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Are Carbon Leader Indexes Related with Carbon Prices under Different Regimes?

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ABSTRACT

With the rising importance of carbon markets, the new derived financial instruments and indicator indexes related to carbon markets have been raising researchers' appetite. According to that aspect, to investigate the relationship between price formation in carbon markets and equity prices of these firms trading in carbon markets is one of the aims of this study. This study examines CO₂ prices of European Union Emission Allowances and daily closing values of Morgan Stanley Capital International Low Carbon Leaders USD Dollar Price Indexes via Markov Regime Switching Models from a non-linear perspective. Among the findings, there is a relationship between the index derived from the stock performances of North American firms trading in carbon markets and carbon prices. Furthermore, the strength of the relationship increases during periods of recession identified by the MRS models.

Keywords: Carbon Markets, Energy Prices, Markov Regime Switching Model, Kyoto Protocol

JEL Classifications: F30, G15

1. INTRODUCTION

Increasing technological developments and inventions have accelerated industrial activities and brought environmental pollution and climate change together in recent years. Environmental pollution is referred to as a contagion of ecosystem and atmosphere by greenhouse gases while climate change is the abnormal change in weather conditions due to pollution. The issue of environmental pollution and climate change has become an international concern. To find a permanent solution that couldn't have been achieved individually before, the first step has been taken collectively by Kyoto Protocol which was held in Kyoto, Japan on December 11, 1997, and put into effect on February 16, 2005. This protocol, based on the United Nations Framework Convention on Climate Change (UNFCCC), aims to reduce greenhouse gas emissions to 1990 levels.

These days, the emission reductions units are traded in various capital markets as financial products, which were derived from the emission trading mechanisms of the Kyoto Protocol. These

emission reduction units can be obtained from projects such as renewable energy projects that contribute to emission reductions in countries. After the Kyoto Protocol, the European Union (EU) presented a green paper and built the basis of its policy named under the European Union Emission Trade System to avoid climate change and global warming determinedly. As the first major and also the biggest carbon market, EU ETS is the key vehicle to reduce greenhouse emissions under the "cap and trade" principle. A cap is the greenhouse emission capacity which is allowed by the system and reduces over time. By this principle, companies are obligated to receive or buy emission allowances to emit greenhouse gases. They can trade emission allowances with each other as well as they can buy limited amounts of international credits from emission-saving projects. Every year companies must have enough carbon emission allowances or heavy fines are enforced to punish them. Conversely, when a firm can reduce greenhouse gas emissions, spare allowances can be kept for future needs or can be sold in the carbon markets.

The Kyoto Protocol brings three market-based mechanisms in the direction of the emission allowances (reduction unit acquisition).

These mechanisms, identified as joint implementation (JI), clean development mechanism (CDM) and emission trading, represent the methods that industrialized countries will use to achieve their protocol objectives. In line with the common implementation mechanism, participating companies can earn an “Emission Reduction Unit (ERU)” unit corresponding to 1 ton of carbon dioxide while each firm can also acquire a “Certified Emission Reductions (CERs)” unit for emission reduction projects under the clean development mechanism. Besides, emission reductions made in accordance with clean development and co-implementation mechanisms but not in compliance with certified emission reduction units (CER) standards are approved by UNFCCC-accredited organizations and are referred as “verified emission reduction (VER).” These so-called “CO₂ emission certificates” are traded on carbon markets mostly operating in a voluntarily.

The new derived financial instruments and indicator indexes related to carbon markets have been raising researchers’ appetite. Low Carbon Indexes launched by Morgan Stanley Capital International (MSCI) in 2014, are intended to help identify potential risks associated with the transition to a low carbon economy while representing the performance of the broad equity market (Available from: <https://www.msci.com/low-carbon-indexes>). These indexes are subtypes of ESG indexes which are indicators linked to social and ethically responsible investment.

ESG is an abbreviation of “environmental,” “social” and “corporate governance” which in measuring the sustainability and ethical impact of an investment but also they are criteria that are set of standards for potential investments attracting the attention of environmentally sensitive investors. ESG criteria are a popular way to evaluate companies and assets (Roy and Gitman, 2012). It is argued that companies with strong ESG profiles might be better positioned for future challenges and experience fewer instances of bribery, corruption, and fraud. To monitor these potential alternative investments, a lot of indexes have been designed by many financial institutions for conscious investors such as MSCI and FTSE ESG Indexes. These indexes are created to encourage collective mentality to ESG investing referring to sustainable investing or socially responsible investing. By these indexes, it is easy to manage, measure and report on ESG mandate upon alternative investments. They also provide transparency into ESG sustainability as well as the ability to compare assets. Besides that, ESG indexes can help investors to avoid companies that may have greater financial risks due to their environmental operations. A positive significant relationship between ESG disclosure and firm performance must emerge in the decision process of potential investors or firms before investing (According to US SIF Foundation’s “Report on US Sustainable, Responsible and Impact Investing Trends,” \$11.6 trillion in assets under ESG manner which has already risen 44% of \$8.1 trillion in 2 years period. In years past, financial intermediary firms such as JP Morgan Chase, Goldman Sachs, and Wells Fargo have begun to publish similar annual reports on ESG finance and indexes just to show their interest in this business decisively (Roca and Searcy, 2012). The ESG finance has been continuously growing as it is a reason that index providers announce lots of new ESG indexes year by year. The

Index Industry Association recorded a 60% rise in the number of ESG indexes in the year to June 2018 which means a variety of investor perspectives to ESG finance.

While MSCI Global Low Carbon Target Indexes re-weight stocks based on their carbon exposure in the form of carbon emissions and fossil fuel reserves, the MSCI Global Low Carbon Leader Indexes aim to achieve at least 50% reduction in the carbon footprint of the parent index by excluding companies with the highest carbon emissions intensity and the largest owners of carbon reserves. One of the aims of this study is to establish a relationship between price formation and share values of these firms which constitute important parts of carbon trade. On this content, we try to examine the relations between CO₂ prices of European Union Emission Allowances and daily closing values of MSCI Low Carbon Leaders USD Dollar Price Indexes. MSCI World Low Carbon Leaders USD Dollar Price Index (W Index), MSCI North American Low Carbon Leaders USD Dollar Price Index (NA Index) and MSCI Europe Low Carbon Leaders USD Dollar Price Index (EU Index) are analyzed on the relationship between CO₂ prices a non-linear perspective.

2. LITERATURE REVIEW

While literature does not include directly analyzing the relationship between the ESG criteria and carbon prices, there is widening literature related to ESG indexes and low-carbon indexes, and also separated studies related to carbon prices.

Since the carbon markets related issues become more important, the number of studies, which have investigated them in financial aspects, increased considerably. Most of the studies analyzed to investigate the long-term interaction between financial performance and eco-efficiency. For instance, Guenster et al. (2011) investigate long-running corporate environmental-financial performance by using a new database of eco-efficiency ratings produced by Innovest Strategic Value Advisors containing monthly scores for the period December 1996 - December 2002. Their results suggest that there is a positive and significant relationship between environmental management policies and Tobin’s q with a delay. Dorfleitner et al. (2013) examine the long-term performance of stocks with high corporate social performance measured by ESG scores representing the three dimensions of ESG. According to the findings of the study financial markets are not capable of pricing different levels of corporate social performance in the short run as well as in the long run so properly. Also, Hillman and Keim (2001) claim that there is no certain relationship between corporate social performance and corporate financial performance. They tested the relationship between shareholder value, stakeholder management, and social issue participation propositions with data from S&P firms. But conversely, Evans and Peiris (2010) found that there is a significant positive relationship between ESG rating criteria, and both returns on assets and market to book value measures.

Uhrig-Homburg and Wagner (2007) focus on the relationship between spot and futures markets in the EU ETS. It is seen in the study that spot prices plus interest is equal to futures prices

after December 2005 as a matter of the cost of carrying approach. Mansanet-Bataller et al. (2007) examine the daily price changes during 2005 in EU ETS focusing on weather and non-weather variables as the determinants of the CO₂ prices. The empirical findings show that energy prices are the main factors for CO₂ prices. Fezzi and Bunn (2007) question the interaction between electricity, gas and carbon prices in terms of UK daily spot market data. It is investigated in the study that the shocks on gas prices act on carbon prices so notably and fast. Alberola et al. (2008) investigate the determinants of price in EU ETS and detect that the lagged price of fossil-derived energy prices and weather events might affect CO₂ prices. The Carbon price changes seem to be related to marginal abatement costs by Hintermann (2010). Carbon prices are driven in fact which also affected by weather temperature and precipitation in the First Phase of the EU ETS. Keppler and Mansanet-Bataller (2010) analyzing the relationship between daily carbon, electricity, and gas in EU ETS for both spot and futures prices, find that coal and gas prices have got an impact on CO₂ futures prices during Phase I of the EU ETS (January 2005 until December 2007).

Volatility is another aspect that is analyzed by many other researchers for carbon markets (Mansanet-Bataller and Soriano, 2012; Bunnag, 2015; Wei and Lin, 2016). Mansanet-Bataller and Soriano (2012) examine the transmission of volatility between daily returns of CO₂ prices, oil and natural gas prices during Phase II (April 2005- February 2011). The findings of the study express that CO₂ is influenced by oil and natural gas price volatility as well as its volatility. Bunnag (2015) analyzes oil futures and the carbon emissions futures volatility spreads for crude oil, gasoline, heating oil and also as carbon emissions by using daily data from 2009 to 2014. The study concludes that oil futures volatility has a significant effect on carbon emissions futures volatility. The interactions, the volatility spread and transmission between CO₂ and oil prices are studied by Wei and Lin (2016).

Many other studies are investigating the effect of coal price on carbon prices (Aatola et al., 2013; Lutz et al., 2013; Koch et al., 2014; Rickels et al., 2015; Fell et al., 2015), applying cointegration analysis focusing on fuel and allowance prices (Creti et al., 2012; Koch et al., 2014; and Fell et al., 2015). As a result of this literature review, most of the studies draw attention to the importance of fossil-derived energy prices on CO₂ prices and it is also clear that a consensus is in an agreement amongst literature that carbon prices are mostly driven by fuel prices.

3. DATA AND MODEL

The dataset of the study which starts on November 10, 2010, and ends on February 21, 2018, consists of daily settlement CO₂ prices of European Union Emission Allowances and daily closing values of MSCI Low Carbon Leaders USD Dollar Price Indexes. Data is gathered from Thomson Reuters EIKON Database. Logarithmic differences of the series are used. The variables used in the study are represented as the following:

- CO₂ Price: EEX-EU CO₂ Emissions E/EUA – Settlement Price.
- W Index: MSCI World Low Carbon Leaders USD Dollar Price Index.

- NA Index: MSCI North American Low Carbon Leaders USD Dollar Price Index.
- EU Index: MSCI Europe Low Carbon Leaders USD Dollar Price Index.

The model used is the Markov Regime Switching (MRS) model. With the MRS model, the regime of the economy (s_t) which cannot be directly observed, can be identified with some probability with the help of the observed time series variable (y_t) (Krolzig, 2000). This can be written as follows:

$$f(y_t|Y_{t-1}; X_t; \Theta_1) \text{ if } s_t = 1 \tag{1}$$

$$p(y_t|Y_{t-1}; X_t; s_t) = \{f(y_t|Y_{t-1}; X_t; \Theta_m) \text{ if } s_t = m$$

X_t: exogenous variables; Θ_m is the parameter vector associated with regime m.

The regime-generating process in the model is an ergodic Markov chain with a finite number of states defined by the transition probabilities (Krolzig, 2000).

$$p_{ij} = P_r(s_{t+1} = j | s_t = i); \sum_{j=1}^m P_{ij} = 1; i, j = \{1, m\} \tag{2}$$

s_t follows an ergodic M-state Markov process with an irreducible transition matrix:

$$P = \begin{bmatrix} p_{11} & \dots & p_{1m} \\ \dots & \dots & \dots \\ p_{m1} & \dots & p_{mm} \end{bmatrix} \tag{3}$$

The transition probabilities of moving from one state to the other in a two-state model is:

$$\begin{aligned} P(s_{t+1}=1 | s_t = 1) &= p_{11}, \\ P(s_{t+1}=2 | s_t = 1) &= p_{12}, \\ P(s_{t+1}=1 | s_t = 2) &= p_{21}, \\ P(s_{t+1}=2 | s_t = 2) &= p_{22}. \end{aligned} \tag{4}$$

The probability of which regime is in operation at time t conditional on the information at time t = -1 only depends only on the statistical inference on s_{t-1}:

$$Pr(s_t|Y_{t-1}; X_t; S_{t-1}) = Pr(s_t|s_{t-1}) \tag{5}$$

The ergodic probabilities for a two state model are given as (Bildirici, 2010):

$$P_r(s_t=1) = \frac{1-p_{22}}{1-p_{11}-p_{22}}, P_r(s_t=2) = \frac{1-p_{11}}{1-p_{11}-p_{22}} \tag{6}$$

The two main types of MRS models are the Markov switching model of conditional mean (MSM) and the Markov switching intercept (MSI). In the MSM model, the regime switches according to the conditional mean (μ_t), while in the MSI model, the regime switches according to the constant (cst). The Markov switching model with an intercept and heteroscedasticity is another powerful model (MSIH). While the basic p lagged VAR(p) model process is:

$$y_t = c + [A_1 y_{t-1} + \dots + A_p y_{t-p}] + u_t \tag{7}$$

An is (n*n) coefficient matrices

The general form of a Markov-switching vector autoregressive (MS-VAR) model is (Krolzig, 1998; 2000):

$$y_t = c(s_t) + [A_1(s_t)y_{t-1} + \dots + A_p(s_t)y_{t-p}] + u_t \quad (8)$$

A VAR with regime shifts in the mean is called a MSM(M)-VAR(p):

$$y_t = \mu(s_t) + A_1(s_t)(y_{t-1} - \mu(s_{t-1})) + \dots + A_p(s_t)(y_{t-p} - \mu(s_{t-p})) + u_t \quad (9)$$

$$u_t \sim \text{NID}(0, \Sigma(s_t))$$

If the regime shifts affect the intercept of the VAR, this is called a MSI(M)-VAR(p):

$$y_t = c(s_t) + A_1(s_t)y_{t-1} + \dots + A_p(s_t)y_{t-p} + u_t \quad (10)$$

The transition in the MSI-VAR, is smooth comparing to the MSM-VAR model. These models are the subclass of MS-VAR models (Krolzig, 1998; 2000).

If the regime shifts affect the intercept of the VAR and the model includes a variance-covariance matrix, this is called an MSIH(M)-VAR(p) process:

$$y_t = c(s_t) + A_1(s_t)y_{t-1} + \dots + A_p(s_t)y_{t-p} + u_t + \Omega_{1/2} \quad (11)$$

These models also explain the fat tails, periods of turbulence followed by periods of low volatility, and skewness of many financial series. Moreover, these models can capture nonlinear stylized dynamics of asset returns in a framework based on linear specifications, or conditionally normal or log-normal distributions, within a regime (Ang and Timmermann, 2011).

4. EMPIRICAL ANALYSIS

Vector autoregressive models with different numbers of regimes (2 or 3) and different lags are applied to price-index duals. Taking linearity as our null hypothesis, and following Davies' (1987), we consider a $P < 0.05$ to constitute a statistically significant rejection of the null hypothesis. Among the several models that have been found, the model that best explains the nonlinear relationship for every relationship that investigated is the MSIH model with three regimes for all variable duals (Table 1). The regime-switching mechanism in the MSIH model is specified by the intercept (I) and volatility/heteroskedasticity (H).

The coefficients of the models are shown in Table 2. The estimation procedure implemented in the "Ox Metrics program" identifies regime 1 (recession), regime 2 (moderate growth) and regime 3 (expansion) of the model. In the first regime, the constants of all indexes are negative. In the second regime and the third regime, the constants differ as positive or negative. The first and third regimes are also high volatility regimes. In this model, it is also important that the difference between the second and third regimes is volatility. Although the second regime is a moderate growth regime and the third regime is a high growth regime, negative coefficients might be encountered depending on the data structure or volatility.

Transition probability represents the likelihood that the indexes will stay in the original regime or switch to another regime. According to the matrix of Transition Probabilities, the maximum probabilities are seen from switching any regime to Regime 2 in Model 1 and Model 2 (Model 1, p_{12} : 0.05; Model 1, p_{32} : 0.05; Model 2, p_{12} : 0.05; Model 1, p_{32} : 0.04). The third model does not have a dominant switching regime. While the last regime is known as Regime 1, the next regime will be 0.04% Regime 2 or 0.06% Regime 3. Vice versa the maximum probability of switching from Regime 2 or Regime 3 is Regime 1 (Table 3).

In the 7, 20 years, the greatest number of observations with the highest probability and longest duration is seen in regime 2 for Model 1 and Model 2, and regime 3 for Model 3. While the probabilities evaluated generally, regime 2 is stronger in all three models (Table 4).

The impulse response tests of Model 1-3 are shown in Figures 1-3. The general evidence does not point to significant relationships between CO₂ prices and indexes in the short term for Model 1 (CO₂ - W Index) and Model 3 (CO₂ - EU Index) for any of the regime recession (1), moderate growth (2) or expansion (3).

CO₂ price does not give responses to the shocks applied to W Index, however, it gives positive responses to the shocks applied to itself in the first model. The largest response can be seen in the expansion regime (0.05) and the weakest response is in the moderate growth regime (0.015).

In model 1, W Index gives positive responses to the shocks applied to itself. The largest responses of W Index are seen in the recession regime (0.015), then the expansion regime follows it (>0.005) and the weakest response is seen in the moderate growth (>0.005).

In the next figure, the results of the impulse-response test for the model investigating the relationship between CO₂ prices and the

Table 1: Information criterions model 1-3

Model	Variables	Model	Log-likelihood	AIC	HQ	SIC	LR linearity	DAVIES (5%)
Model 1	CO ₂ Price-W Index	MSIH (3) -VAR (1)	10821.5322(Linear: 10183.3873)	-11.4735 (Linear: -10.8123)	-11.4464 (Linear: -10.8026)	-11.3999 (Linear: -10.7858)	1276.2897	[0.0000]
Model 2	CO ₂ Price-NA Index	MSIH (3) -VAR (4)	10664.6291 (Linear: 10027.3610)	-11.2940 (Linear: -10.6338)	-11.2539 (Linear: -10.6110)	-11.1851 (Linear: -10.5719)	1274.5362	[0.0000]
Model 3	CO ₂ Price-EU Index	MSIH (3)} -VAR (1)	10098.9245 (Linear: 9488.2849)	-10.7056 (Linear: -10.0736)	-10.6784 (Linear: -10.0639)	-10.6320 (Linear: -10.0471)	1221.2792	[0.0000]

Table 2: Coefficients

Constant/ Variable/ Standard error	Model 1		Model 2		Model 3	
	Price	World index	Price	North America index	Price	Europe index
Constant	-0.004144	-0.001132	-0.002344	-0.001170	-0.004068	-0.000306
Constant	0.001660	0.000542	-0.001925	0.001521	0.000256	-0.000140
Constant	-0.000798	0.000914	0.001599	0.000863	0.001572	0.000550
PRICE (-1)	-0.000006	-0.003397	-0.002480	0.000102	0.007655	0.000183
PRICE (-2)			-0.067738	0.003049		
PRICE (-3)			-0.015238	0.001822		
PRICE (-4)			0.009309	0.002231		
INDEX (-1)	-0.044551	0.102209	0.001182	-0.050310	-0.012691	0.013540
INDEX (-2)			0.101207	-0.000070		
INDEX (-3)			-0.062694	-0.057618		
INDEX (-4)			0.038475	-0.025221		
SE (Reg. 1)	0.028473	0.013726			0.053729	0.017665
SE (Reg. 2)	0.017151	0.005128			0.012571	0.011524
SE (Reg. 3)	0.055327	0.005694			0.025346	0.006317

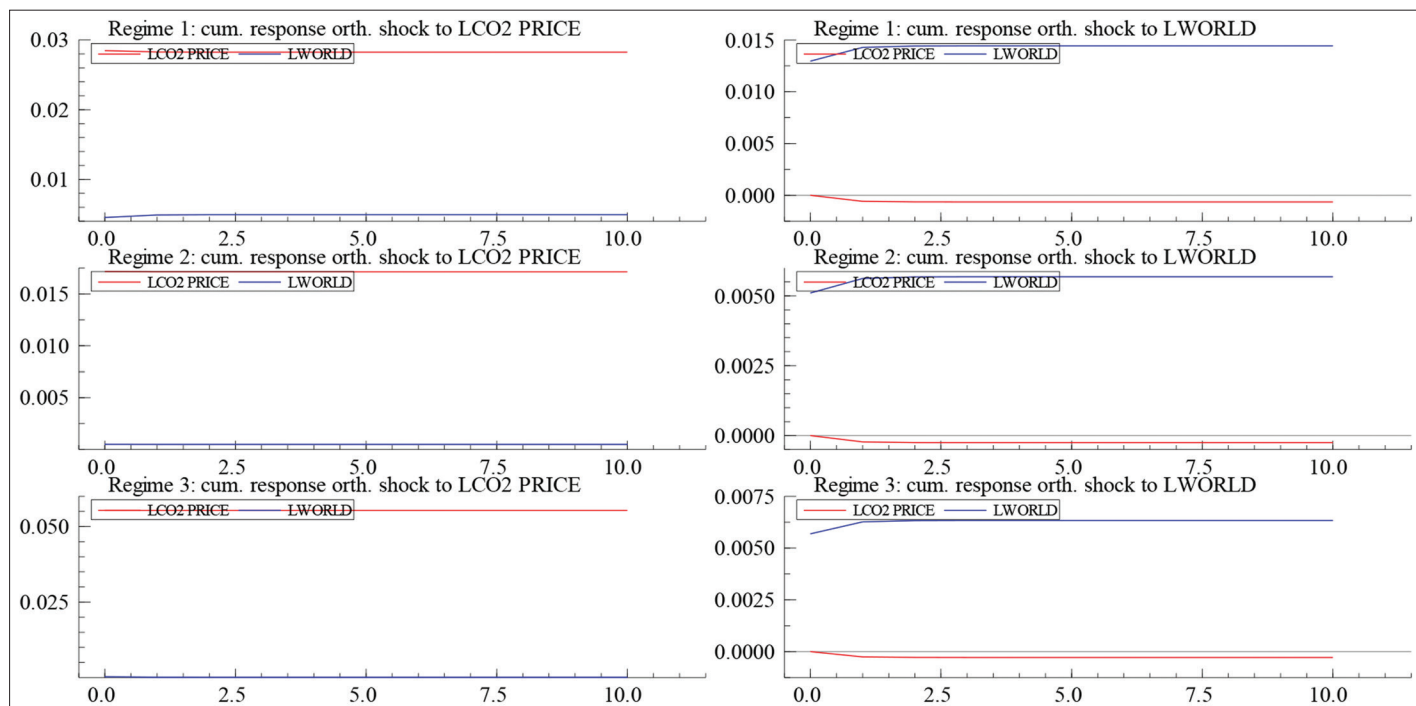
Table 3: Matrix of transition probabilities

Regime	Model 1			Model 2			Model 3		
	Regime 1	Regime 2	Regime 3	Regime 1	Regime 2	Regime 3	Regime 1	Regime 2	Regime 3
Regime 1	0.93	0.05	0.02	0.92	0.05	0.03	0.90	0.04	0.06
Regime 2	0.02	0.96	0.02	0.03	0.95	0.02	0.04	0.95	0.01
Regime 3	0.02	0.05	0.93	0.03	0.04	0.93	0.03	0.00	0.97

Table 4: Regime properties

Regime	Number of obs.	Prob.	Duration	Number of obs.	Prob.	Duration	Number of obs.	Prob.	Duration
Regime 1	415	0.2207	13.47	512	0.2731	12.63	483	0.2559	10.12
Regime 2	1005	0.5335	22.82	938	0.4980	21.11	507.8	0.2608	22.49
Regime 3	462	0.2458	15.02	430	0.2290	14.67	890.9	0.4833	28.61

Figure 1: Impulse response tests - model 1



NA index are shown under different regimes. The NA Index does not respond significantly to the shocks applied to CO₂ prices,

however, CO₂ prices give weak responses to NA Index for 2 days. The effects of the shocks stabilize before the 5th day. Moreover,

Figure 2: Impulse response tests – model 2

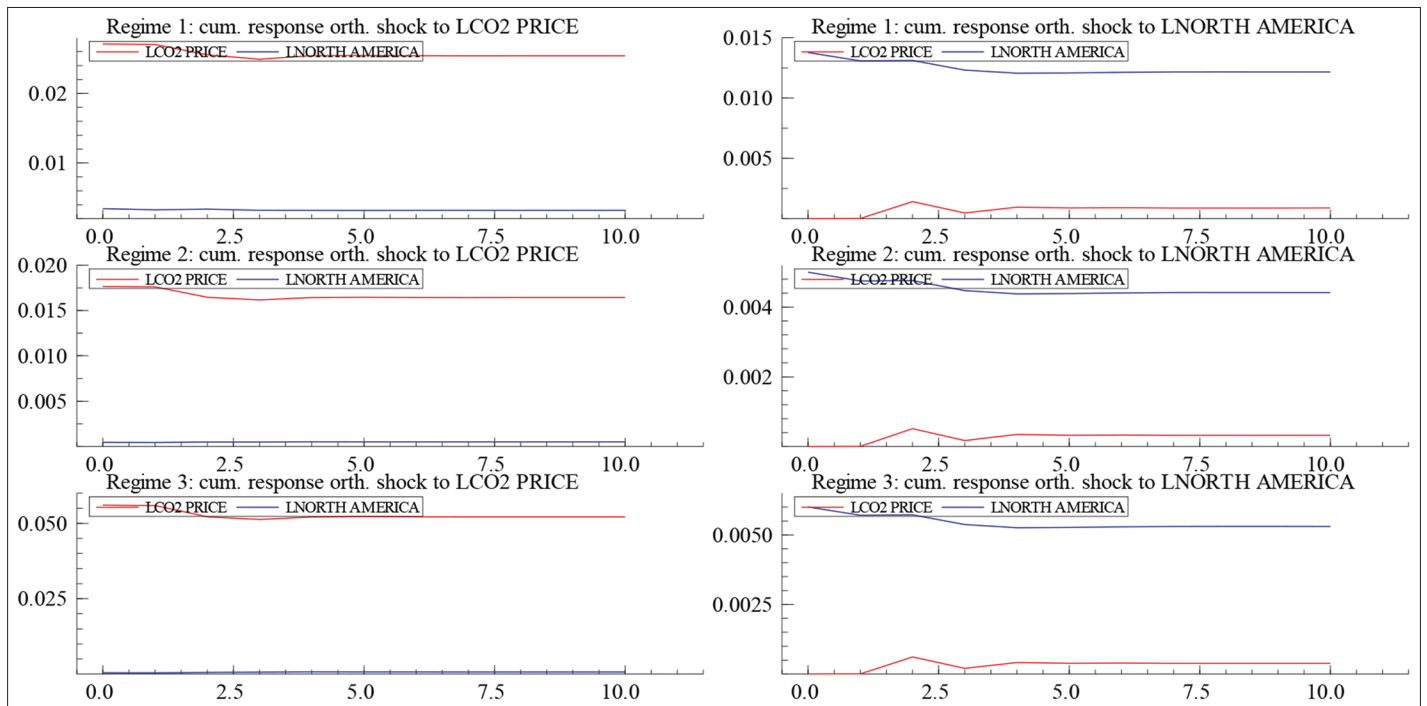
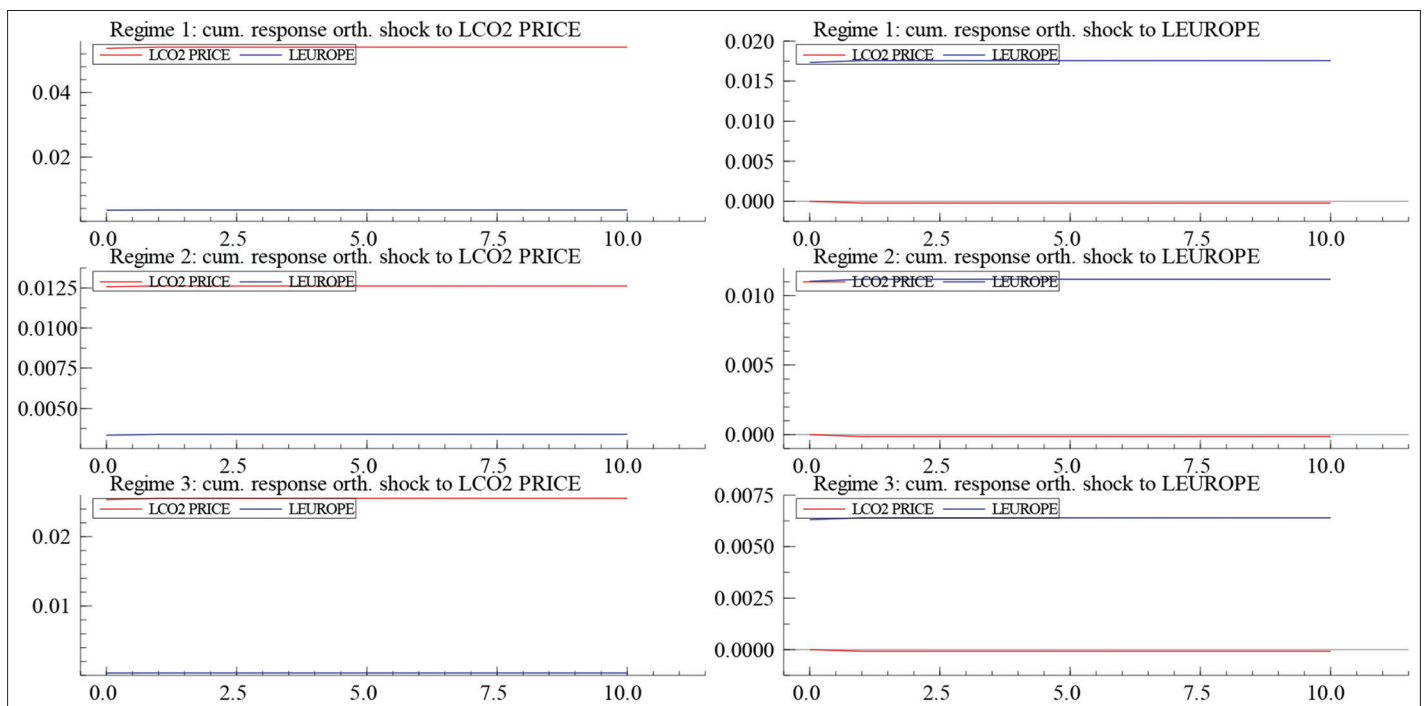


Figure 3: Impulse response tests – model 3



the responses are more prominent in the recession regime (>0.002) than moderate growth (<0.002) and expansion (<0.0025). CO₂ gives positive responses to the shocks applied to itself too. The results are similar as seen in the first model. The largest response can be seen in the expansion regime (0.05) and the weakest response is in the moderate growth regime (0.015).

In model 1, NA Index gives positive responses to the shocks applied to itself. The largest responses of W Index are seen in the recession regime (>0.010), then the expansion regime follows it

(>0.005) and the weakest response is seen in the moderate growth (>0.004).

The third model with CO₂ prices and EU Index does not provide any evidence supporting the relationship between carbon prices and low carbon indices. CO₂ prices are affected by the shocks applied to itself positively in the 1st day. The largest response is given in the recession regime (>0.040), then the following largest response is seen the expansion regime (>0.020), and the weakest response takes place in the moderate growth (>0.0125).

Similar to the results obtained in previous models, EU Index is positively affected by the shocks applied to itself. EU Index responds largest in the recession regime (>0.015), then moderate growth (>0.010) and responds weakest in the expansion (>0.005).

5. CONCLUSION

With the market-based designed mechanisms of the Kyoto Protocol, companies are obligated to receive or buy emission allowances to emit greenhouse gases. Since the carbon markets' importance increase in the global economy, the analysis of them in a financial manner increase as well. This study examines the relations between CO₂ prices of European Union Emission Allowances and daily closing values of MSCI Low Carbon Leaders USD Dollar Price Indexes via Markov Regime Switching Model from a non-linear perspective.

Among the several models that have been found in the study, the model that best explains the nonlinear relationship for every relationship that investigated is the MSIH model with three regimes for all variable duals. While the general evidence shown by impulse response tests does not point to significant relationships between CO₂ prices and indexes in the short term for Model 1 (CO₂ - W Index) and Model 3 (CO₂ - EU Index). On the other hand, CO₂ prices give weak responses to NA Index. Moreover, the responses are more pronounced in the recession regime. The results can be explained by the fact that the North American market is the leader in the whole carbon market. These underline the need to use a firm-based approach with the firms involved in carbon trading in North America.

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