The rise in investors'awareness of climate risks after the Paris Agreement and the clean energy-oil-technology prices nexus

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Abstract

Investors' awareness of climate risks and attention to green investments are on the rise especially after the Paris Agreement. It stands to reason that this rise in awareness has an impact on the connection between clean energy prices, oil prices and technology prices. In this paper, we test this hypothesis by fitting an exogenous smooth transition regression model to the cycle of clean energy with oil and technology stock prices as exogenous regime driving variables before and after the Paris Agreement. After controlling for carbon price, market volatility, and policy uncertainty, we find that oil price has a stronger asymmetric persistence on the cycle of clean energy assets pre-Paris Agreement. In the period post Paris Agreement, however, the roles are reversed. Technology stock prices are the best regime drivers for clean energy assets with strong nonlinear asymmetric persistence, and the impact of oil price is completely absent. The superiority of technology stock prices over oil prices in driving the cyclical behavior of clean energy assets supports our argument that the Paris Agreement and other recent climate-related events are contributing to the decoupling of the clean energy sector from traditional energy markets. Our findings are particularly important for climate mitigation and adaptation policies.

Keywords: Clean energy prices; crude oil price; technology stock prices; exogenous smooth transition regression; Paris Agreement; climate adaptation and mitigation

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1 Introduction

Understanding the impact of oil and technology prices on the performance of clean energy companies is an important topic for policy makers, regulators, and investors in energy and financial markets. The importance of this topic has been significantly increasing recently especially after the Paris Agreement, which was announced to the world on December 12, 2015, and entered into force in November 2016. This historic event and the recent climate crisis around the globe have increased investors' awareness of climate risks (Alok et al., 2019; Choi et al., 2019; Krueger et al., 2019) and the negative environmental impacts of fossil fuels (Lauri et al., 2014). This increase in awareness, in turn, has recently sparked a surge in equity and capital investments in renewable energy (McCrone et al., 2018). It stands to reason that this recent noticeable increase in investors' awareness of green instruments, among other factors, had an impact on the connection between clean energy prices and oil and technology stock prices.

Indeed, investors are paying more attention to climate risks and to the rewards of holding green instruments amid the Paris Agreement and the recent climate-related events. Following Da et al. (2011), who propose a direct measure of investor attention using Google's Search Volume Index (SVI), we depict in Figure 1 plots of Google Trends' monthly SVI for the *worldwide* search terms "Paris Agreement," "Climate Risk," "Green Investment," "Green Bonds," and "Invesco Clean Energy ETF" in Panels a, b, c, d, and e, respectively, over the period between 2010 and 2020.[1] Each SVI represents the monthly search volume of the corresponding term scaled by the average search volume of the term. Numbers represent search interest relative to the highest point on the chart for the given time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term. By looking at the SVI of the term "Climate Risk" in Figure 1 (panel b), we notice that the term achieves a score of 40 in November 2016; the month where the Paris Agreement entered into force. We notice another peak, though not significant, around the signing of the agreement. In the period post Paris Agreement, the term exhibits a positive trend and reaches its peak popularity twice in 2019; namely, in March 2019 and September 2019. March and April of 2019 were filled with climate-related events. Most notably the

[1] Invesco Clean Energy ETF is a clean energy exchange traded fund that includes stocks of publicly traded U.S. companies that are engagged in business of advancement of clean energy and conservation. The WilderHill Clean Energy Index (ECO) is the underlying asset.

youth climate change demonstrations across the world that started with a teenager in Sweden and spread across the world on Friday, March 15, 2019.[2] Soon after the youth strike, the September 2019 climate strikes took place. This week, which is also known as the Global Week for Future, witnessed a series of protests around the globe to demand actions to address climate change. It is clear from the previous worldwide SVI for "Climate Risk" that people worldwide, including investors, are paying attention to climate risks around major climate-related events especially the most recent ones. To focus more on investors' reactions to climate risks, which are typically manifested as a change in preference towards green instruments, we perform a worldwide search for the terms "Green Investment," "Green Bonds," and "Invesco Clean Energy ETF" and plot the corresponding SVI's in Figure 1, panels c, d, and e respectively. Despite the early spikes in popularity of the term "Green Investment," it exhibits a significant increasing trend after the signing of the Paris Agreement in December 2015 until reaching its peak popularity in November 2016; the date where the agreement entered into effect. It is also clear that the attention to the terms "Green Bonds" and "Invesco Clean Energy ETF" is more significant in the recent period. The previous analysis reveals that the increase in global awareness of the clean energy sector is more noticeable around the recent major events post Paris Agreement, e.g., the withdrawal of the U.S. from the Paris Agreement under the Trump administration in June 2017 and the climate strikes in September 2019. Since our data set consists mainly of clean energy and technology stocks of U.S. companies, we repeat the same analysis but confine the search to the U.S. region. We plot the U.S. SVI of the previous search terms in Figure 2. By looking at the U.S. SVI of the term "Climate Risk" in panel b, we confirm the previous argument that public attention rises around climate-related events. For instance, the significant spike in attention in August 2011 is due to hurricane Irene. According to the National Oceanic and Atmospheric Administration (NOAA), hurricane Irene is the first U.S. landfalling hurricane since 2008. It caused at least 45 deaths and more than 7.3 million in damages.[3] The hurricane made three landfalls along the Atlantic coast including a landfall in New York on August 28, 2011. In fact, according to NOAA scientists, the year 2011 was record-breaking year for climate extremes including historic levels of heat, flooding, and severe weather. December 2012 marks another spike in the U.S. SVI for "Climate Risk." This month corresponds to the Doha Amendment to Koyoto Proto-

[2]Source: https://www.npr.org.

[3]Source: https://www.climate.gov.

col for a second commitment period, starting in 2013 and lasting until 2020. The U.S. SVI index reaches a score of 60 in October 2015. According to a report by the United Nation Climate Change, October 2015 was the warmest month on record. The globally averaged temperature over land and ocean surfaces for October 2015 was the highest for October since record keeping began in 1880.[4] It is worth noting that the spike in attention to climate risk around October 2015 could also have been due to the news reports and the media coverage of the anticipated signing of the Paris Agreement, which took place in December 2015. We also notice a spike in July 2017, where the SVI for "Climate Risk" reaches a score of almost 80. This spike is due to the mounting worries and anxiety about climate risks following the Trump administration's withdrawal from the Paris Agreement. A second noticeable spike in November 2017 corresponds to the twenty third conference (COP23) to the United Nations Framework Convention on Climate Change (UNFCCC), which took place in Germany in November 2017. Finally, in accordance with the previous worldwide SVI for the term "Climate Risk" that is depicted in Figure 1 (panel b), we find that the term reaches its peak popularity in the U.S. around the exact same events; the youth strikes in March 2019 and the September 2019 climate strikes. Again, it is evident from the previous analysis that public attention to climate risks in the U.S. rises around global climate-related events. This rise in public attention is consistent across the analysis period. However, investors' reactions to climate risks, as reflected in the demand for green instruments, seem to be more apparent in the recent period. Judging by the U.S. SVI scores for "Green Investment," "Green Bonds," and "Invesco Clean Energy ETF," in Figure 2, panels c, d, e, respectively, we notice the rise in attention towards green instruments coincides with the recent global climate-related events. A plausible explanation of this delay in attention to green instruments is that, although some organizations have already provided creative solutions (e.g., the World Bank Green Bonds) that have attracted investors' interest in climate-related investments, investors are still unenthusiastic about investing in clean energy and green instruments. This lack of enthusiasm is mainly attributed to investors' lack of knowledge about the potential impact of climate change on various asset classes (Shen et al., 2019) and/or investors' belief that green investment is more of a moral choice than a reward (Walley and Whitehead, 1994; Riedl and Smeets, 2017).

Against the previous backdrop, it is interesting to study how this recent rise in investors' attention to climate risks and green investments is shaping

[4] https://unfccc.int/news/october-2015-was-the-warmest-on-record.

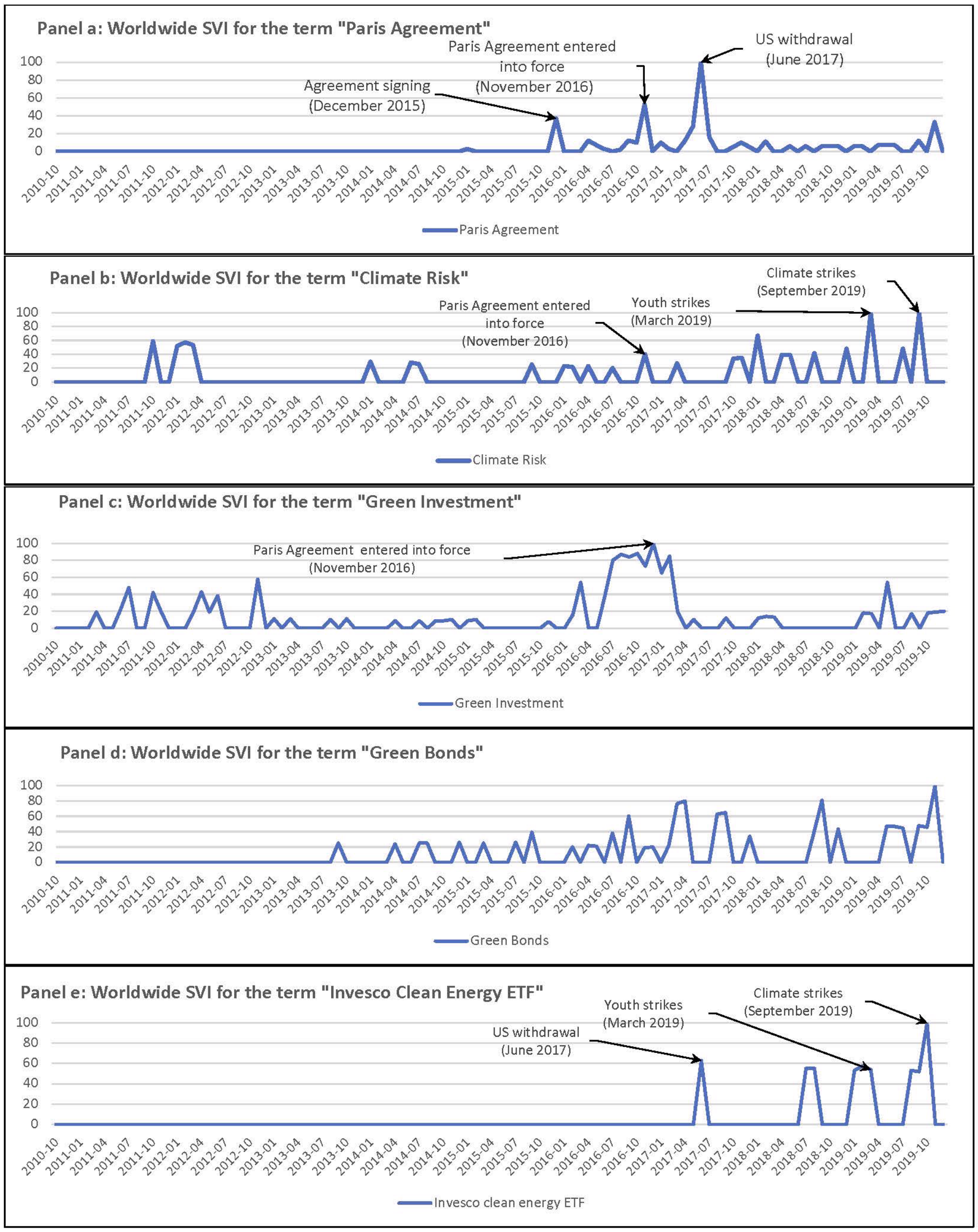

Figure 1: Plots of Google Trends' monthly Search Volume Index (SVI) for the worldwide search terms "Paris Agreement," "Climate Risk," "Green Investment," "Green Bonds," and "Invesco Clean energy ETF" in Panels a, b, c, d, and e, respectively, over the period between 2010 and 2020. Each SVI represents the monthly search volume of the corresponding term scaled by the average search volume of the term. Numbers represent search interest relative to the highest point on the chart for the given time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term.

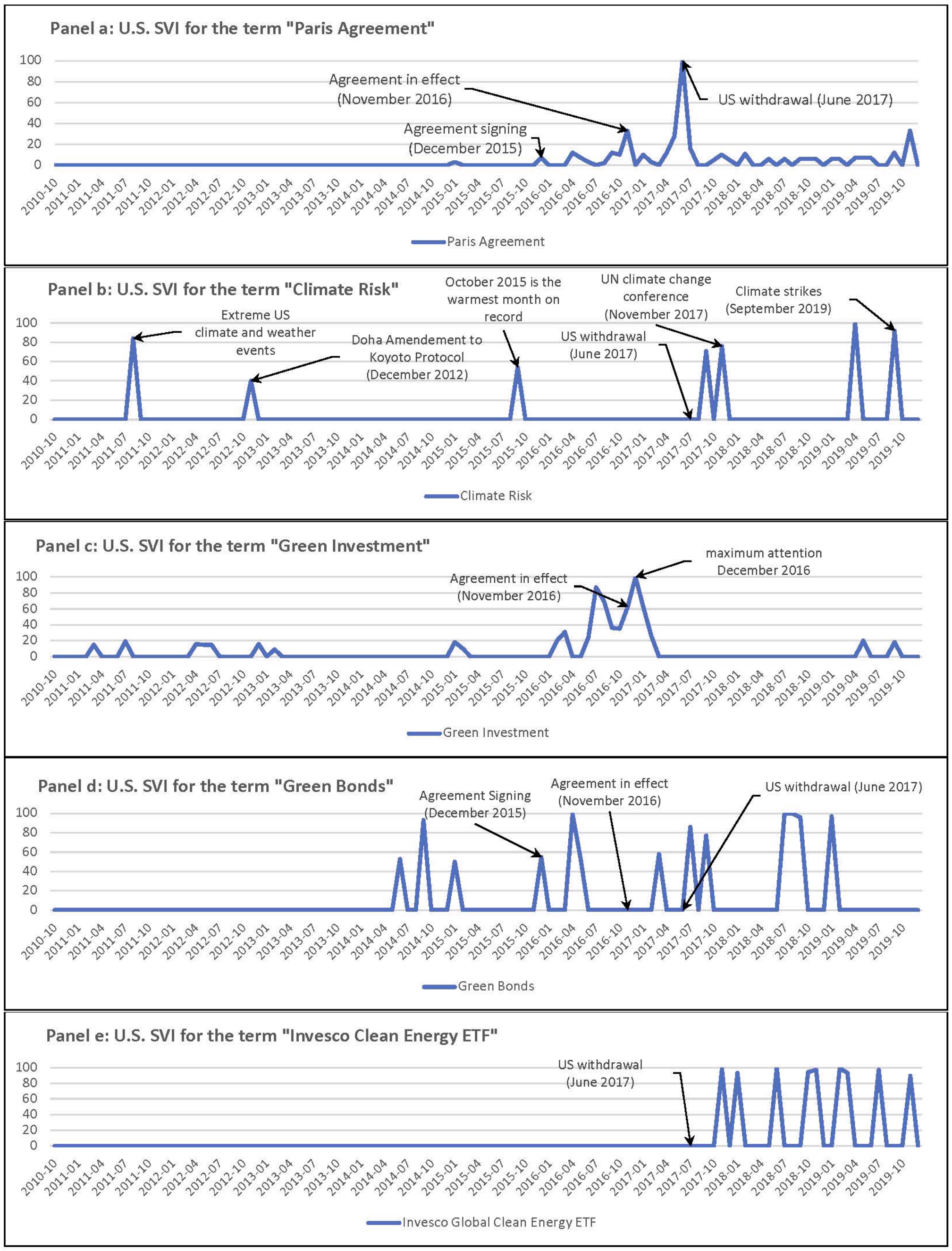

Figure 2: Plots of Google Trends' monthly Search Volume Index (SVI) for the US search terms "Paris Agreement," "Climate Risk," "Green Investment," "Green Bonds," and "Invesco Clean energy ETF" in Panels a, b, c, d, and e, respectively, over the period between 2010 and 2020. Each SVI represents the monthly search volume of the corresponding term scaled by the average search volume of the term. Numbers represent search interest relative to the highest point on the chart for the given time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term.

the connection between clean energy prices and oil and technology stock prices. More precisely, the objective of this paper is to investigate the clean energy-oil-technology prices nexus by studying the nonlinear dynamic behavior of the cycle of clean energy prices in response to changes in crude oil price and technology prices pre and post the signing of the Paris Agreement. Our rationale behind choosing the Paris Agreement as the breakpoint that defines the recent period of our analysis is twofold: First, from the previous discussion, attention to clean energy is more significant around the global climate-related events that took place after the agreement. It is worth noting that the U.S. withdrawal from the Paris Agreement has attracted even more attention than the signing of the agreement itself. Second, the agreement itself has been widely hailed as a triumph and breakthrough in global climate cooperation. It is, therefore, sensible to expect the data generating process, i.e., the cycle of clean energy in the present analysis, to display a change in variability around the signing of the Paris Agreement. In fact, as we will discuss shortly, our structural break analysis confirms the existence of one breakpoint in the clean energy cycle in February 2016; right after the signing of the agreement.

The rationale behind the positive co-movement of clean energy prices and the stock prices of technology companies is that the success/failure of alternative energy companies often depends on the success/failure of related technologies (Henriques and Sadorsky, 2008) or because investors perceive the stocks of alternate energy sources as similar to other technological stocks (Kumar et al., 2012). As for the positive co-movement of oil price and clean energy prices, the rationale is that the rise in oil price encourages the substitution of alternate energy sources for conventional energy sources. This shift in investors' preferences, in turn, causes renewable energy stock prices to rise (Henriques and Sadorsky, 2008; Kumar et al., 2012, Managi and Okimoto, 2013). Following a similar argument in the opposite direction, the fall in oil price encourages the substitution from clean energy sources to cheaper oil sources. This, in turn, causes stock prices of clean and renewable energy companies to drop. Therefore, from a regime switching perspective, the previous hypotheses imply that changes in crude oil price and technology stock prices are causing clean energy prices to switch or oscillate between two regimes: an upper regime, where the driving (also called threshold or transition) variables, i.e., oil prices and technology stock prices, rise above certain threshold values, and a lower regime, where they drop below these values. This cyclical switching of clean energy prices between multiple equilibria, in turn, implies that clean energy prices are nonlinear, and this nonlinearity is driven by two transition variables: changes in oil price and changes in technology stock prices. In this paper, we test the existence of nonlinearity in an index of clean energy prices and characterize the regime switching dynamic of the index, as the data generating process, when oil price and technology stock prices are the driving variables. To this end, we use a time series approach to extract the *cycle* of the clean energy index while controlling for market volatility, policy uncertainty, and carbon price. We then fit a variant of Granger and Teräsvirta (1993) and Teräsvirta (1994)'s smooth transition regression (STR) model to the clean energy cycle. The modification, which is suggested and used by Fahmy (2011, 2014), lies in using changes in crude oil price and changes in technology stock prices as *exogenous* regime-driving variables in the statistical nonlinearity tests of the STR model in addition to the commonly used autoregressive lags of the data generating process, i.e., the lags of the clean energy cycle. Augmenting the transition set in the specification of the STR model with potential transition candidates has the advantage of capturing the nonlinear causality from these exogenous regime driving variables to the data generating process (Fahmy, 2011).

In addition to capturing the nonlinear regime switching behavior of the clean energy cycle, which is driven by oil and technology prices, we also assess the strength of this behavior pre and post the Paris Agreement. Early empirical studies on the subject prior to the implementation of the Paris Agreement (e.g., Bondia et al., 2016; Dutta, 2017; Henriques and Sadorsky, 2008; Kumar et al., 2012; Reboredo, 2015; Reboredo et al., 2017; Sadorsky, 2012) seem to agree on the existence of a strong positive association between the performance of the stocks of renewable energy companies and the movements in oil and technology prices. Some recent studies, however, document weak or no association between clean energy prices and the price of oil (e.g., Elie et al., 2019; Ferrer et al., 2018; Nasreen et al., 2020). Against the previous background, we investigate the hypothesis of whether the influence of oil and technology prices, as regime driving variables, on the cycles of clean energy has strengthened or weakened after the implementation of the Paris Agreement. To this end, following the structural break test result, we divide the analysis period into two subsamples: pre-Paris Agreement period (January 2009 - February 2016) and post Paris Agreement period (March 2016 - December 2019). We then proceed to fit, in each subsample, the STR model to the cycle of the clean energy index using oil and technology prices as exogenous regime-driving variables. Finally, we measure and compare the nonlinear asymmetry and persistence in the cyclical regimes pre and post the Paris Agreement and document the results.

The present work contributes to the existing literature in several ways: Firstly, it is the first study that employs a smooth transition regression with *exogenous* threshold variables to test whether crude oil price and technology prices nonlinear cause clean energy prices.

Secondly, the exogenous STR model employed in this paper has two key advantages: First, it permits, as mentioned above, to statistically test whether crude oil price and technology stock prices nonlinear cause the cyclical behavior in clean energy stock prices. This exogenous nonlinear causality test within the context of the STR model is an alternative to the conventional Granger causality test that often accompany VAR models (e.g., Henriques and Sadorsky, 2008; Kumar et al., 2012, Managi and Okimoto, 2013). Investigating nonlinearity from a different angle is noteworthy to energy economists and other stakeholders in this sector. Second, by analyzing the dynamic behavior of the estimated autoregressive regimes, one can measure and quantify the degree of *persistence* of the clean energy cycle in each regime following the movements of transition variables, i.e., oil price and technology stock prices. This, in turn, provides an assessment of the degree of connectedness between clean energy prices and crude oil and technology stock prices over time. This is a significant contribution to the existing literature on measuring these connections; while nonlinearity and regime switching in clean energy prices are affirmed by most of the studies on the subject, the literature does not seem to agree on the co-movement of clean energy prices and oil and technology stock prices in the short- and long-run (e.g., Ferrer et al., 2018; Kocaarslan and Soytas, 2019) or on the degree of association between crude oil and clean energy stock prices. Most studies (e.g., Dutta et al., 2020; Henriques and Sadorsky, 2008; Kocaarslan and Soytas, 2019; Kumar et al., 2012; Managi and Okimoto, 2013; Reboredo, 2015; Sadorsky, 2012) report strong association between crude oil price and clean energy stock prices. Other studies, however, document weak (Bondia et al., 2016; Elie et al., 2019; Nasreen et al., 2020) or even no association (Ferrer et al., 2018).

Finally, our results are particularly important for climate mitigation and adaptation policies. As we will demonstrate in the following sections, by applying the previous analysis before and after the Paris Agreement, and after controlling for the impact of market volatility, carbon price, and policy uncertainty, we document that oil price is leading technology stock prices as a regime driver for clean energy assets during the early period before the implementation of the Paris Agreement. In post Paris Agreement period, however, the roles are reversed. Technology stock prices are the best regime-drivers for clean energy assets, and the impact of oil price is completely absent in this period. In other words, the degree of connectedness between crude oil price and clean energy prices has weakened in post Paris Agreement period whereas the connectedness between technology stock prices and clean energy prices has strengthened. Furthermore, we find technology stock prices have a nonlinear asymmetric impact on the cycle of clean energy assets. A rise (fall) in technology prices pushes the cycle of clean energy into an upper (lower) autoregressive regime with a +(-) autocorrelation coefficient that is relatively stronger post Paris Agreement. Thus, the asymmetric persistence in the cycle of clean energy assets following changes in technology stock prices is stronger in the recent period. These results are useful for investors and fund managers in mitigating the risks of their portfolios. For policy makers, the failure of crude oil prices to capture the nonlinear dynamic behavior of the cycle of clean energy assets in the recent period implies that the clean energy sector does not require policies of protection against the fluctuations in crude oil price. Finally, the argument that the Paris Agreement and the recent climate-related events are contributing to weakening the connection between clean energy prices and oil prices has significant implications for climate mitigation and adaptation policies for it confirms the fruitful efforts of these policies in the battle against climate change. The idea here is that, in the absence of global efforts to combat climate change, upward movements in the price of oil encourage the substitution of conventional oil-dependent energy sources to alternate clean energy sources. Global efforts like the Paris Agreement, efforts of global institutions, e.g., the World bank, in creating effective green solutions, and the effect of major climate crises tend to have positive impact on investors' awareness regarding the devastating risks of climate change over time. We argue that the continuous increase in awareness over time will potentially alter investors' preferences towards green instruments without the need for a spike in oil price to motivate the switch from conventional energy sources to clean ones. The present study supports this claim by showing that the connection between oil price and clean energy prices weakens after the Paris Agreement. One plausible consequence of this argument is the potential inevitable decoupling of the clean energy sector from the traditional energy market.

The remainder of the paper is organized as follows: Section 2 presents a brief literature review. Section 3 describes the data. Section 4 presents the exogenous STR model and discusses the nonlinearity tests and the model selection criteria. Section 5 presents the estimation results and discusses the dynamic analysis. Finally, Section 6 concludes and provides implications for climate mitigation and adaptation policies.

2 Brief literature review

The impacts of crude oil price movements and technology stock prices on the stock prices of clean energy companies have been well documented in the empirical literature on the subject. In the early studies before December 2015, i.e., before the announcement of the Paris Agreement, Henriques and Sadorsky (2008) show that oil prices Granger cause the stock prices of alternative energy companies. The authors also study the impact of technological shocks on alternative energy companies and find, using an impulse-response analysis, that these technological shocks have a larger impact on the stock prices of alternative energy companies than oil price shocks. Broadstock et al. (2012) investigate the dynamics of international oil prices on energy related stock returns in China and report a stronger relation following the 2008 financial crisis. Kumar et al. (2012) show that oil prices and technology stock prices separately affect the stock prices of clean energy firms. Sadorsky (2012) examines the spillover between oil prices and the stock prices of clean energy companies and technology companies. Using mutlivariate GARCH models, the author finds that the stock prices of clean energy companies correlate more highly with technology stock prices than with oil prices. Managi and Okimoto (2013), using Markov-switching VAR model, find that both oil prices and technology stock prices have positive impact on clean energy stock prices after the structural break of the 2008 recession. Bondia et al. (2016) report that technology stock prices and oil prices Granger cause clean energy prices in the short run but not the long run. Reboredo (2015), using copulas, studies the tail dependence structure between crude oil price and clean energy stock prices and finds significant time-varying average and symmetric tail dependence between oil returns and several clean energy indices. The author shows that oil price dynamics contributes around 30% to downside and upside risk of renewable energy companies. Inchauspe et al. (2015), using a state space multifactor model, show that the impact of oil prices on renewable energy stock returns has increased since 2007. Lundgren et al. (2018) document that crude oil is a net receiver while clean energy stocks are significant net transmitter of spillover during the recent global financial crisis.

As for post Paris Agreement studies, Dutta (2017) studies the relation between oil uncertainty as reflected in the information contained in the implied oil volatility index (OVX) and the stocks of clean energy companies. The author documents that the OVX index is superior to the traditional oil price series in forecasting the clean energy stock market, and oil price volatility has an inverse influence on clean energy stocks, implying their movement in the same direction. Reboredo et al. (2017), using wavelets, find the existence of short-run co-movement between clean energy prices and technology stock prices. Dutta et al. (2018) examine the return and volatility spillover between carbon price and clean energy assets using a VAR-GARCH approach and document a significant association in the EU market. Ahmad et al. (2018) report that crude oil, OVX, and the implied market volatility index (VIX) are the best assets to hedge for clean energy. Kocaarslan and Soytas (2019), using a nonlinear autoregressive distributed lag model, document that the increased investment in clean energy stocks is due to speculative attacks along with an increase in oil prices in the short run. In the long run, however, the increased oil price has a negative impact on clean energy stock prices. In other words, the impacts of positive and negative changes in oil prices and technology stock prices on clean energy stock prices vary significantly over time. More recently, Pham (2019) studies the sub-sectors of clean energy assets and shows that oil is a good hedging investment for the sector. Elie et al. (2019), however, report an opposite result. Using copula method, the authors show that oil is not a good hedging instrument for clean energy assets. Dutta et al. (2020), using Markov regime switching regression approach, report a positive, yet insignificant, effect of crude oil prices on environmental investments. Zhang et al. (2020), using wavelet-based quantile-on-quantile methods, find that the effects of exogenous oil price structural shocks on clean energy stocks vary across quantiles and investment horizons and are asymmetric at higher quantiles of oil shocks in the long run. Uddin et al. (2019), using cross-quantilogram approach, report clean energy returns have a strong positive dependence on oil prices, and this relation is asymmetric across quantiles with higher asymmetry in the longer lags. Yahya et al. (2021) examine the connection between the price of crude oil and clean energy stock prices using a combination of a two-regime threshold vector error correction with dynamic conditional correlation GARCH model. The authors find nonlinear regime-dependent long-term connectedness among the two asset classes. In particular, the clean energy index is found to be the dominant influencer on the crude oil price in the recent period post the financial crisis. Some recent studies (e.g., Elie et al., 2019; Nasreen et al., 2020) document weak association between the two asset classes. A particular study by Ferrer et al. (2018) finds no association between the two asset classes in the short-term or the long-term. After controlling for business cycle fluctuations, interest rates, market uncertainty, and the performance of the traditional fossil fuel energy industry, the authors show clean energy prices and crude oil prices follow a very similar pattern in the early period before the 2008 financial crisis. However, they behave differently in post-financial crisis period as the clean energy index becomes more independent of the ups and downs of crude oil prices. Thus, using a different analysis than ours, the authors reach the same conclusion regarding the decoupling of the clean energy industry from the traditional energy market.

The previous brief literature survey does not give a clear verdict on the association between the price of crude oil and clean energy prices. This is perhaps due to the variations in selecting the sample periods of the analyses, e.g., around structural breaks or including structural breaks, the selection of the type of nonlinear model (e.g., VAR, GARCH, or other variants) that captures this association, and the frequency of the time series. Data on crude oil price and clean and technology indices is available daily, weekly, and monthly. High frequency data, for instance, is usually suitable for models that capture the variability in the variance of the data generating process, e.g., GARCH models. But aside from these discrepancies in the literature, it seems that most of the recent studies suggest that the degree of association between the price of oil and clean energy prices is weakening or even breaking recently. Our analysis supports this point of view and, to the best of our knowledge, is the first to bring the impact of the recent noticeable rise in investors' awareness about climate risks following the Paris Agreement to the discussion. It is worth noting, however, that while the recent increase in investors' awareness of climate risks is a plausible explanation to the decoupling of clean energy sector from the traditional energy market, there are other factors that contribute to this connection. For instance, the connectedness between stock prices of new energy and technology firms and crude oil prices rises amid international financial crisis such as the 2007-2008 financial crisis (Broadstock et al., 2012; Ahmad, 2017; Ferrer et al., 2018). Other factors such as business cycle fluctuations and oil demand and supply shocks also provide plausible explanations to changes in connectedness between these asset classes. Ferrer et al. (2018) argue that the decline in connectedness during the year 2014 could be related to the collapse in crude oil price in July 2014, which was caused by the economic slowdown in China, India, and other emerging economies, the significant growth in Canadian oil sands and U.S. shale oil, and the refusal of Saudi Arabia to cut crude oil production.

3 Data description and stationarity tests

In this paper, we study the connection between clean energy prices and crude oil and technology stock prices over the period between January 2009 and December 2019. The analysis period begins in 2009 and ends in 2019 to avoid the effect of the 2008 recession and the recent effects of the COVID-19 pandemic on the estimation of the threshold values, i.e., the values taken by the threshold variables that define the regime switching borders. As we will discuss shortly, the estimation of the threshold value is based on an initial grid search over all possible values taken by the threshold variable. Thus, high swings that are brought by structural breaks could affect the estimated threshold value, which could, in turn, affect the estimated dynamic behavior of the clean energy cycle.

We measure the performance of clean energy assets via the WilderHill Clean Energy Index (ECO). This index, which acts as the data generating process in the present analysis, is widely used in the literature as a representative of clean energy assets. ECO tracks businesses listed on the New York Stock Exchange that benefit significantly from the shift towards cleaner energy use and zero carbon renewable and conservation. Stocks and sector weights within the index are based on significance for clean energy, technological influence, and relevance to prevention of pollution. The two exogenous regime-driving variables for the cycle of ECO are the NYSE Arca Technology Index (PSE), as a proxy for technology prices, and the crude oil spot prices for the West Texas Intermediate (WTI) as a proxy for oil prices.[5] PSE is a price weighted index of 100 multi-industry technology companies. The wide scope of the PSE makes it a good representative of the stock prices of technology-related companies. The WTI index is commonly used in the literature as a benchmark for oil price in studying the connection between clean energy prices and oil prices (e.g., Ahmad, 2017; Ferrer et al., 2018; Henriques and Sadorskly, 2008; Kumar et al., 2012; Managi and Okimoto; 2013). Daily closing prices on ECO and PSE are sourced from DataStream. Data on daily closing spot prices of the WTI index is sourced from the U.S. Energy Information Administration.[6] All daily prices are converted into monthly averages over the study period.[7]

[5] For robustness, we also use the Brent crude oil price index for analyses throughout the paper and document similar findings. The results are available from the author upon request.

[6] Source: https://www.eia.gov.

[7] The nonlinearity analysis was repeated with daily data, weekly averages, and monthly averages and the results were the same. In particular, the type of the smooth transition

Several studies (e.g., Ferrer et al., 2018, Lundgren et. al, 2018; Yahya et al., 2021, among others) ascertain the impact of control variables such as carbon price, market volatility, and policy uncertainty on the connection between clean energy prices and the oil and technology prices. To control for these effects, we consider the following three indexes: The U.S. Economic Policy Uncertainty Index (EPU) as a proxy for the uncertainty of the U.S. economic policy, the Chicago Board Options Exchange (CBOE) volatility index (VIX) as a benchmark for market volatility, and the European Energy Exchange (EEX) Carbon Emissions Allowance settlement price within the EU emission trading system (ETS) as a proxy for carbon price (CO2). Daily prices on VIX and CO2 are sourced from DataStream. Daily prices on the EPU index are sourced from Economic Policy Uncertainty website.[8] The EPU index is used by various studies, e.g., Uddin et al. (2019) and Yahya et al. (2021), among others, to control for the effect of U.S. economic policy. Several empirical studies show that equity and other asset prices are sensitive to changes in the EPU. Kang and Ratti (2015), for instance, show that a positive shock to EPU leads to a negative impact on global oil production. Arouri et al. (2016) document an inverse relation between EPU and stock returns. Raza et al. (2018) show that gold is impacted by EPU. The VIX index captures the extent of implied volatility in options markets of the S&P 500 over the next 30 days period. It is broadly recognized as a measure of fear for it captures investors' risk aversion. The VIX index is used extensively in the literature as a measure of market volatility (e.g., Ahmad et al., 2018; Basher and Sadorsky, 2016; Ferrer et al., 2018). Finally, to capture the impact of carbon price on clean energy, we use the EU-ETS settlement price index (CO2). Although the impact of carbon price is not as significant as that of oil price (Kumar et al., 2012) and could be country or region specific (Dutta et al., 2018), many empirical studies (e.g., Managi and Okimoto, 2013; Yahya et al., 2021) control for this variable in their analyses.

We convert the three control variables, i.e., EPU, VIX, and CO2, into growth rates by taking the first difference of the logarithm of each time series. Following Box and Jenkins (1970), we extract the cycle of ECO, which will be denoted by y in the text, while accounting for the growth rates of the previous control variables, as the least squares residuals from regressing the first difference of the logarithm of ECO, denoted by $\triangle \log(\text{ECO})$, on the first difference of the logarithm of the control variables; that is, y is the

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regression model, the threshold values, and the dynamic analysis of the regimes were pretty much the same using all frequencies. The monthly averages, however, gave the best fit and yielded the best graphical presentations of the regimes.

[8] Source: https://www.policyuncertainty.com.

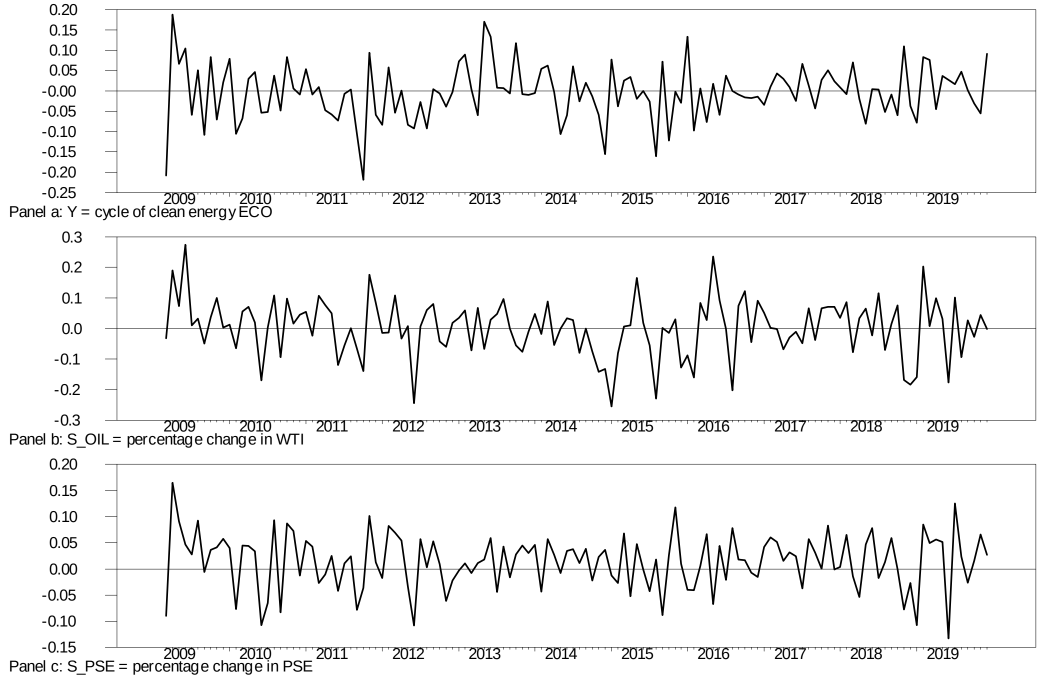

Figure 3: The cycle of the monthly average of the clean energy index ECO (Panel a), the monthly percentage change in the WTI crude oil prices (panel b), and the monthly percentage change in NYSE Arca Tech 100 (PSE) index (panel c) between January 2009 and December 2019.

residual from the following regression:

$$\triangle \log(\mathrm{ECO}_t) = \alpha \triangle \log(\mathrm{EPU}_t) + \beta \triangle \log(\mathrm{VIX}_t) + \gamma \triangle \log(\mathrm{CO2}_t) + error_t, \quad (1)$$

for $t = 1, ..., T$, where T is the sample size.

The first exogenous threshold variable, denoted by s_{OIL}, that captures the performance of crude oil prices is the percentage change in WTI; that is, $s_{OIL} = \triangle \log(\mathrm{WTI})$. The percentage change in PSE is the second threshold variable, denoted by s_{PSE}, and is defined as $s_{PSE} = \triangle \log(\mathrm{PSE})$. The monthly averages of the clean energy cycle, y, and the two exogenous threshold variables, s_{OIL} and s_{PSE}, are plotted in panels a, b, and c, respectively, in Figure 3 over the analysis period (January 2009 - December 2019).

Before fitting the nonlinear STR model, it is crucial in the data investigation stage to run stationarity tests on the data generating process, y, and the regime deriving variables, s_{OIL} and s_{PSE}, to ensure the adequacy

Table 1: Unit root tests.

Time Series	ADF(m)	PP	KPSS	KSS
y	$-4.66(3)$	-13.25	0.14	-9.22
s_{OIL}	$-6.68(3)$	-10.32	0.21	-7.15
s_{PSE}	$-9.98(1)$	-13.32	0.06	-7.26

ADF, PP, KPSS, KSS are respectively the test statistics of the Augmented Dickey Fuller, Phillips and Perron, Kwiatkowski-Phillips-Schmidt-Shin, and Kapetanios-Snell-Shin unit root tests. The Schwarz information criterion is used to select the lag length, m, in the ADF regression. All tests except KSS include an intercept. The 5% critical values are -2.88 for ADF and PP, 0.46 for KPSS, and -2.22 for KSS.

of using such a model. We test the stationarity of the time series using four different tests; namely, the augmented Dickey and Fuller (1979) test, the Phillips and Perron (1988) test, the Kwiatkowski et al. (1992) test, and the Kapetanios et al. (2003) test. The latter test is particularly significant in the present analysis for it detects the presence of nonstationarity against nonlinear but globally stationary smooth transition autoregressive process, which is precisely the STR model that we intend to use. The test statistics pertaining to the previous three tests, denoted by ADF, PP, KPSS, and KSS respectively, are reported in Table 1. Judging by the 5% critical value, which is -2.88 for ADF and PP, we reject the null hypothesis that the data series has a unit root. Judging by the 5% critical value, which is 0.46 for the KPSS, we do not reject the null hypothesis that the series are stationary. Finally, judging by the 5% critical value, which is -2.22 for KSS, we also reject the unit root hypothesis and conclude that all the series are stationary. To confirm the robustness of the results, we apply the KSS test to the level of ECO, WTI and PSE series. Guided by the test statistics, which are -2.25, -2.37, and -2.88 for ECO, WTI, and PSE respectively, we confirm the stationarity of the series in the levels as well as in the rate of growth.

The results of the previous unit root tests imply that if nonlinearity is present in the ECO cycle, y, and if either s_{OIL} or s_{PSE} is the regime-driving variable, then, y will be exogenously pushed to different regimes. However, by stationarity, it will not permanently stay in one particular regime for ever. It can persist in one regime for a while, but it will always revert back to the other regime. The previous stationarity results, therefore, justify the application of the exogenous STR model.

4 Empirical framework and methodology

4.1 Identifying the pre and post Paris Agreement subsamples

Although, regime switching models, e.g., Markov switching model (Hamilton, 1989), threshold autoregressive model (Tong, 1983), smooth transition autoregressive (STAR) model (Granger and Teräsvirta, 1993; Teräsvirta, 1994), and Fahmy's (2011, 2014) exogenous STR model, share the common objective of modelling the regime switching behavior or the cyclical behavior of the data generating process, they differ in their treatment of the switching mechanism. For instance, Markov switching models assume that the switching mechanism between the regimes is an unobserved (latent) Markov chain. Threshold and STR models, on the other hand, assume that the regime driving variable is one of the autoregressive lags of the data generating process, i.e., one of the lags of the clean energy cycle in this study. The exogenous STR model allows for the possibility that the data generating process is driven by an exogenous variable. This model often yields a better fit than the classic STR model especially if there is a reason to believe that the exogenous regime driving variable is causing the regime switching dynamic in the data generating process (Fahmy, 2011, 2014).

In this paper, we employ the exogenous STR model to the clean energy cycle, y, with changes in oil prices, s_{OIL}, and changes in technology stock prices, s_{PSE}, as potential exogenous transition/threshold variables. This model is particularly suitable here since the intention is to test the *observed* impact of the movements in oil and technology stock prices on the dynamic behavior of clean energy. Furthermore, the recent literature that documents an increase in investors' awareness of climate risks (e.g., Alok et al., 2019; Choi et al., 2019; Krueger et al., 2019) and our earlier analysis suggest a change in the impact of oil and technology prices on clean energy prices around the signing of the Paris Agreement. To test the validity of this argument before fitting the STR model, we employ the iterative cumulative sum of squares (ICSS) structural break test to the cycle of clean energy. The ICSS is a procedure that searches for breaks in variance using the algorithm described in Inclan and Tiao (1994). The underlying assumption of the procedure is that the data generating process, i.e., y, has a common mean, but possibly different variances within subsamples. The test statistic has a non-standard distribution because the procedure does a search in breaks. In particular, the procedure takes the significance level (or critical value) as an input and searches for break points where the variance is significantly different before and after those points. This procedure is, therefore, suitable here since the STR model describes nonlinearity in the mean of the data generating process allowing for the possibility of having different variances within subsamples.

Using 5% level of significance, the ICSS test reveals the existence of a breakpoint in the monthly cycle of clean energy in February 2016; right after the announcement of the Paris Agreement. Guided by the results of this test, we break the analysis period (January 2009 - December 2019) into two subsamples: The period between January 2009 and February 2016, and the period between March 2016 and December 2019. We will refer to the former as pre-Paris Agreement period and to the latter as post Paris Agreement period. To visualize the breakpoint, we compute the variance (sum of squares over the number of observation) for each of the subsamples and create two standard deviation upper and lower bounds relative to the common mean of the series y. The two bounds and the cycle y are depicted in Figure 4. Notice how the bounds change from the early subsample to the recent one at the breakpoint.

4.2 The exogenous STR model

The standard exogenous STR model of order p fitted to y_t is expressed, in general, as follows:

$$y_t = \mathbf{\Psi}' z_t + \mathbf{\Theta}' z_t G(s_t) + \varepsilon_t, \ t = 1, ..., T, \tag{2}$$

where y_t is the clean energy cycle, $z_t = (1, y_{t-1}, ..., y_{t-p})' = \left(1, \widetilde{z}_t'\right)'$ is a vector of lags of y_t, $\mathbf{\Psi} = (\psi_0, \psi_1, ..., \psi_p)' = \left(\psi_0, \widetilde{\mathbf{\Psi}}'\right)'$ and $\mathbf{\Theta} = (\theta_0, \theta_1, ..., \theta_p)' = \left(\theta_0, \widetilde{\mathbf{\Theta}}'\right)'$ are parameter vectors, ε_t is an $i.i.d(0, \sigma^2)$ error term, and $G(s_t)$ is a continuous logistic transition function of the regime driving variable s_t such that $s_t \in \Omega$, where

$$\Omega = \{y_{t-1}, ..., y_{t-p}, s_{OILt}, s_{OILt-1}, ..., s_{OILt-p}, s_{PSEt}, s_{PSEt-1}, ..., s_{PSEt-p}, t\} \tag{3}$$

is a transition set that includes the p lags of y_t, the exogenous threshold variables s_{OILt} and s_{PSEt} and their lags, and a time trend t.

The function G is a logistic function of order k in the transition variable s_t, and is defined by the equation

$$G = \frac{1}{1 + \exp\{-\gamma (s_t - c_1) \times \cdots \times (s_t - c_k)\}}, \qquad \gamma > 0, \tag{4}$$

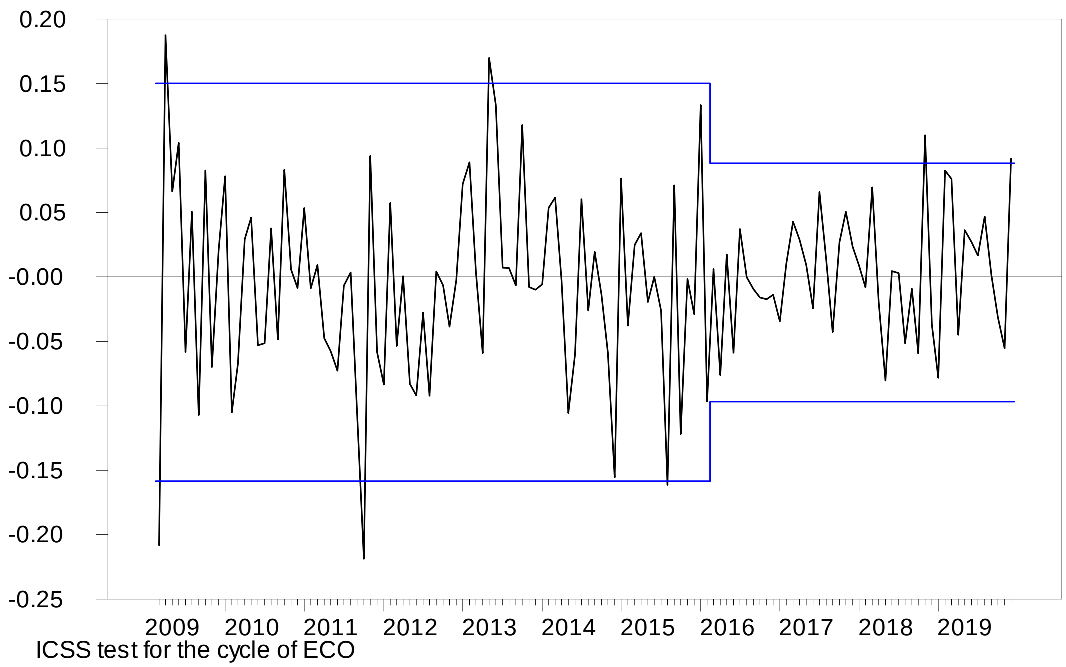

Figure 4: A plot of the cycle of ECO around a common mean of -0.0043 and the upper and lower two standard deviations relative to the common mean. The break occurs in February 2016.

where γ is a slope coefficient, and c_j, $j = 1, ..., k$, are k locations parameters such that $c_1 \leq \cdots \leq c_k$. The behavior of G depends on the choice of the number of location parameters, i.e., the order k. Testing nonlinearity in y_t against each transition candidate in the set Ω and the selection of the model type, i.e., the order of the logistic function, are performed in the specification stage of the STR model building. For instance, a STR(p) model with a logistic function of order $k = 1$, or STR1 for short, has the following logistic function:

$$G = \frac{1}{1 + \exp\{-\gamma\,(s_t - c)\}}, \qquad \gamma > 0, \qquad s_t \in \Omega, \tag{5}$$

and c is the threshold value. The function in Equation (5) is bounded between 0 and 1. This gives rise to two distinct regimes around the threshold value c. When the regime-driving variable s_t is less than the threshold value c, the function G approaches 0 and the data generating process, i.e., y_t in Equation (2), displays a lower $AR(p)$ regime defined as

$$y_t = \psi_0 + \psi_1 y_{t-1} + \cdots + \psi_p y_{t-p} + \varepsilon_t,\ t = 1, ..., T. \tag{6}$$

The upper regime, on the other hand, is defined when $s_t > c$, i.e., $s_t \longrightarrow +\infty$. In this case, G tends to 1, and y_t in Equation (2) displays an upper $AR(p)$ regime defined as

$$y_t = (\psi_0 + \theta_0) + (\psi_1 + \theta_1)\,y_{t-1} + \cdots + (\psi_p + \theta_p)\,y_{t-p} + \varepsilon_t,\ t = 1, ..., T. \tag{7}$$

In other words, in the STR1 model in Equation (2) with G defined as in Equation (5), the parameter vectors $\mathbf{\Psi}$ and $\mathbf{\Theta}$ change monotonically as a function of the exogenous transition variable s_t from $\mathbf{\Psi}$ to $\mathbf{\Psi}+\mathbf{\Theta}$. The speed and the smoothness of transition between the lower and the upper regimes depend on the slope of the function, γ. Figure 5 shows three different logistic functions of order 1; a smooth function with a small slope $\gamma = 0.8$ (solid thin line), a smooth function with a moderate slope $\gamma = 4$ (dashed thin line), and an abrupt transition function with a large slope $\gamma = 30$ (dashed thick line).

4.3 Nonlinearity tests and model selection

Before fitting the STR model in Equation (2) to the clean energy cycle y_t in both subsamples, the analysis begins by identifying the lag order p of the STR model. Guided by the Schwarz information criterion, which is

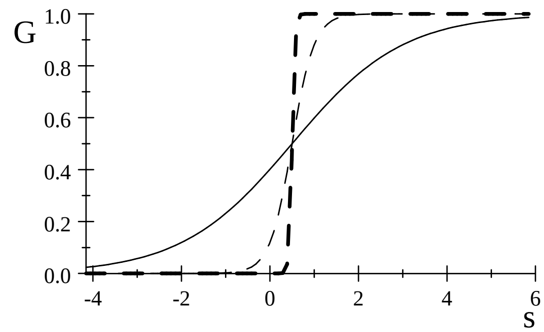

Figure 5: A first order logistic function with a small slope $\gamma = 0.8$ (solid thin line), moderate slope $\gamma = 4$ (dashed thin line), and a large slope $\gamma = 30$ (dashed thick line). The location parameter $c = 0.5$.

minimized at the first lag of y_t, we fit an exogenous STR model with $p = 1$ to the clean energy cycle; that is,

$$y_t = \psi_0 + \psi_1 y_{t-1} + (\theta_0 + \theta_1 y_{t-1})\, G + \varepsilon_t, \quad t = 1, ..., T, \tag{8}$$

where G is a logistic function of order k, $s_t \in \Omega$, and

$$\Omega = \{y_{t-1}, s_{OILt}, s_{OILt-1}, s_{PSEt}, s_{PSEt-1}, t\}\,. \tag{9}$$

The next step is nonlinearity testing. Since the nonlinear STR model in Equation (2) is only identified under the alternative hypothesis, Luukkonen, Saikkonen, and Teräsvirta (1988) and Teräsvirta (1994) suggest replacing the transition function G in Equation (2) by a Taylor approximation about the null hypothesis $\gamma = 0$. In particular, the authors assume a first order logistic function, i.e., $k = 1$ in Equation (4), and perform a third order Taylor approximation about the null hypothesis $\gamma = 0$. The approximation yields

$$y_t = \mathbf{\Psi}' z_t + \frac{1}{4}\gamma \mathbf{\Theta}' z_t (s_t - c) - \frac{1}{48}\gamma^3 \mathbf{\Theta}' z_t (s_t - c)^3 + \varepsilon_t. \tag{10}$$

Using $z_t = (1, \tilde{z}_t')'$, $\mathbf{\Psi} = (\psi_0, \widetilde{\mathbf{\Psi}}')'$, and $\mathbf{\Theta} = (\theta_0, \widetilde{\mathbf{\Theta}}')'$, and reparameterizing, equation (10) can be expressed as

$$y_t = \delta_0 + \delta_1' \tilde{z}_t + \pi_1' \tilde{z}_t s_t + \pi_2' \tilde{z}_t s_t^2 + \pi_3' \tilde{z}_t s_t^3 + \varepsilon_t^*, \tag{11}$$

where $\varepsilon_t^* = \varepsilon_t + R(\gamma, c, s_t)$; $R(\cdot)$ being the remainder and π_j, $j = 1, 2, 3$, is of the form $\gamma \tilde{\pi}_j$, where $\tilde{\pi}_j \neq 0$ is a function of $\widetilde{\mathbf{\Theta}}$. The null hypothesis of linearity is then $H_{0L}: \pi_1 = \pi_2 = \pi_3 = 0$. Also note that because $\varepsilon_t^* = \varepsilon_t$ under the null hypothesis, the asymptotic theory will not be affected if an LM test is used. Following Luukkonen et al. (1988) and Teräsvirta (1994), a convenient procedure for computing the LM statistic by OLS is to estimate Equation (11) under the null hypothesis and compute the sum of squares of the residuals (SSR_0), then estimate (11) under the alternative hypothesis and compute SSR_1. The LM statistic is computed as $LM = \frac{T(SSR_0 - SSR_1)}{SSR_1}$. The test statistic has an asymptotic chi-square distribution with $3p$ degrees of freedom when the null hypothesis is valid. However, the F statistic is recommended because the chi-square statistic can be size-distorted in small and even moderate samples. In this paper, the F distribution with $3p$ and $T-4p-1$ is used when the null hypothesis H_{0L} is valid. The test is repeated for each transition candidate in the transition set Ω in Equation (9). If the null hypothesis of linearity, H_{0L}, using the F test (F_L) is rejected for at least one of the models, the model against which the rejection, measured in the p-value, is strongest is chosen to be the STR model to be estimated.

Another purpose of conducting linearity tests is to use the results for model selection. If linearity is rejected and a transition variable is selected, the next step is to choose a model type, e.g., to choose between STR1 and STR2 models. The choice between the models can be based, again, on the auxiliary regression in Equation (11). Teräsvirta (1994) shows that when $c = 0$ then $\pi_2 = 0$ when the model is an STR1, whereas $\pi_1 = \pi_3 = 0$ when the model is an STR2. The author suggests the following F tests sequence based on the auxiliary regression in (11):

1. Test the null hypothesis: $H_{04}: \pi_3 = 0$ with an ordinary F test (F_4). A rejection of H_{04} can be interpreted as a rejection of the STR2.

2. Test the null hypothesis that $\pi_2 = 0$ given that $\pi_3 = 0$, $H_{03}: \pi_2 = 0|\pi_3 = 0$, using another F test (F_3). Failure to reject H_{03} indicates that the model is an STR1.

3. The last F test (F_2) in the sequence is to test the null hypothesis that $\pi_1 = 0$ given that $\pi_2 = \pi_3 = 0$ as $H_{02}: \pi_1 = 0|\pi_2 = \pi_3 = 0$. Rejecting H_{02} after accepting H_{03} supports the choice of the STR1 model. Accepting H_{02} after rejecting H_{03} points to the STR2 model.

4. After carrying out the three F tests and noting which hypotheses are rejected, if the test H_{03} yields the strongest rejection measured in the p-value, choose the STR2 model; otherwise select the STR1 model.

We execute the previous sequence of nonlinearity tests for each of the potential transition variables in the transition set Ω in Equation (9) pre and post the Paris Agreement and report the results, respectively, in Tables 2 and 3. For pre Paris Agreement subsample, the current change in oil price, s^{**}_{OILt}, tagged with the symbol **, is the variable with the strongest test rejection, i.e., the variable with the smallest p-value of the F_L statistic as shown from the second column of Table 2. The second-best variable in the transition set is the current change in technology stock prices, s^{*}_{PSEt}. The suggested model type in each case is the STR model of order 1. The previous results show that the two exogenous transition variables, s_{OILt} and s_{PSEt}, are the best two candidates in the transition set Ω that can drive the regime switching behavior of the clean energy cycle y_t in the period before the Paris Agreement. This confirms the connection (and the exogenous causality) between clean energy prices and oil and technology stock prices in this early subsample. Furthermore, the superiority of oil over technology prices is confirmed from the highest rejection of linearity in case of oil. This suggests that oil has a dominant impact on the cycle of clean energy assets in this subsample. As for post Paris Agreement subsample, the nonlinearity and model selection tests results in the first column of Table 3 show that the first lag of technology stock prices, s^{**}_{PSEt-1}, is the best exogenous regime-driving variable for the clean energy cycle during this recent period. The striking result of the nonlinearity tests in Table 3 is that oil price fails to capture the nonlinearity in the cycle of clean energy assets in this subsample. The suggested linear model in the last column of Table 3 confirms this result. The previous results confirm the existence of an *exogenous* one-way directional causality from oil price and technology stock prices to clean energy prices in the early subsample and an exogenous one-way causality from technology stock prices to clean energy in the latter subsample.[9] In the present STR context, the above-mentioned exogenous nonlinearity tests can be considered as an alternative to the Granger causality tests that are normally executed in the VAR context.

In sum, the previous analysis reveals two key results: First, both oil price and technology stock prices have an impact on the cyclical behavior of clean energy assets. Second, despite the superiority of oil as a leading regime-

[9] We also examine the other directional exogenous causality and find insignificant results. In particular, we apply the same nonlinearity tests to the cycle of crude oil price and to the cycle of the NYSE Arca Technology Index with changes in the WilderHill Clean Energy Index as exogenous transition variable. We find that the null hypothesis of linearity is not rejected in both cases and, therefore, we rule out this directional exogenous causality. The results are, however, omitted due to space limitation.

Table 2: Nonlinearity tests and model type pre Paris Agreement (January 2009 - February 2016).

s_t	F_L	F_4	F_3	F_2	Suggested Model
y_{t-1}	1.037×10^{-2}	4.198×10^{-2}	7.788×10^{-1}	7.215×10^{-3}	STR1
s^{*}_{PSEt}	9.775×10^{-3}	3.446×10^{-1}	1.713×10^{-1}	1.367×10^{-3}	STR1
s^{**}_{WTIt}	1.408×10^{-3}	1.127×10^{-1}	1.627×10^{-1}	9.614×10^{-4}	STR1
s_{PSEt-1}	2.821×10^{-1}	2.566×10^{-1}	3.247×10^{-1}	2.920×10^{-1}	Linear
s_{WTIt-1}	8.813×10^{-1}	5.853×10^{-1}	8.237×10^{-1}	6.317×10^{-1}	Linear
t	2.884×10^{-2}	3.674×10^{-2}	3.449×10^{-2}	7.494×10^{-1}	STR2

P-values of the linearity F-tests sequence applied to the cycle of ECO when the percentage change in oil price and technology stock prices are transition variables. The variable tagged with the symbol ** shows the highest rejection of linearity.

Table 3: Nonlinearity tests and model type pre Paris Agreement (March 2016 - December 2019).

s_t	F_L	F_4	F_3	F_2	Suggested Model
y_{t-1}	5.611×10^{-2}	1.967×10^{-1}	7.072×10^{-2}	1.036×10^{-1}	Linear
s_{PSEt}	1.359×10^{-1}	1.324×10^{-2}	8.154×10^{-1}	8.829×10^{-1}	Linear
s_{WTIt}	7.196×10^{-1}	9.728×10^{-1}	2.019×10^{-1}	7.982×10^{-1}	Linear
s^{**}_{PSEt-1}	1.930×10^{-2}	3.733×10^{-2}	9.685×10^{-2}	1.536×10^{-1}	STR1
s_{WTIt-1}	5.489×10^{-1}	2.767×10^{-1}	4.503×10^{-1}	7.057×10^{-1}	Linear
t	5.951×10^{-1}	3.809×10^{-1}	4.914×10^{-1}	5.443×10^{-1}	Linear

P-values of the linearity F-tests sequence applied to the cycle of ECO when the percentage change in oil price and technology stock prices are transition variables. The variable tagged with the symbol ** shows the highest rejection of linearity.

Table 4: Nonlinearity tests and model type over the entire analysis period (January 2009 - December 2019).

s_t	F_L	F_4	F_3	F_2	Suggested Model
s^{***}_{JOINTt}	4.124×10^{-3}	2.979×10^{-1}	1.643×10^{-1}	1.384×10^{-3}	STR1
s^{**}_{PSEt}	1.216×10^{-2}	4.556×10^{-1}	8.230×10^{-2}	7.137×10^{-3}	STR1
s^{*}_{WTIt}	1.505×10^{-2}	1.511×10^{-1}	3.500×10^{-1}	6.771×10^{-3}	STR1
$s_{JOINTt-1}$	8.252×10^{-1}	9.707×10^{-1}	9.964×10^{-1}	2.409×10^{-1}	Linear
s_{PSEt-1}	3.641×10^{-1}	3.617×10^{-1}	9.969×10^{-1}	1.026×10^{-1}	Linear
s_{WTIt-1}	7.715×10^{-1}	4.655×10^{-1}	8.243×10^{-1}	5.034×10^{-1}	Linear
t	1.834×10^{-1}	1.549×10^{-1}	8.836×10^{-2}	9.094×10^{-1}	Linear

P-values of the linearity F-tests sequence applied to the cycle of ECO when the percentage change in oil price, the percentage change in technology stock prices, and the percentage change in their product (joint effect) are transition variables. The variable tagged with the symbol *** shows the highest rejection of linearity.

driving variable for the cycle of clean energy in the early period, its impact has weakened after the Paris Agreement whereas the impact of technology stock prices has strengthened. We confirm the robustness of the previous two results over the entire sample period by executing the previous sequence of nonlinearity tests one more time on each variable in the set

$$\Pi = \{s_{PSEt}, s_{PSEt-1}, s_{WTIt}, s_{WTIt-1}, s_{JOINTt}, s_{JOINTt-1}, t\}, \qquad (12)$$

where $s_{JOINT} = \triangle \log(WTI \times SPE)$ represents the joint impact of oil and technology prices when both variables enter simultaneously as one exogenous transition variable in the STR model, and everything else is defined as before.[10] We document the results in Table 4 and note that s^{***}_{JOINT} is the best transition variable in the set followed by s^{**}_{PSE} and s^{*}_{WTI} in that order. The fact that s^{***}_{JOINT} is the best transition variable over the entire sample confirms the validity of the first result that documents the joint impact of oil and technology prices on the cycle of clean energy. The previous ranking also shows that the growth rate of the PSE index is the second best regime-driving variable and oil comes last. This confirms the robustness of the superiority of technology stock prices over oil price in driving the cyclical behavior of clean energy assets that is deduced by the second result. Finally, another robust result that is consistent across the two subsamples

[10] Notice that the percentage change of the product of two variables is the sum of their percentage changes.

and the entire sample is that the model associated with s_{OIL} and s_{PSE} is the STR1 model in Equation (8) with a first order logistic function as defined in Equation (5). This model, as discussed earlier, displays two distinct AR(1) regimes around the parameter c, i.e., the threshold value taken by the corresponding transition variable. It is worth noting that the result that the same STR1 model fits both regime driving variables does not necessarily imply that the clean energy cycle y_t displays the same behavior with each transition variable. As we will discuss shortly in the following section, the estimation results and the dynamic analysis reveal different degrees of persistence and asymmetry in the cycle of clean energy assets for each transition variable in the two subsamples of the analysis.

5 Estimation results and dynamic analysis

In this section, we fit the exogenous STR1 model to the clean energy cycle with the exogenous regime-driving variables that are suggested by the nonlinearity analysis in Section 4 pre and post the Paris Agreement. We discuss the dynamic analysis of the regime switching behavior of the clean energy cycle in each case and document the results of the analysis. The estimation is carried out individually for each transition variable using maximum likelihood method conditional on the two parameters γ (the slope of the transition function) and c (the threshold parameter). The conditional log-likelihood function of the STR1 model in Equation (8), which is defined as

$$\begin{aligned}\mathcal{L}(\psi_0, \psi_1, \theta_0, \theta_1, \sigma, \gamma, c) = &-\frac{1}{2}\ln(2\pi) - \frac{1}{2}\ln(\sigma^2) \\ &- \frac{1}{2}\frac{\{y_t - (\psi_0 + \psi_1 y_{t-1} + (\theta_0 + \theta_1 y_{t-1})\, G)\}^2}{\sigma^2},\end{aligned} \tag{13}$$

is maximized using the iterative Broyden-Fletcher-Goldfarb-shanno (BFGS) algorithm. The starting values for the algorithm are obtained by constructing a two-dimensional grid in γ and c. The values that minimize the residuals sum of squares (SSR) are taken to be the starting values of the maximization procedure.

5.1 Grid search analysis

Guided by the nonlinearity tests results in Table 2 for pre-Paris Agreement subsample, we apply the previous grid search procedure for y_t when s_{OILt} and s_{PSEt} are exogenous transition variables. We find that the starting values that minimize the SSR are $\gamma = 2$ and $c = -9.1\%$ when s_{OILt} is the transition variable, and $\gamma = 2.895$ and $c = 4.76\%$ with s_{PSEt}. We plot three-dimensional grids in (γ, c, SSR) space in Figures 6 and 7 in case of oil and technology stock prices respectively. The previous preliminary values of the slopes of the transition function suggest that, in this subsample, the transition between the upper and lower regime of the clean energy cycle is expected to be moderately smoother when the percentage change in technology stock prices is the regime driving variable. Indeed, as we will show in the next subsection, the estimation results confirm this prediction. As for post Paris Agreement subsample, the results of the nonlinearity tests in Table 3 show that the one period lag of the growth rate of technology stock prices, s_{PSEt-1}, is the best exogenous transition variable in this subsample. Oil price fails to capture the cyclical nonlinear behavior of clean energy assets in this subsample. We, therefore, apply the previous grid search procedure only for s_{PSEt-1}. The starting values in this case are $\gamma = 1.7271$ and $c = 7.19\%$. The three-dimensional grid in (γ, c, SSR) space is plotted in Figure 8.

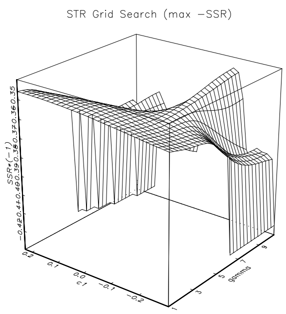

Figure 6: Three-dimensional grid for $s_O ILt$ in (γ, c, SSR) space pre-Paris Agreement. The minimum sum of squares of the residuals $SSR = 0.3456$ is achieved at $\gamma = 2$ and $c = -9.1\%$.

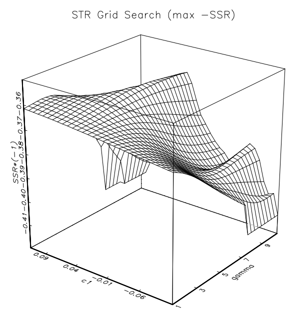

Figure 7: Three-dimensional grid for $s_P SEt$ in (γ, c, SSR) space pre-Paris Agreement. The minimum sum of squares of the residuals $SSR = 0.3495$ is achieved at $\gamma = 2.895$ and $c = 4.76\%$.

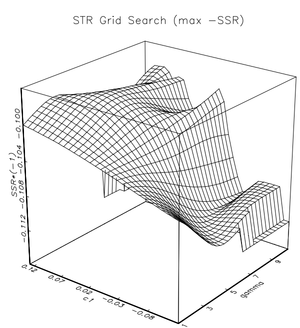

Figure 8: Three-dimensional grid for $s_P SEt - 1$ in (γ, c, SSR) space post Paris Agreement. The minimum sum of squares of the residuals $SSR = 0.0980$ is achieved at $\gamma = 1.7271$ and $c = 7.19\%$.

5.2 Estimation results

The estimation results of fitting the STR1 model in Equation (8) with s_{OILt} and s_{PSEt} as exogenous transition variables in the period before the Paris Agreement, and with s_{PSEt-1} in the period after the agreement, and the misspecification tests results are reported, respectively, at the top and the bottom of Table 5.[11] The figures in brackets underneath the models' coefficients are p-values, $\widehat{\sigma}_s$ is the standard deviation of the corresponding exogenous transition variable s, $\widehat{\sigma}^2$ is the variance of the residuals, $\overline{R}^2$ is the adjusted coefficient of determination, AUTO(j) is the p-value of the Ljung and Box (1978) test of no serial correlation of order j, ARCH(i) is the p-value of Engle's (1982) test of no ARCH of order i, NRNL is the p-value of Eitrheim and Teräsvirta (1996) and Teräsvirta (1998)'s test of no remaining nonlinearity in the fitted STR model, JB is the p-value (at the 5% significance level) of the Jarque and Bera (1987) test of normality, and finally SK and KU are skewness and kurtosis respectively.

Other than the insignificant intercept coefficient of the linear part in the STR1 model fitted to y with s_{PSEt-1} at the bottom of Table 5, which was dropped from the analysis, all models' coefficients in both subsamples are significant at the 5% level as shown from the corresponding p-values. The values of the adjusted coefficients of determination are $\overline{R}^2 = 0.69$ and $\overline{R}^2 = 0.64$ in the case of s_{OIL} and s_{PSE} in the early subsample, and $\overline{R}^2 = 0.62$ in case of s_{PSEt-1} in the recent subsample, which is indicative of a good fit. This is also confirmed from Figures 9, 10, and 11, where the original and fitted series of y_t are respectively plotted for s_{OILt} and s_{PSEt} in the early subsample and for s_{PSEt-1} in the recent subsample. All models pass the no remaining nonlinearity, no serial correlation, and no ARCH tests as shown from the reported p-values of these tests. The hypothesis that the error term is normally distributed is not rejected at the 5% level of significance as shown from the p-values of Jarque and Bera (1987) test for all models, and from the plot of the standardized residuals series in Figures 12, 13, and 14. In the early subsample, when oil price is the driving variable, the transition function G has a slightly larger moderate slope of $\gamma = 4.4$ in comparison to $\gamma = 2.76$ in case of technology prices. This indicates a smooth but swifter transition of y_t between the two regimes when oil price is the regime driving variable. This behavior is confirmed from the dot plots of the transition functions in Figures 15 and 16 in the case of oil and technology

[11] To render the slope of the transition function in Equation (5) scale free, the exponent of the transition function G is divided by the standard deviation of the transition variable $\widehat{\sigma}_s$ in all regressions.

prices respectively. For post Paris Agreement subsample, the transition function G is plotted in Figure 17. The function has a moderate slope of $\gamma = 4.24$ when the transition variable is s_{PSEt-1}. Thus, the impact of the one period lag change in technology stock prices on the cycle of clean energy is smooth but slightly swifter after the Paris Agreement. The dynamic analysis in the following section documents more interesting results about the previous connections.

Table 5: Estimation and misspecification tests results pre and post the Paris Agreement.

The STR1 model fitted to y_t with s_{OILt} as threshold variable pre-Paris Agreement

$$y_t = -\underset{(0.008)}{0.116} - \underset{(0.04)}{0.35} y_{t-1}$$

$$+ \left(\underset{(0.009)}{0.122} + \underset{(0.04)}{0.52} \right) y_{t-1} \left(\frac{1}{1+\exp\left\{ -\underset{(0.03)}{4.4} \left(s_{OILt} + \underset{(0.0001)}{0.10} \right) \right\} / 0.0913} \right) + \widehat{\varepsilon}_t,$$

$\overline{R}^2 = 0.69$, $\widehat{\sigma}_{OIL} = 0.0913$, $\widehat{\sigma}^2 = 0.0047$,

AUTO(1)†= 0.52, AUTO(4) = 0.44, AUTO(8) = 0.65,

ARCH(1)‡= 0.10, ARCH(4) = 0.16,

NRNL*= 0.92, JB = 0.78, SK = 0.18, KU = 2.86.

The STR1 model fitted to y_t with s_{PSEt} as threshold variable pre-Paris Agreement

$$y_t = -\underset{(0.03)}{0.03} - \underset{(0.04)}{0.06} y_{t-1}$$

$$+ \left(\underset{(0.01)}{0.09} + \underset{(0.03)}{0.16} y_{t-1} \right) \left(\frac{1}{1+\exp\left\{ -\underset{(0.04)}{2.76} \left(s_{PSEt} - \underset{(0.03)}{0.05} \right) \right\} / 0.0495} \right) + \widehat{\varepsilon}_t,$$

$\overline{R}^2 = 0.64$, $\widehat{\sigma}_{PSE} = 0.0495$, $\widehat{\sigma}^2 = 0.0048$,

AUTO(1)†= 0.82, AUTO(4) = 0.37, AUTO(8) = 0.47,

ARCH(1)‡= 0.54, ARCH(4) = 0.65,

NRNL*= 0.69, JB = 0.43, SK = 0.06, KU = 3.6.

The STR1 model fitted to y_t with s_{PSEt-1} as threshold variable post Paris Agreement

$$y_t = -\underset{(0.03)}{0.41} y_{t-1}$$

$$+ \left(\underset{(0.03)}{0.04} + \underset{(0.04)}{0.63} y_{t-1} \right) \left(\frac{1}{1+\exp\left\{ -\underset{(0.04)}{4.24} \left(s_{PSEt-1} - \underset{(0.04)}{0.06} \right) \right\} / 0.0518} \right) + \widehat{\varepsilon}_t,$$

$\overline{R}^2 = 0.62$, $\widehat{\sigma}_{PSE} = 0.0518$, $\widehat{\sigma}^2 = 0.0023$,

AUTO(1)†= 0.25, AUTO(4) = 0.27, AUTO(8) = 0.14,

ARCH(1)‡= 0.87, ARCH(4) = 0.29,

NRNL*= 0.81, JB = 0.77, SK = 0.25, KU = 2.97.

†AUTO(k) is p-value of Ljung and Box (1978) test of no serial correlation of order k.

‡ARCH(i) is p-value of Engle's (1982) test of no ARCH of order i.

*p-value of Eitrheim and Teräsvirta (1996) and Teräsvirta (1998)'s test of no remaining nonlinearity.

JB is the p-value of Jarque and Bera (1987) test. SK is skewness. KU is kurtosis.

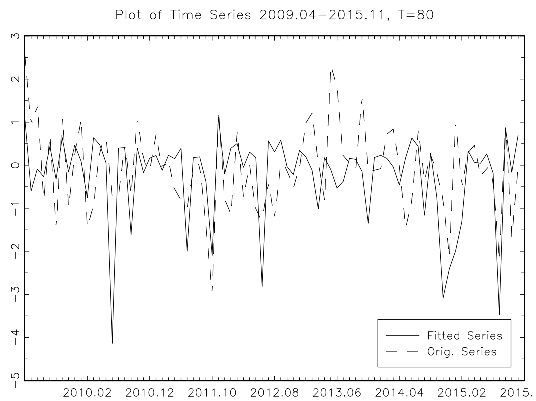

Figure 9: Original series (solid line) and fitted series (dashed line) of the clean energy cycle y_t when the percentage change in oil price is the transition variable over the period pre-Paris Agreement.

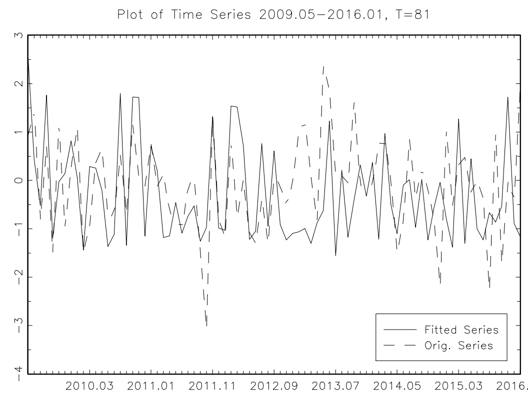

Figure 10: Original series (solid line) and fitted series (dashed line) of the clean energy cycle y_t when the percentage change in technology stock prices is the transition variable over the period pre-Paris Agreement.

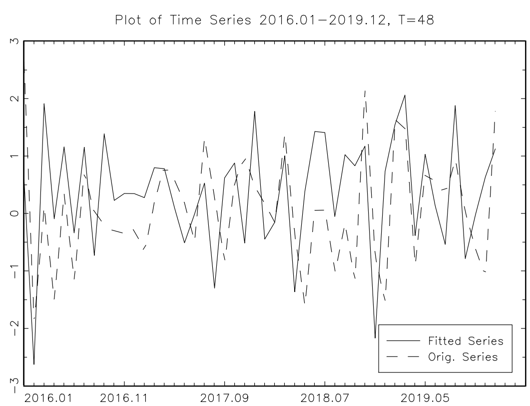

Figure 11: Original series (solid line) and fitted series (dashed line) of the clean energy cycle y_t when the one period lag percentage change in technology stock prices is the transition variable over the period post Paris Agreement.

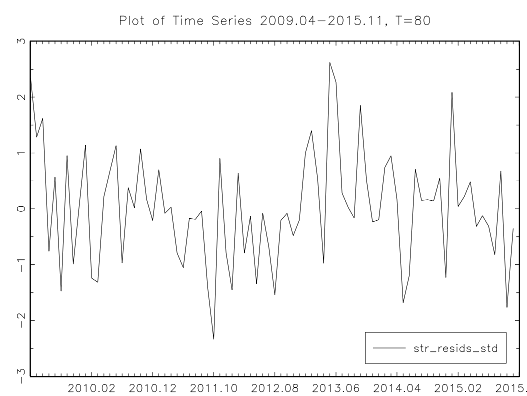

Figure 12: The standardized residuals of the STR1 model fitted to the cycle of clean energy with the percentage change in oil price as transition variable over the period pre-Paris Agreement.

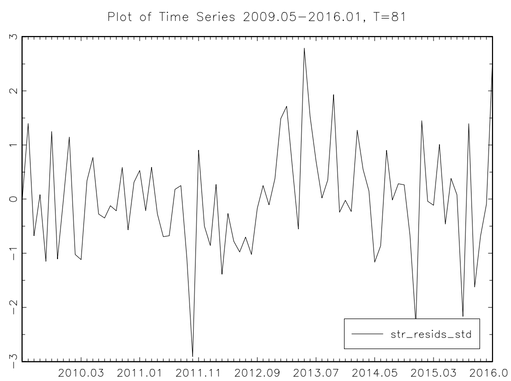

Figure 13: The standardized residuals of the STR1 model fitted to the cycle of clean energy with the percentage change in technology stock prices as transition variable over the period pre-Paris Agreement.

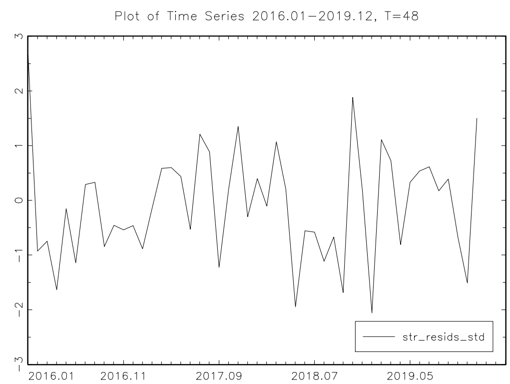

Figure 14: The standardized residuals of the STR1 model fitted to the cycle of clean energy with the one period lag percentage change in technology stock prices as transition variable over the period post Paris Agreement.

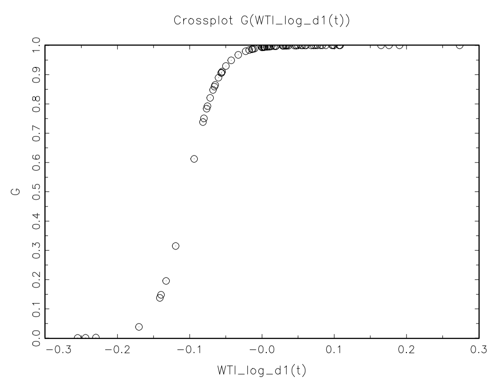

Figure 15: A plot of the transition function $G(\gamma, c; s_OIL)$ of the STR1 model fitted to the clean energy cycle when the percentage change in oil price is the transition variable over the period pre-Paris Agreement. Each dot corresponds to one observation.

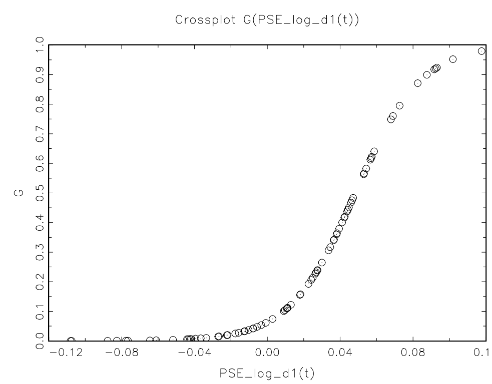

Figure 16: A plot of the transition function $G(\gamma, c; s_PSE)$ of the STR1 model fitted to the clean energy cycle when the percentage change in technology prices is the transition variable over the period pre-Paris Agreement. Each dot corresponds to one observation.

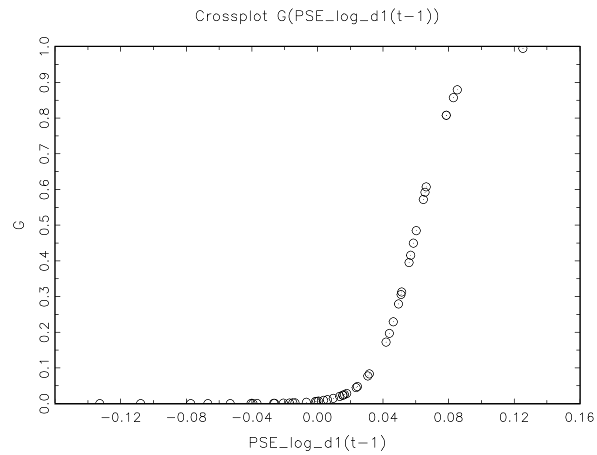

Figure 17: A plot of the transition function $G(\gamma, c; s_PSEt-1)$ of the STR1 model fitted to the clean energy cycle when the one period lag percentage change in technology prices is the transition variable over the period post Paris Agreement. Each dot corresponds to one observation.

5.3 Dynamic analysis

In this section, we discuss the estimation results in Table 5 and presents a dynamic analysis of the regime switching behavior of the clean energy cycle in response to changes in crude oil price and technology stock prices before and after the Paris Agreement. The discussion reveals the role played by this agreement and the recent climate events in shaping the connection between these asset classes. We document the results of the dynamic analysis in Table 6. In what follows, we analyze the findings in Table 6 from two perspectives. First, we compare the performance of the clean energy cycle before and after the Paris Agreement with each driving variable; that is, we compare the results in the second and third columns of Table 6. Second, within each subsample, we compare the degree of persistence in the cycle of clean energy in the lower and upper regimes following changes in each regime-driving variable; that is, we compare the top and the bottom of each column in Table 6.

As discussed earlier, the price of oil fails to capture the nonlinear oscillation in the cycle of clean energy assets after the Paris Agreement. However, in the period pre-Paris Agreement, oil was the best transition variable that can capture this nonlinear behavior. After controlling for carbon price, policy uncertainty, and market volatility, the cycle of clean energy in this subsample follows a stationary two-regime AR(1) model around a threshold value $c = -10\%$ as documented in second column of Table 6. When the percentage change in the WTI crude oil index falls below the threshold value of -10%, the cycle of the clean energy index, ECO, is pushed to a lower AR(1) regime with a moderate negative autocorrelation coefficient $\widehat{\psi}_1 = -0.35$; that is,

$$s_{OILt} < -10\% \Longrightarrow G = 0 \Longrightarrow y_t = -0.116 - 0.35 y_{t-1} + \widehat{\varepsilon}_t. \tag{14}$$

On the other hand, when $s_{OILt} > -10\%$, then $G = 1$ and y_t moves to an upper stationary regime with a relatively weaker positive autocorrelation coefficient $\widehat{\psi}_1 + \widehat{\theta}_1 = 0.17$;

$$s_{OILt} > -10\% \Longrightarrow G = 1 \Longrightarrow y_t = 0.006 + 0.17 y_{t-1} + \widehat{\varepsilon}_t. \tag{15}$$

Guided by the sign and magnitude of the autocorrelation coefficients in both regimes, we deduce that oil price has a nonlinear asymmetric impact (in sign and magnitude) on the cycle of ECO in this period. The degree of persistence weakens in the upper regime. Figure 18 depicts the previous dynamic behavior between the pervious time series. Notice how the transition function in panel c picks up the extreme drops in the percentage change in the WTI crude oil price index (panel b) below the threshold value of -10% in 2010, 2012, and the collapse of crude oil price in July 2014, which was due to the economic slowdown in several emerging economies, e.g., China and India, and to the significant growth in North American oil production.

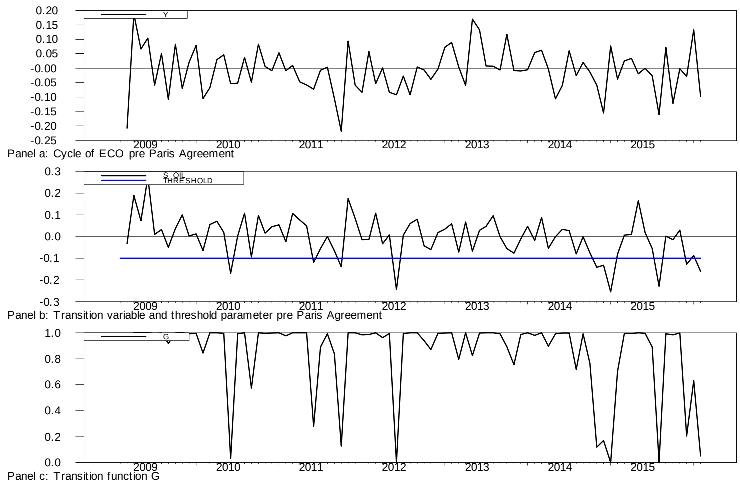

Figure 18: The behavior of the clean energy cycle y_t (panel a), the threshold variable s_{OILt} and the threshold value $c = -10\%$ (panel b), and the transition function G (panel c) in the early period before the Paris Agreement.

As for the impact of technology stock prices on the cycle of clean energy assets, we document an asymmetric impact (in sign) in the early period; namely, when technology stock prices spiral down below 5%, the cycle of clean energy is pushed to a lower stationary AR(1) regime with a weak negative autocorrelation coefficient of $\widehat{\psi}_1 = -0.06$. Judging by the autocorrelation coefficient of 0.10 in the upper regime, the persistence is still weak, but relatively stronger compared to the lower regime. In post Paris Agreement period, technology stock prices do not only lead oil prices in driving the cyclical behavior of clean energy assets, but they also display an asymmetric impact (in sign) and a *stronger* persistence in the regimes as opposed to the period pre-Paris Agreement. The second and third columns at the bottom of Table 6 summarize the previous characterizations of regimes.

In summary, by comparing the performance of the regime-driving variables pre and post the Paris Agreement, we deduce that oil price leads technology stock prices in the early period with a relatively strong asymmetric persistence impact on the cycle of clean energy assets. The roles, however, are reversed in the recent subsample after the Paris Agreement. In particular, technology stock prices take the lead with a strong asymmetric impact on the cycle of clean energy assets. Oil price fails to capture the nonlinearity of clean energy assets in this subsample. Thus, the connection between technology stock prices and clean energy assets is strengthened over time especially after the Paris Agreement. This behavior can also be detected from the plots of the transition function in panel c, the regime-driving variable, s_{PSE}, in panel b, and the clean energy cycle in panel a before and after the Paris Agreement in Figures 19 and 20 respectively. By comparing the transition function in panel c in both figures, we notice that the oscillation between the two regimes is tamed in the recent period after the Paris Agreement. This indicates the relatively strong persistence in both regimes of the clean energy cycle in this period.

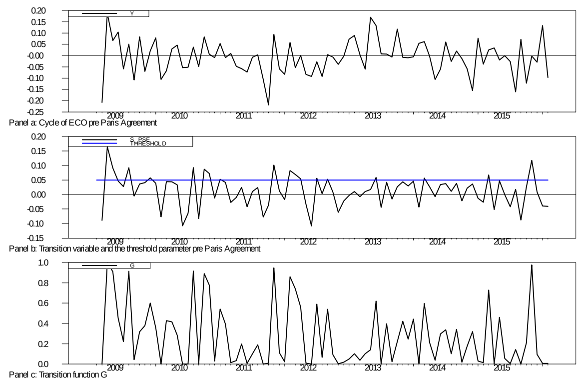

Figure 19: The behavior of the clean energy cycle y_t (panel a), the threshold variable s_{PSEt} and the threshold value $c = 5\%$ (panel b), and the transition function G (panel c) in the early period before the Paris Agreement.

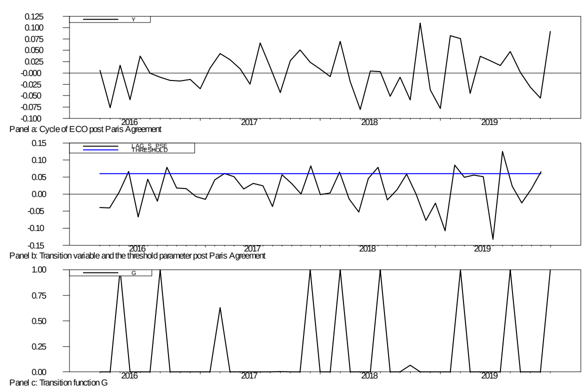

Figure 20: The behavior of the clean energy cycle y_t (panel a), the threshold variable s_{PSEt-1} and the threshold value $c = 6\%$ (panel b), and the transition function G (panel c) in the recent period after the Paris Agreement.

Another way of looking at the dynamic results in Table 6 is to compare the clean energy cycle within each subsample. By comparing the results at the top and the bottom of the second column of Table 6, we find that the AR(1) clean energy cycle displays a stronger negative (positive) autocorrelation in the lower (upper) regime when oil price is the driving variable as opposed to technology stock prices; that is, before the Paris Agreement, a fall in oil price has more negative impact on clean energy prices then a fall in technology stock prices. One plausible explanation of this behavior is the limited awareness of climate risks along with investors' perceptions of the high risk of substitution from clean energy sources to conventional sources that comes with a downward oil price spiral. This result also means that the connection between clean energy prices and oil price is stronger than that of technology stock prices in the period before the Paris Agreement. The superiority of oil price is, however, completely absent after the Paris Agreement. By comparing the results in the top and the bottom of the third column of Table 6, we deduce that not only technology stock prices are the dominant influencer on clean energy assets in this period, but they also have a strong persistence on the clean energy cycle.

The previous analysis supports the argument that the rise in investors' awareness that is brought by the announcement of the Paris Agreement and the recent climate events is a major factor that has contributed to weakening the connection between clean energy price and the price of crude oil. The rationale here is that, in the absence of global efforts to combat climate change, rising oil prices cause investors to shift their preferences to clean energy companies because expensive oil prices encourage the substitution of alternate clean sources for conventional energy sources. Global efforts like the Paris Agreement or major climate crises tend to have positive impact on investors' awareness regarding the devastating risks of climate change over time. The continuous increase in awareness over time will potentially alter investors' preferences towards green instruments without the need for a spike in oil prices to motivate the switch from conventional energy sources to clean ones. In other words, the Paris Agreement and other similar climate attempts ought to reduce (and potentially break) the positive association between oil prices and clean energy prices. Thus, global efforts to combat climate change are effective in reducing the effects of oil price movements on clean energy markets. This result, which suggests a decoupling of the clean energy sector from the conventional energy market, is consistent with the one documented by Ferrer et al. (2018).

Table 6: The dynamic behavior of the upper and lower regimes of the clean energy cycle with changes in oil and technology stock prices as exogenous transition variables pre and post the Paris Agreement.

Dynamic analysis of y_t	Pre Paris Agreement	Post Paris Agreement
Exogenous regime-driving variable is oil price		
Threshold c :	$c = -10\%$	NA*
Transition variable s :	$s_{OILt}= \triangle \log(WTI_t)$	NA
Transition type:	$\gamma= 4.4$ (moderate)	NA
Residual variance:	$\widehat{\sigma}^2= 0.0047$	NA
Lower regime: $s < c \implies$	$y_t= -0.116 - 0.35y_{t-1}+\widehat{\varepsilon}_t$	NA
Autocorrelation coefficient:	$\widehat{\psi}_1= -0.35$	NA
Stationarity and model type:	stationary AR(1)	NA
Persistence (degree; sign):	moderate negative	NA
Mean of lower regime:	$Ey_t = -0.086$	NA
Variance of lower regime:	$var(y_t) =\frac{\widehat{\sigma}^2}{1-\widehat{\psi}_1^2} = 0.0054$	NA
Upper regime: $s > c \implies$	$y_t= 0.006 + 0.17y_{t-1}+\widehat{\varepsilon}_t$	NA
Autocorrelation coefficient:	$\widehat{\psi}_1+ \widehat{\theta}_1 = 0.17$	NA
Stationarity and model type:	stationary AR(1)	NA
Persistence (degree;sign):	weak positive	NA
Mean of upper regime:	$Ey_t = 0.007$	NA
Variance of upper regime:	$var(y_t) =\frac{\widehat{\sigma}^2}{1-\left(\widehat{\psi}_1+\widehat{\theta}_1\right)^2} = 0.0048$	NA
Persistence between regimes:	weakens from lower to upper	
Asymmetry between regimes:	in sign and magnitude	NA
Exogenous regime-driving variable is technology stock prices		
Threshold c :	$c = 5\%$	$c = 6\%$
Transition variable s :	$s_{PSEt}= \triangle \log(PSE_t)$	$s_{PSEt-1}= \triangle \log(PSE_{t-1})$
Transition type:	$\gamma= 2.76$ (moderate)	$\gamma= 4.24$ (moderate)
Residual variance:	$\widehat{\sigma}^2= 0.0048$	$\widehat{\sigma}^2= 0.0023$
Lower regime: $s < c \implies$	$y_t= -0.03 - 0.06y_{t-1}+\widehat{\varepsilon}_t$	$y_t= -0.41y_{t-1}+\widehat{\varepsilon}_t$
Autocorrelation coefficient:	$\widehat{\psi}_1= -0.06$	$\widehat{\psi}_1= -0.41$
Stationarity and model type:	stationary AR(1)	stationary AR(1)
Persistence (degree; sign):	weak; negative	moderate; negative
Mean of lower regime:	$Ey_t = -0.086$	$Ey_t = 0$
Variance of lower regime:	$var(y_t) =\frac{\widehat{\sigma}^2}{1-\widehat{\psi}_1^2} = 0.0054$	$var(y_t) = 0.0028$
Upper regime: $s > c \implies$	$y_t= 0.06 + 0.10y_{t-1}+\widehat{\varepsilon}_t$	$y_t= 0.04 + 0.22y_{t-1}+\widehat{\varepsilon}_t$
Autocorrelation coefficient:	$\widehat{\psi}_1+ \widehat{\theta}_1 = 0.10$	$\widehat{\psi}_1+ \widehat{\theta}_1 = 0.22$
Stationarity and model type:	stationary AR(1)	stationary AR(1)
Persistence (degree and sign):	weak; positive	moderate; positive
Mean of upper regime:	$Ey_t = 0.007$	$Ey_t = 0.051$
Variance of upper regime:	$var(y_t) =\frac{\widehat{\sigma}^2}{1-\left(\widehat{\psi}_1+\widehat{\theta}_1\right)^2} = 0.0048$	$var(y_t) = 0.0024$
Change in persistence between regimes:	no significant change	no significant change
Asymmetry between regimes:	in sign only	in sign only

*Not Applicable.

6 Conclusions and policy recommendations

Investors are becoming more aware of climate risks and the attention to green investments is more noticeable in the recent period post Paris Agreement. In this paper, we investigate the connection between clean energy prices and oil and technology stock prices before (January 2009 - February 2016) and after (March 2016 - December 2019) the Paris Agreement. Using a nonlinear STR model, we test the exogenous impact of oil price and technology stock prices on the cycle of the ECO index after controlling for carbon price, market volatility, and policy uncertainty. In addition to the exogenous causality, we also test the hypothesis of whether the Paris Agreement and the recent climate-related events around the globe are contributing to shaping these connections. To this end, we use Google Trends' monthly Search Volume Index for the worldwide search terms "Paris Agreement," "Climate Risk," "Green Investment," "Green Bonds," and "Invesco Clean energy ETF," and find a rise in investors' attention to the risks and rewards of climate change especially in the period post Paris Agreement. We repeat the same search analysis in the U.S. and reach the same conclusion. We then confirm the robustness of this result by employing a structural break test to the cycle of the clean energy index over the entire analysis period (January 2009 - December 2019). We document a breakpoint in February 2016; right after the signing of the Paris Agreement in December 2015. Guided by the previous analysis, we fit the STR model to the cycle of clean energy before and after the breakpoint. We document the following results.

First, the results of the nonlinearity tests over the entire analysis period reveal that changes in oil price and technology stock prices are the best regime-driving variables of the cyclical behavior of clean energy assets. The previous finding confirms the existence of *exogenous* one-way directional causality from oil and technology stock prices to clean energy prices; changes in these two asset classes drive the cyclical behavior of clean energy prices. Focusing on the period before the Paris Agreement, we confirm once again this one-directional causality with crude oil prices leading technology stock prices in capturing the cyclical behavior of clean energy assets. This nonlinear exogenous causality, albeit from a different perspective than the conventional Granger causality of VAR specifications, is consistent with the consensus in the early literature on these connections (e.g., Dutta et al., 2020; Henriques and Sadorsky, 2008; Kocaarslan and Soytas, 2019; Kumar et al., 2012; Managi and Okimoto, 2013; Reboredo, 2015; Sadorsky, 2012; among others).

Second, we find that the connection between clean energy prices and crude oil prices is weaker in the period after the Paris Agreement. In fact, we show that the price of crude oil has no impact on the cycle of clean energy during this recent period. This finding is consistent with several recent studies that document weak association between the stock prices of clean energy companies and the price of crude oil (e.g., Dutta et al., 2020; Elie et al., 2019; Ferrer et al., 2018; Nasreen et al., 2020). It is also consistent with the prediction that, in the recent period, technology stock prices are the dominant influencer on the crude oil price (Yahya et al., 2021).

Third, we show that the impact of technology stock prices on the cycle of clean energy assets is stronger after the Paris Agreement. More specifically, we find that the degree of persistence in the two autoregressive regimes of the cycle of clean energy is relatively stronger in this period. We find the existence of a nonlinear asymmetric persistence in the cycle of clean energy assets after the Paris Agreement when technology stock prices are the driving variables. Moreover, we show that this persistence is relatively stronger in this period. Finally, the superiority of technology stock prices over oil prices in driving the cyclical behavior of clean energy assets supports our argument that the Paris Agreement and other recent climate-related events are contributing to increasing investors' awareness regarding climate risks and the noticeable shift in preference towards green instruments. We are the first to bring the effect of the Paris Agreement and investors' awareness to the discussion on these connections.

In the present analysis, we demonstrate that the connection between clean energy and technology stock prices is stronger, and the oil-clean energy connection is absent post Paris Agreement. We argue that the recent rise in investors' awareness amid the Paris Agreement and the recent climate events is contributing to this behavior of the clean energy-oil-technology nexus. However, we acknowledge the role played by other factors such as carbon price, economic policy, and market uncertainty, in impacting this connection. While we control for these factors in our analysis, and we bring investors' awareness of climate risks as a plausible explanation to the recent decoupling of the clean energy sector from the traditional energy market, it is worth noting that our analysis does not include any variable that directly capture investors' awareness. Investigating the direct impact of investors' awareness on these connections is a potential area for future research on the subject.

The results of this paper have significant implications for investors and other stakeholders in the energy sector and, specifically, for climate mitigation and adaptations policies. Global efforts like the Paris Agreement have positive impact on investors' awareness regarding the devastating risks of climate change. The continuous increase in awareness over time will potentially alter investors' preferences towards green instruments without the need for a spike in oil prices to motivate the switch from conventional energy courses to clean ones. Hence, breaking, eventually, the connection between oil price and clean energy prices. Weakening the oil price-clean energy prices connection is indeed good news for the battle against climate change. However, policy makers, regulators, and key players in financial markets need to increase their efforts to effectively break this connection. While global institutions such as the World Bank are already working on creating more effective green solutions across asset classes, these solutions have been mainly focused on the fixed income class of assets, e.g., green bonds, cool bonds, and eco notes (Reichelt, 2010). Innovative solutions, however, that create more awareness in other asset classes, e.g., domestic and foreign equities, are needed. Many investors are not aware of the carbon footprint and the climate impact of the companies in their portfolios. Few investors who hold oil and gas stocks in their portfolios are aware of the risk they face with respect to those companies' stranded assets (Anderson et al., 2016). Despite the unanimous agreement on climate change following the Paris Agreement, climate risk remains unpriced by the market and, thus, future uncertainty about climate risk remains an increasingly important risk factor for investors, particularly long-term investors. CEO's of private companies should increase their efforts to reduce the carbon footprints of their products and, more importantly, to provide investors with clear signals and transparent rules of how this reduction is done. Fund and portfolio managers should focus on factoring climate risks in their portfolios and design hedging policies that aim at lowering the risk exposure to climate events without compromising the rewards of the portfolios (Anderson et al., 2016).

In conclusion, although more needs to be done, breaking the dependency of clean energy prices on oil price movements is not out of reach. The present analysis demonstrates that a global collective commitment to climate mitigation and adaptation efforts from all parties involved ought to, eventually, break this connection and achieve stability in financial and energy markets.

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