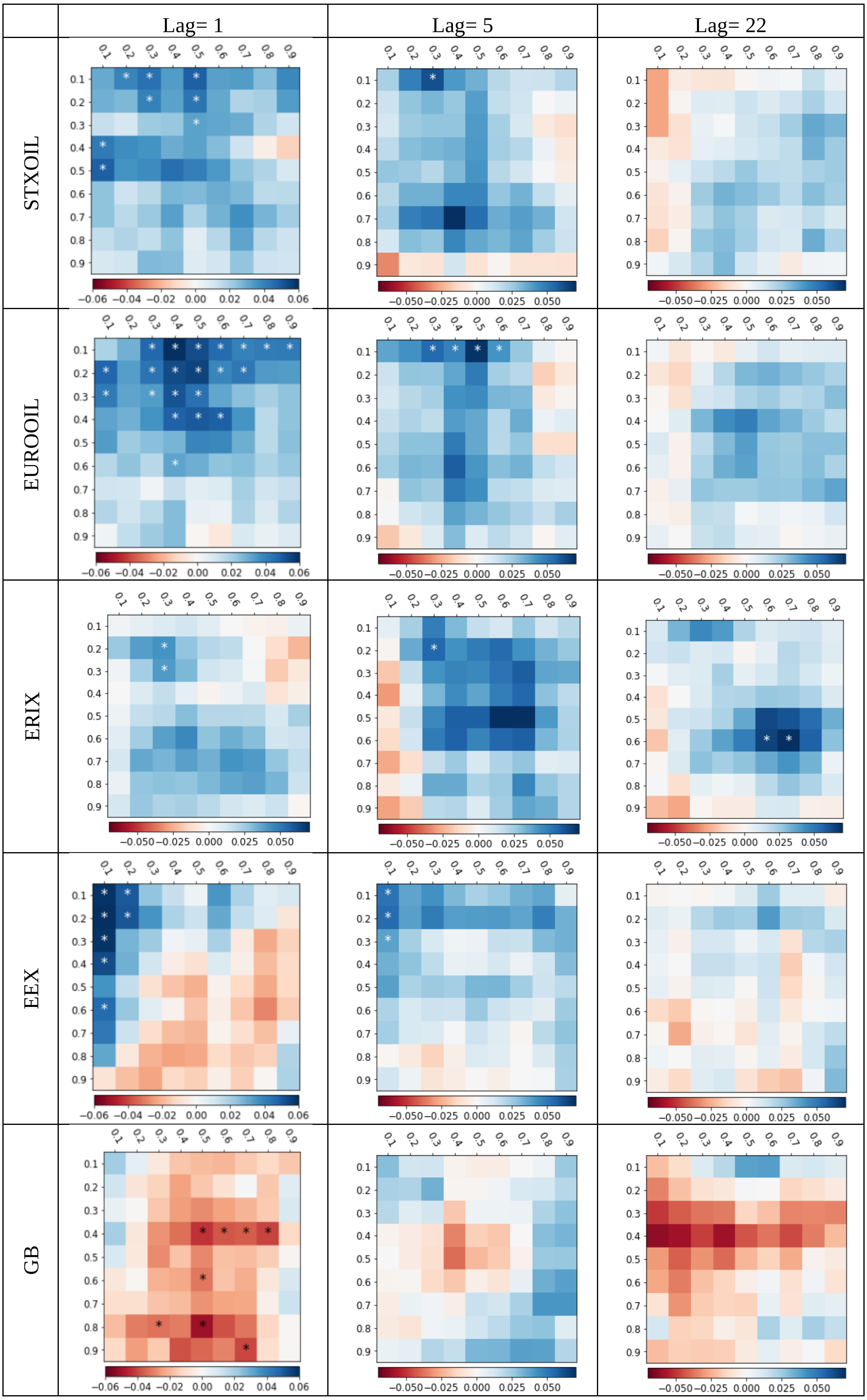
Notes: The vertical axis represents TRI (PRI), and the horizontal axis represents asset returns. The multicoloured bars below the heatmaps measure the magnitude of the effect, which varies from negative (red) to positive (blue). White indicates no effect. Asterisk (*) indicates a significant effect at the10% level. TRI is Transition Risk Index; PRI is Physical Risk Index; STXOIL is STOXX EUROPE 600 OIL & GAS; EUROOIL is EUROSTOXX OIL & GAS in euro; ERIX is European Renewable Energy in euro; EEX is EEX-EU CO2 Emissions EUA; GB is global green bond index.

Figure 3. Predictability from PRI to return series.



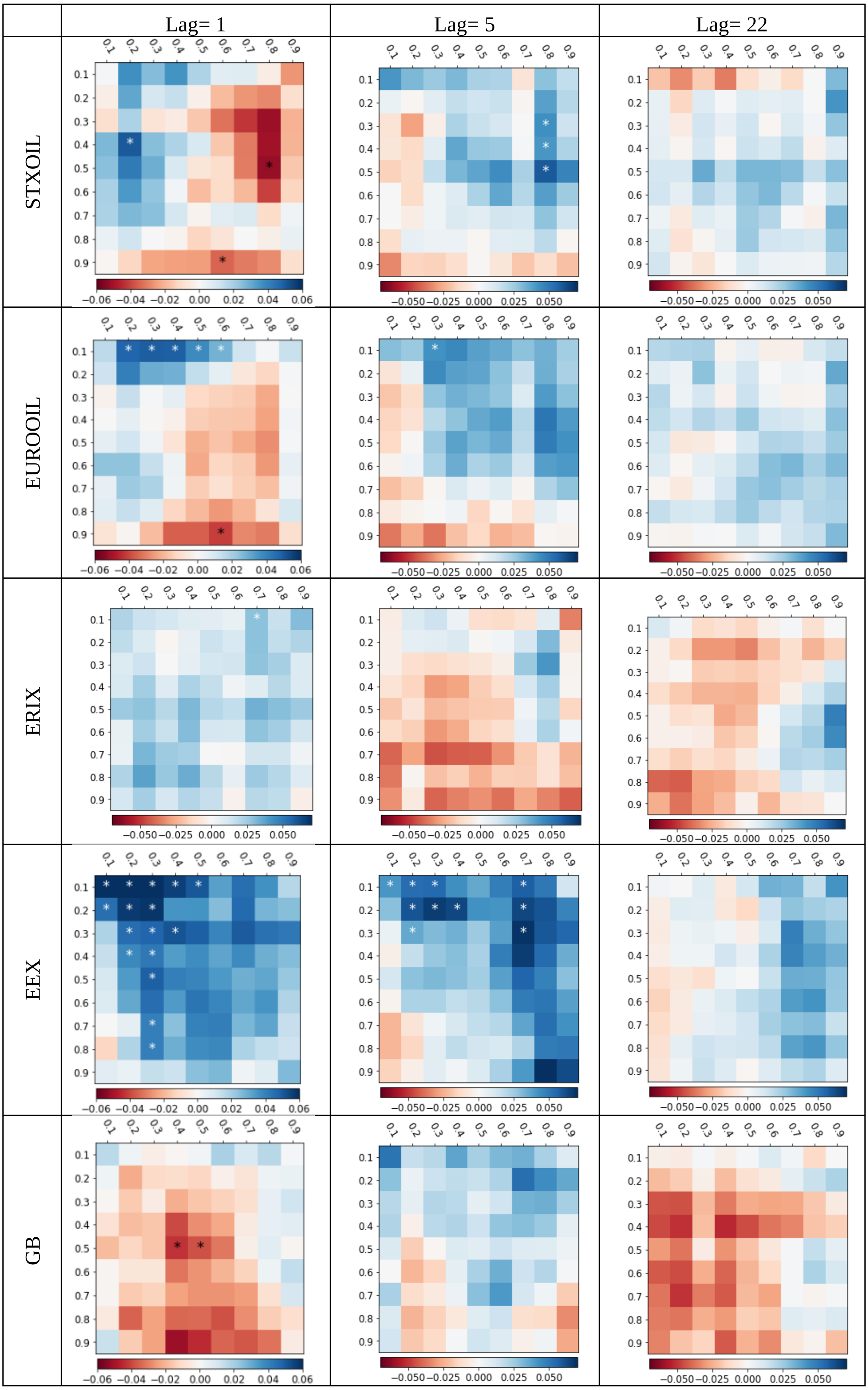
Note: See the notes to Figure 2.

Figure 4. Predictability from TRI to volatility series.



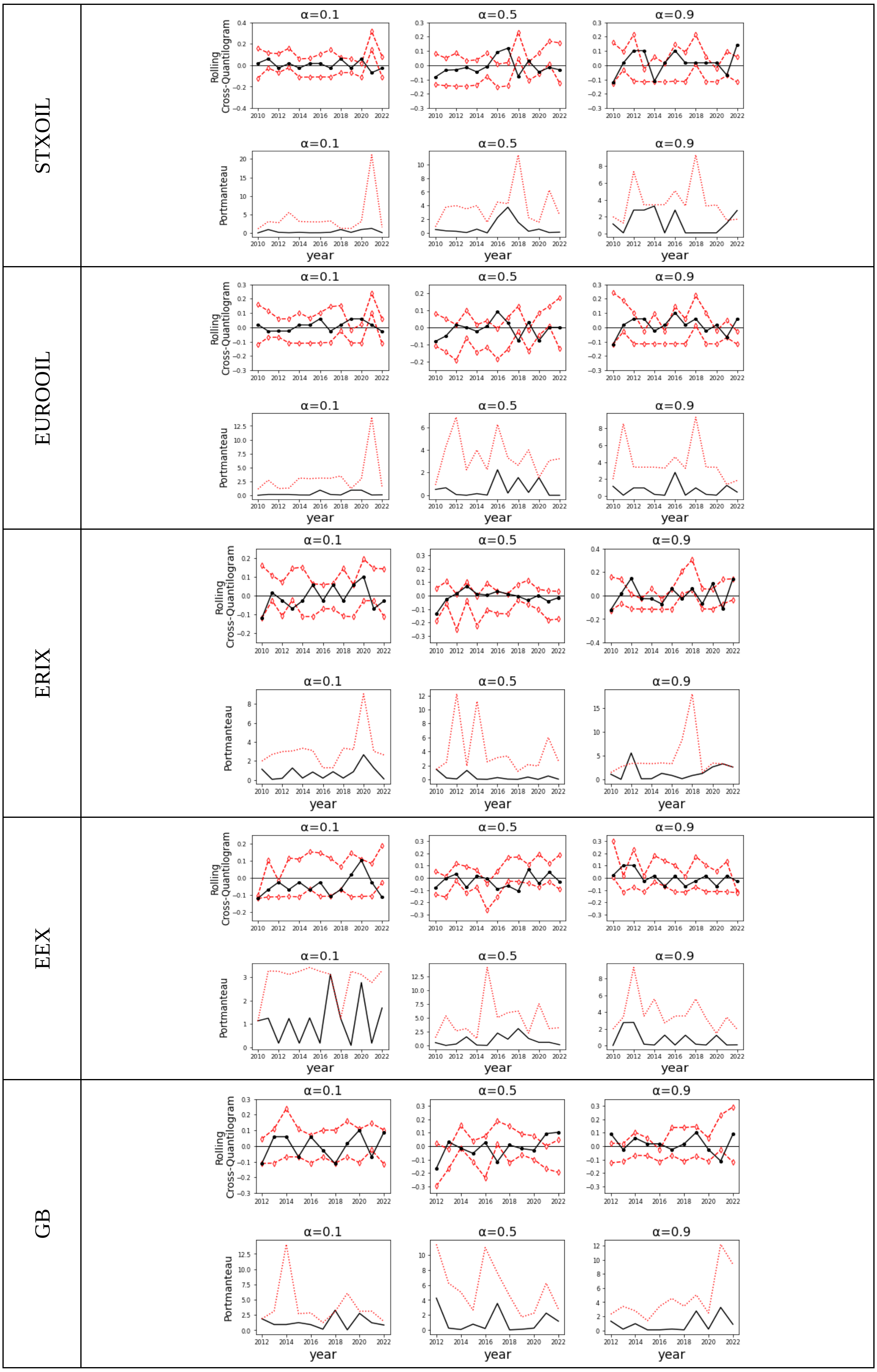
Notes: The vertical axis represents TRI (PRI), and the horizontal axis represents the asset volatility. The multicoloured bars below the heatmaps measure the magnitude of the effect, which varies from negative (red) to positive (blue). White indicates no effect. Asterisk (*) indicates a significant effect at the10 % level. TRI is Transition Risk Index; PRI is Physical Risk Index; STXOIL is STOXX EUROPE 600 OIL & GAS; EUROOIL is EUROSTOXX OIL & GAS in euro; ERIX is European Renewable Energy in euro; EEX is EEX-EU CO2 Emissions EUA; GB is global green bond index.

Figure 5. Predictability from PRI to volatility series.



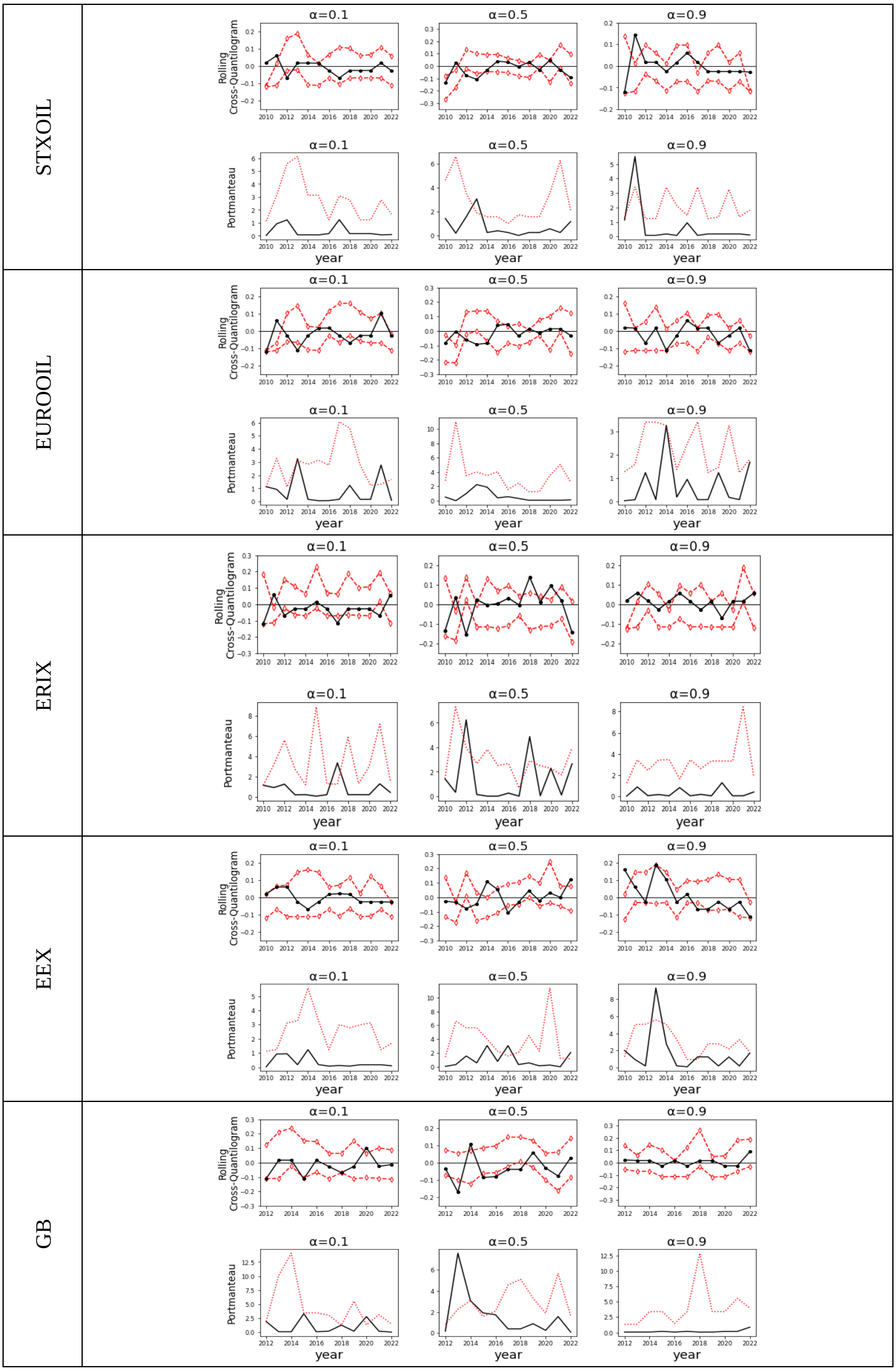
Note: See the notes to Figure 4.

Figure 6. Rolling directional predictability from TRI to return series.



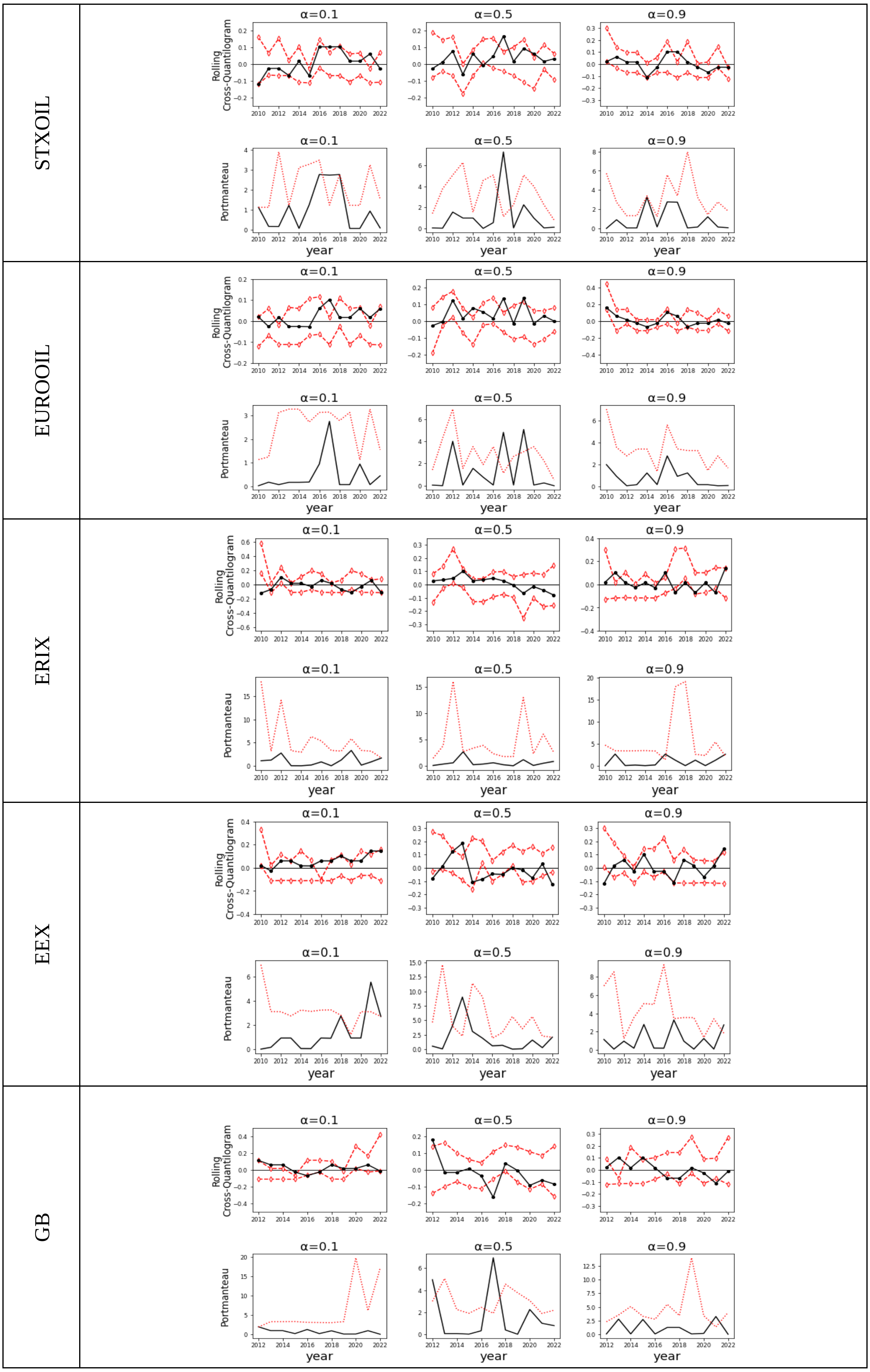
Notes: The upper and lower rows present the cross-quantilogram and the results of the portmanteau test obtained for each year. The dashed lines indicate the 90% confidence interval. 0.1, 0.5, and 0.9 are selected as lower, middle, and upper quantiles for both climate risk measures and returns/volatility series. The portmanteau test is employed to detect directional predictability from TRI/PRI to returns/volatility series at various quantiles. TRI is Transition Risk Index; PRI is Physical Risk Index; STXOIL is STOXX EUROPE 600 OIL & GAS; EUROOIL is EUROSTOXX OIL & GAS in euro; ERIX is European Renewable Energy in euro; EEX is EEX-EU CO2 Emissions EUA; GB is global green bond index.

Figure 7. Rolling directional predictability from PRI to return series.



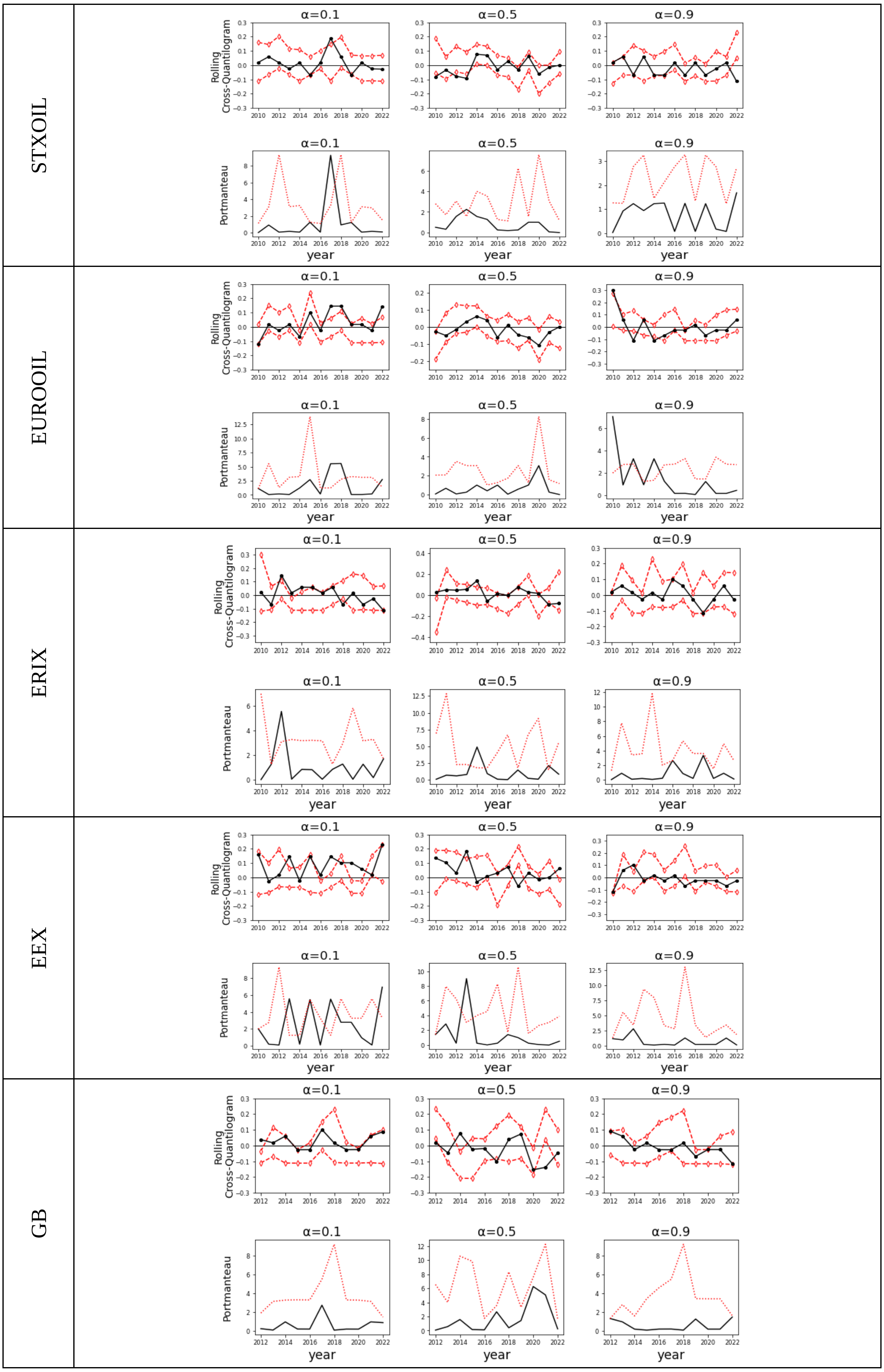
Note: See the notes to Figure 6.

Figure 8. Rolling directional predictability from TRI to volatility series.



Note: See the notes to Figure 6.

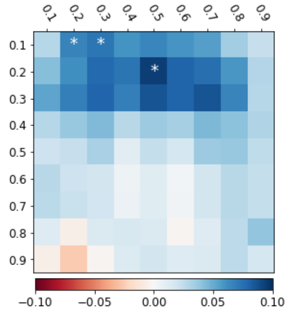
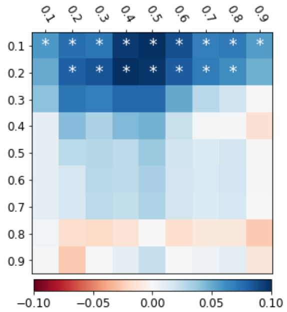
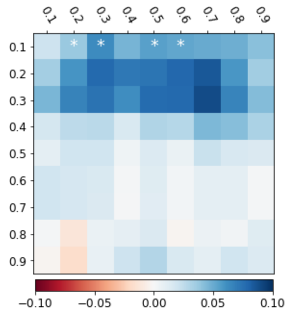
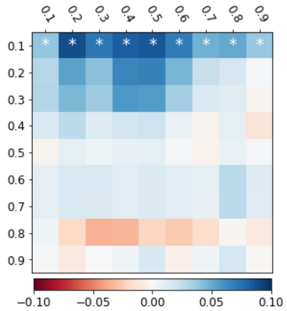
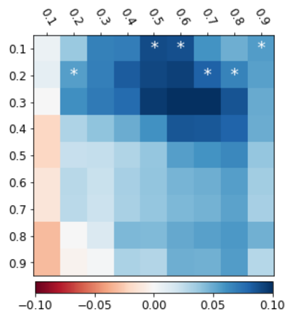
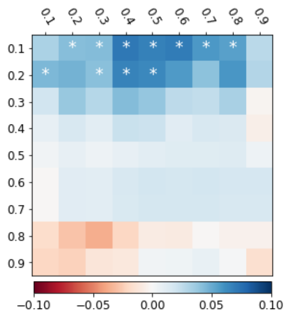
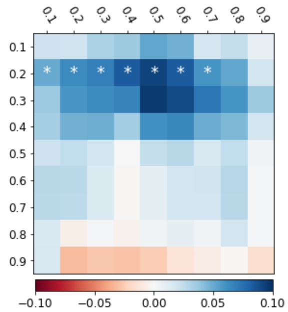
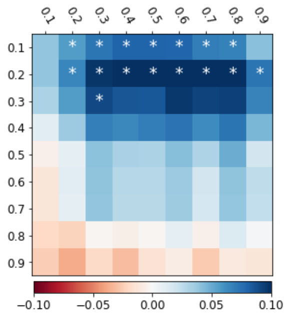
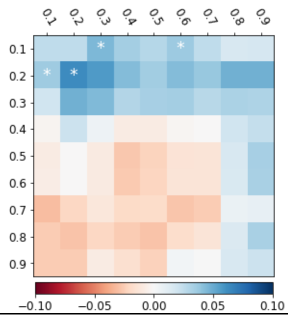
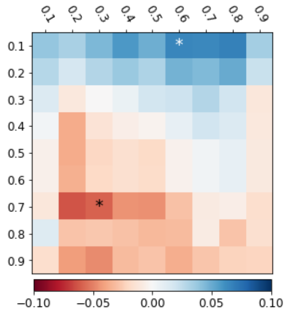
Figure 9. Rolling directional predictability from PRI to volatility series.



Note: See the notes to Figure 6.

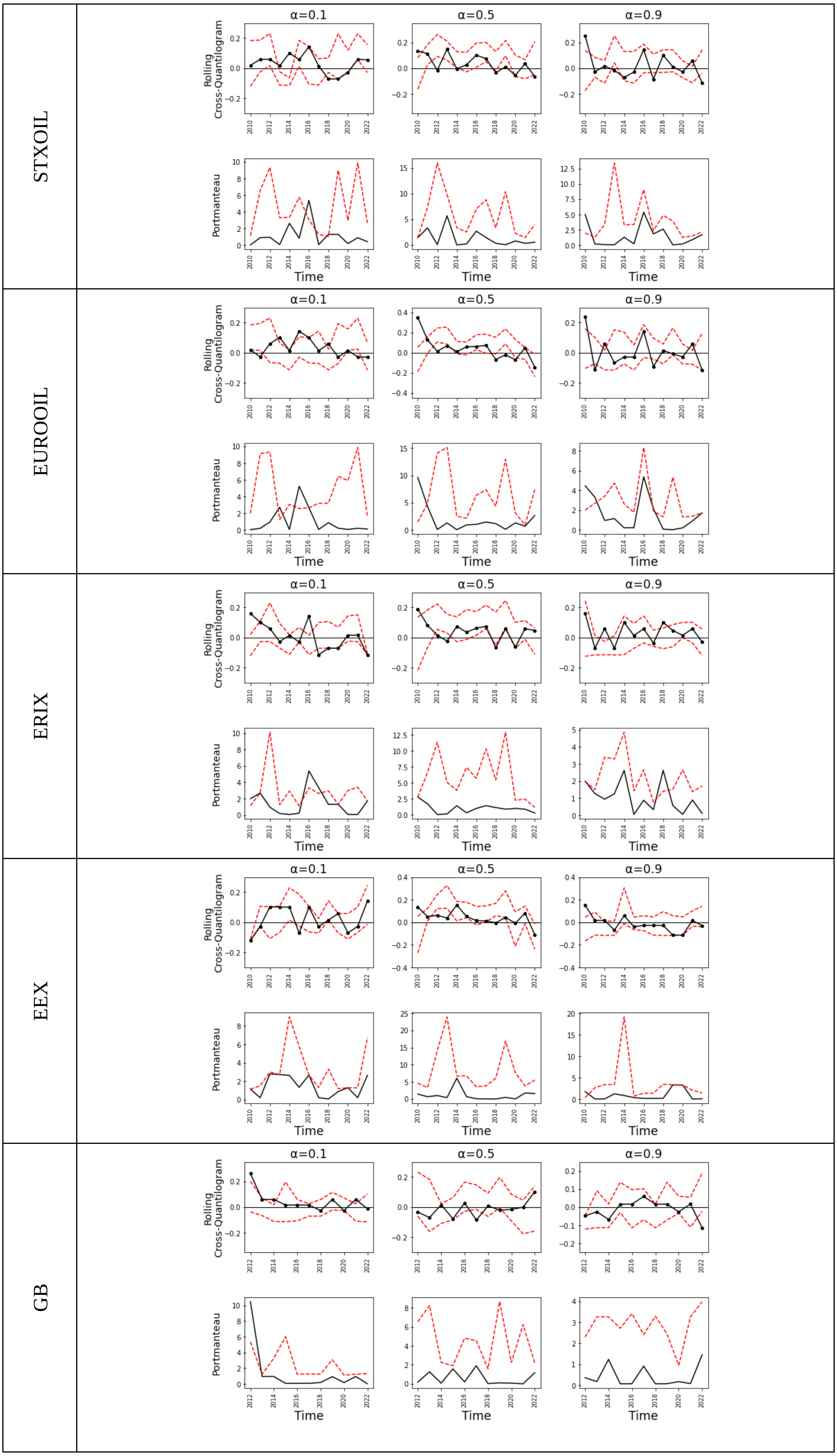
Appendix A. Robustness Check.

Figure A1. Predictability from TRI (a) and PRI (b) to conditional volatility series.

	(a)	(b)
	TRI Lag= 1	PRI Lag= 1
STXOIL		
EUROOIL		
ERIX		
EEX		
GB		

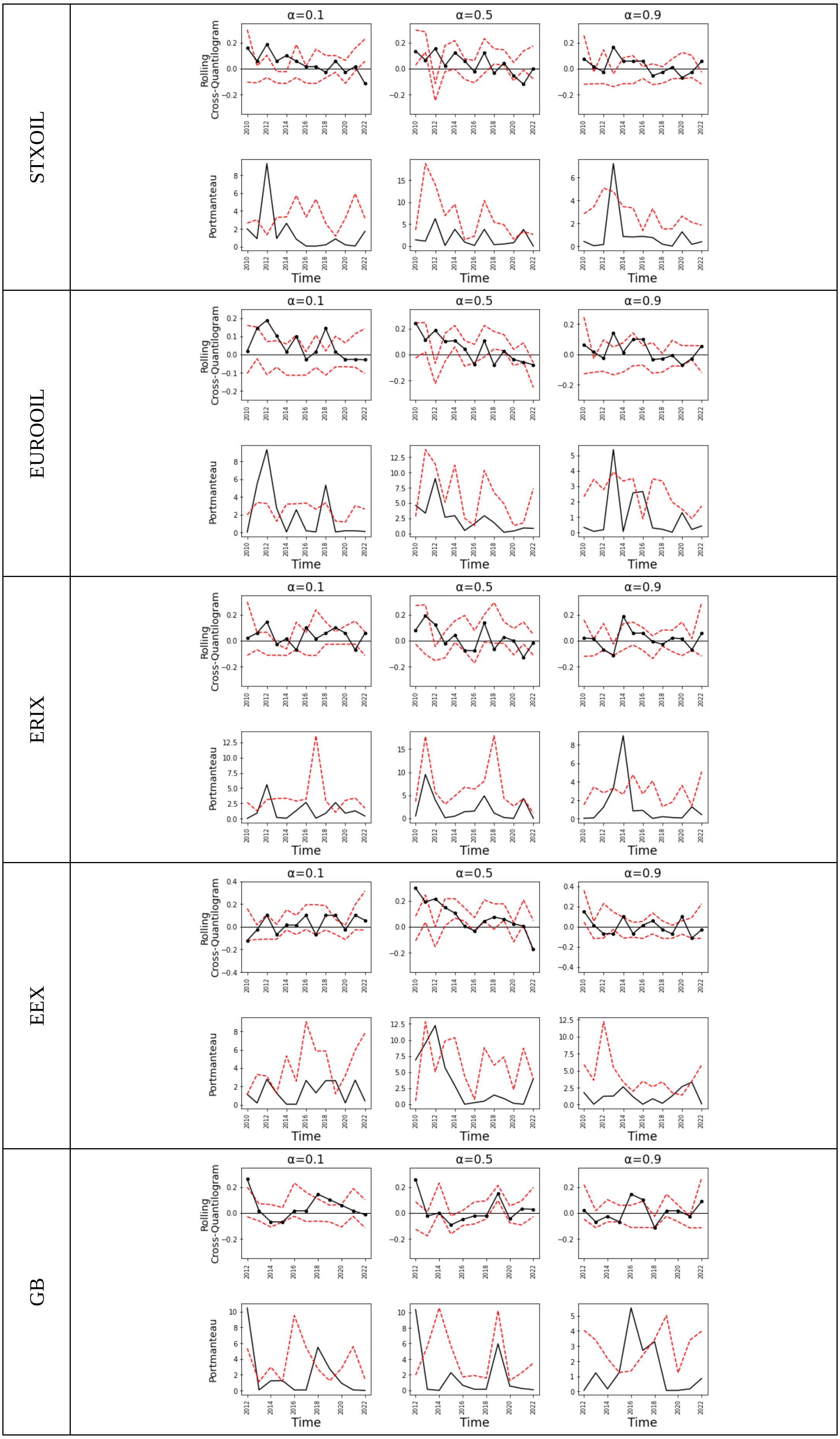
Note: See the notes to Figure 4.

Figure A2. Rolling directional predictability from TRI to conditional volatility series.



Note: See the notes to Figure 6.

Figure A3. Rolling directional predictability from PRI to volatility conditional series.



Note: See the notes to Figure 6.