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A non-parametric test

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Carbon trading thickness and market efficiency: A non-parametric test

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Abstract

This note tests for the efficient market hypothesis (EMH) in the market for CO_2 emission allowances in Phase I and Phase II of the European Union Emissions Trading Scheme (EU ETS). As usually is the case in emerging and non-competitive markets such as the EU ETS, trading often not occurs on a frequent basis. This has adverse implications for both the gains from permit trade as well as biases the EMH tests. Variance ratio tests are employed to adjust for the thin trading effect. The results indicate that Phase I — the trial and learning period — was inefficient, whereas the first period under Phase II shows signs of restoring market efficiency.

Jel classification: C14, G14, Q50

Keywords: pollution markets, carbon trading, efficient market hypothesis, thin trading, variance ratio tests

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1 Introduction

The European Union Emissions Trading Scheme (EU ETS) for trading CO_2 emissions has generated a great interest among academics and practitioners alike to try to assess the functioning and actual behavior of this new market. In this market, regulated firms as well as other investors can buy or sell emission allowances. From an investment point of view, an assessment of the corresponding market behavior is a necessary step for the correct implementation of (carbon) risk management strategies (e.g., Labatt and White, 2007; Paolella and Taschini, 2008). At the heart of this is the martingale hypothesis —or efficient market hypothesis (EMH)— asserting that asset returns are purely random. It essentially implies that investors cannot earn abnormal profit by exploiting past information (e.g., Fama, 1970). However, in non-competitive and emerging markets, such as the EU ETS, there is often too little trade (e.g., Wirl, 2009). It is well known that market frictions characterized through infrequent or "thin" trading adversely affects the gains from permit trade (Liski, 2001) as well as seriously biases the result of the EMH tests (Miller et al., 1994). As a consequence, thin trading has direct implications for effective risk management in CO_2 or other type of pollution markets. This note aims at examining to what extent adjusting for the possibility of thin trading affects the inferences drawn from testing the EMH of the EU ETS, hence assessing the role of expectations with respect to the CO_2 returns in this market.

Whilst the literature on the price dynamics of CO_2 allowances as part of the EU ETS is steadily increasing, the issue of thin trading in relation to the EMH has not been addressed so far. Among other things, Seifert et al. (2008) present a stochastic equilibrium model which incorporates the main features of the EU carbon market. Using a brief autocorrelation analysis they show that CO_2 prices exhibit non-stationary behavior and that its evolution is not different from the US SO_2 market, i.e. the EU ETS is informational efficient. Paolella and Taschini (2008) undertake a pure econometric analysis addressing the heteroskedasticity and the unconditional tail distribution behavior of the SO_2 and CO_2 spot market returns. They propose the use of a mixed-normal GARCH model to describe and forecast the returns on the CO_2 allowances. Benz and Trück (2009) look at the CO_2 spot price dynamics and at the volatility of the returns and advocate the implementation of Markov switching and AR-GARCH models. Finally, Daskalakis et al. (2005) show that the EU ETS spot prices exhibit jumps and non-stationary behavior.

Our contribution extends the discussion by evaluating the EMH for the EU ETS with the explicit adjustment for the possibility of thin trading. We particularly use a series of variance ratio (VR) tests. These tests have been widely used in finance research, but have, to the best of our knowledge, not been applied to analyze the functioning of tradable permit markets or other "commodity" markets.[1] The VR tests resemble the class of non-parametric tests which have the advantage of preserving flexibility in the functional specifications, in particular in the context of tradable permits (or quota) (e.g., Oude Lansink and van der Vlist, 2008, p.488).

The paper proceeds with a description of the data and provides some basic figures on the number of trades in the CO_2 market (Section 2). Then details on the empirical analysis and corresponding results are presented (Section 3). The paper concludes with a summary of the main results (Section 4).

[1] An exception is the study of Charles and Darné (2009) who apply VR tests to the crude oil market.

2 Data and summary statistics

We analyze and test the CO_2 return data for Phase I and the first time period of Phase II. The price data on both phases come from *BlueNext Spot*, which is the major spot market for EU ETS allowances covering about 75% of the market. The sample for Phase I covers the period 27 June 2005 until 28 December 2007; the sample for Phase II covers the period 26 February 2008 until 4 April 2009. This gives us 627 and 250 observations respectively. Fig. 1 shows the evolution of the spot price for CO_2 allowances for both these phases respectively. At a first glance, the graph for Phase I suggests that the CO_2 prices were relatively stable, varying between 20-30 Euro per ton. Fig. 1 also clearly shows the sharp downward fall of the price immediately after the official information was released mid May 2006 that there was a *de facto* overallocation of allowances. After this sharp fall the spot recovers a bit and increases from 10 to about 18 Euro and subsequently varies around 15 Euro for a while. As of September 2006 there is a relatively fast downward adjustment to a price close to zero, which remains low until the end of Phase I. The sample period for Phase II shows a less irregular CO_2 price pattern. Starting off with a price of about 20 Euro in February 2008, there is a steady increase approaching 29 Euro per ton by the end of June 2008.[2] Since then the prices reveal a downward trend until February 2009.

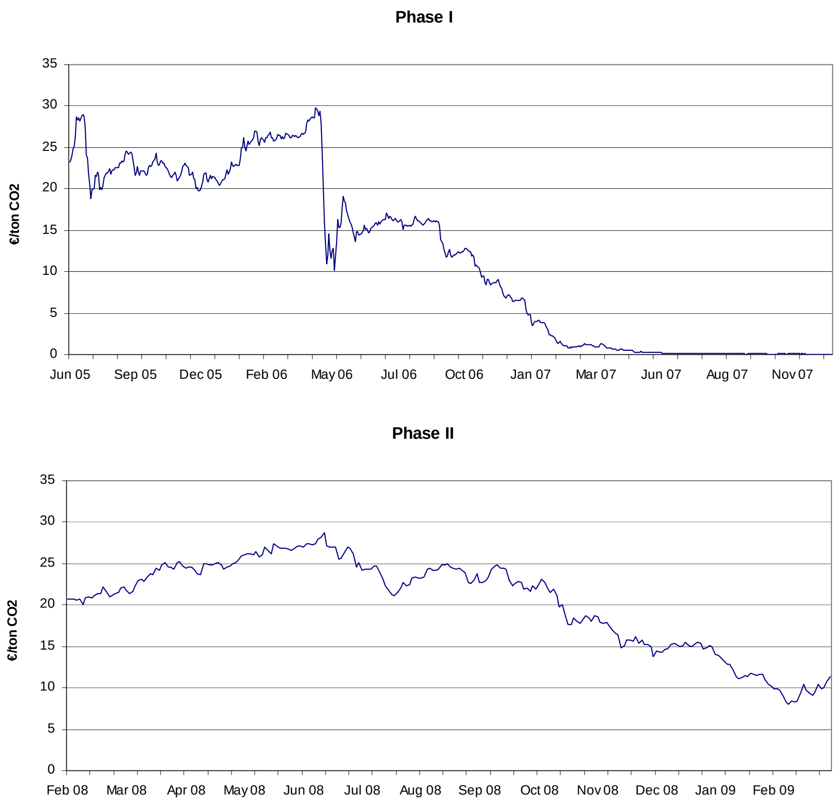

Figure 1: Daily CO_2 spot prices in Phase I (upper panel) and Phase II (lower panel).

[2] The exact price was 28.23 and 28.73 Euro for 30 June and 1 July 2008 respectively.

Figs. 2 and 3 show for both Phase I and II the daily CO_2 returns[3] (upper panel), the corresponding distribution (middle panel) and the QQ-plot[4] (lower panel). Fig 2 shows that the returns are essentially zero during the first period of Phase I; however, deviation from zero starts to occur during the second half of Phase I. Comparing this with the returns during the first period of Phase II (see upper panel Fig. 3), it appears that the CO_2 returns are showing slightly more variation. This is confirmed by the density graphs in Figs. 2 and 3 (see middle panels). The density graph and QQ-plot against the normal distribution shows that the returns distribution also exhibits fat tails, confirming the kurtosis statistics as shown in Table 1.

Table 1: Descriptive statistics, 1970-1997

	Returns Phase I	Returns Phase II
Mean	-0.7875	-0.1876
Median	0.0000	-0.0778
Maximum	66.666	11.124
Minimum	-40.000	-9.7739
Std. deviation	8.1781	2.9228
Skewness	0.9142	0.0867
Kurtosis	14.840	4.9491
Jarque-Bera	3744.2	41.323
Probability	0.0000	0.0000
No. Observations	627	250

The series exhibit significant level of skewness and kurtosis. The positive skewness implies that the returns are flatter to the right compared to the normal distribution. The kurtosis reported indicates that the return distributions have sharp peaks compared to a normal distribution. The Jarque-Bera statistics for testing normality confirm the significant non-normality of returns. Notice, however, that the level of skewness and kurtosis is much smaller in Phase II than in Phase I. This indicates that the distribution of the returns of Phase I shows a longer right tail and they tend to be more concentrated on the tails of the distributions.

Although Fig. 1 indicates some volatility of the CO_2 prices, the number of trades in CO_2 emissions were very limited. In fact, for the covered periods, the average number of trades per day in 2005, 2006, 2007 and 2008 was no more than 4, 8, 3 and 1 respectively.[5] We believe this is rather small and as such we contend the EU ETS can be classified as a thin market. Therefore, we test the EMH for the EU ETS while adjusting specifically for thin trading. To this we turn next.

[3] We calculated the log returns as: $return_t = \ln(p_t/p_{t-1})$, where p_t denotes the permit price at time t.

[4] A QQ-plot is a graphical method for comparing two probability distributions with eachother. In our case we plotted the quantiles of a normal distribution (straight line) against the quantiles of the return data. If the return data follow a normal distribution then the two lines should (more or less) coincide.

[5] These represent the average numeber of trades as recorded by the EEX Emissionsmarkt/Emission Market.

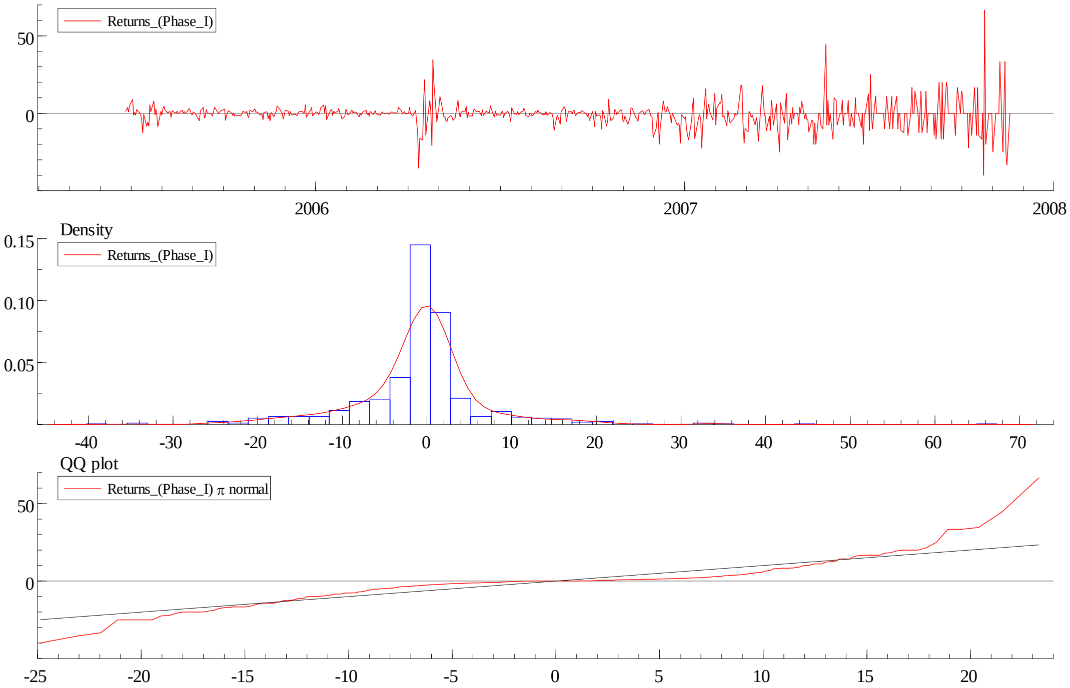

Figure 2: Daily CO_2 returns, density and QQ-plot Phase I.

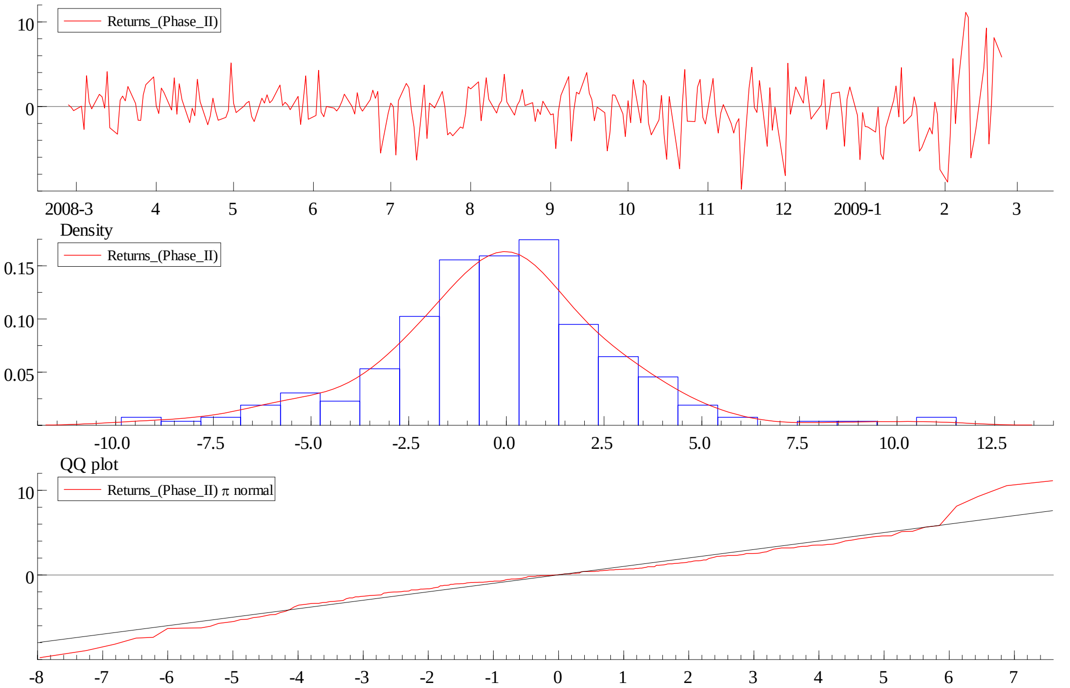

Figure 3: Daily CO_2 returns, density and QQ-plot Phase II.

3 Empirical analysis and results

In this section, we test for the martingale hypothesis in the EU ETS allowance prices of CO_2. Table 2 reports the test statistics for rank-based tests ($R1$ and $R2$) and signed-based test ($S1$) for Phase I and II. Wright (2000) has shown that the non-parametric rank-based test $R1$ exhibits high power against a wide range of models displaying serial correlation.[6]

Under the null hypothesis the series should follow a random walk and the variance-ratios are expected to be equal to one. The test is implemented for short holding periods (time lags), i.e. $k = 2$, $k = 5$ and $k = 10$ days respectively. Table 2 reports the test statistics for the rank-based tests ($R1$ and $R2$) and signed-based test ($S1$) as detailed in Wright (2000) for the observed raw market data over k number of lags. Following Hoque et al. (2007) we reject the EMH in the case of two or more rejections at the usual level of statistic significance. The null hypothesis is rejected in Phase I for all holding periods while the EMH is accepted in Phase II when $k = 5$ and $k = 10$.

Table 2: Wright's VR test results for unadjusted data

		$k=2$	$k=5$	$k=10$
Phase I	$R1$	2.860**	2.993**	2.864**
	$R2$	1.453	1.699**	1.549**
	$S1$	5.675**	6.699**	7.690**
Phase II	$R1$	1.860**	0.760	0.658
	$R2$	2.062**	0.801	0.568
	$S1$	1.553	1.089	1.476

** significant at the 5% level

In testing the EMH in thin markets, it is necessary to take into account thin trading that typically characterizes these markets. This market characteristic is associated with the asset (the tradable permit) not being exchanged at every consecutive time interval. As analyzed in Miller et al. (1994) thin trading introduces the problem of serial correlation and generates statistical biases. To adjust for infrequent trading, we employ their methodology. The adjustment involves removing the effect of thin trading by a moving average process, which reflects the periods of non-trading. In particular, Miller et al. (1994) show that the adjusted data can be obtained by estimating an AR(1) process. For the adjusted data we then repeat Wright's (2000) VR test, which are included in Table 3. The results confirm the rejection of the EMH of Phase I but not for Phase II.

Although Wright's VR test has the ability to perform well when the daily returns are non-normal and non-stationary, it is quite susceptible to size distortions due to sequential trading since it assumes that the test statistics computed at different time intervals, k, are uncorrelated. To overcome this possible problem, we apply a p-value multiple test as in Kim and Shamsuddin (2008) and Belaire-Franch and Opong (2005). Table 4 reports the values of their non-parametric VR-based test on ranks and signs. The results reinforce our previous finding, i.e. reject the null hypothesis that the CO_2 returns during Phase I followed

[6] "The tests based on ranks are exact under the independence and identical distribution assumption, whereas the tests based on signs are exact even under conditional heteroskedasticity" (Belaire-Franch and Opong, 2005, p.1535).

Table 3: Wright's VR test results for adjusted data

		$k = 2$	$k = 5$	$k = 10$
Phase I	$R1$	5.299**	4.920**	4.227**
	$R2$	3.920**	3.469**	2.787**
	$S1$	6.600**	7.887**	8.163**
Phase II	$R1$	-0.07	-1.059	-0.783
	$R2$	0.015	-1.135	-0.931
	$S1$	-0.747	-0.796	0.022

** significant at the 5% level

a i.i.d. process. All overwhelming number of rejections is in the right tail of the distributions, suggesting that serial correlation is positive. This result is confirmed even after the data have been adjusted for thin trade. However, results for Phase II show that the market appears to be efficient; the VR test indicates that we cannot reject the EMH at conventional statistical significance levels.

Table 4: Joint Wright's VR test results for unadjusted and adjusted returns

		Unadj. returns	Adj. returns
Phase I	$R1J$	2.993**	5.299**
	$R2J$	1.612	3.920**
	$S1J$	7.690**	8.163**
Phase II	$R1J$	1.860	1.059
	$R2J$	2.062	1.135
	$S1J$	1.553**	0.796

** significant at the 5% level

Finally, as we observed earlier, the CO_2 market exhibited a higher degree of volatility after the sharp adjustment in April 2006, and this sharp break of the series could have changed the dynamics of the market. To correct for this trend break, we divided the data of Phase I into two sub-samples. The first period goes from 24/06/2005 to 26/04/2006 and the second from 27/04/2006 to 28/12/2007. We repeated all the previous exercises for the two sub-samples of Phase I. However, the empirical outcome remains unchanged, confirming a rejection of the EMH, i.e. Phase I did not resemble market efficiency.[7]

It should be noted that the VR test presented above has the ability to detect *linear* dependency only. Therefore, before drawing a final conclusion about the data generating process characterizing the returns in the carbon permits market, we should be able to reconfirm the hypothesis after testing for the absence of *non-linear* dependence. Following Hsieh (1991), we applied the BDSL test (see Brock et al., 1996) for this independence on the residuals of the ARMA model. If we reject the null hypothesis then the series has a high probability to be non-linear, or exhibits chaotic characteristics. The ability to detect a i.i.d. process is subject to the choice of the embedding dimension m and the bound ε.[8] If we select a

[7] The estimation results are available from the authors upon request.

[8] In the BDSL test m is defined as the number of consecutive points used in the set. While ε is part of

value for ε that is too small, the null hypothesis of a random i.i.d process will be accepted too often irrespective of it being true or false. As well, it is not safe to choose too large a value for m. To deal with this problem Brock et al. (1991) suggest that for a large sample size (i.e., $T > 500$) ε should equal 0.5, 1.0, 1.5 and 2 times the standard deviations of the data. Given these concerns we present both the p-value based on asymptotic theory and on a bootstrap, where the latter was based on 1000 replications. Our results are presented in Table 5 and reconfirms support for the hypothesis that Phase II of the CO_2 market follows (a weak) EMH, while we can reject the i.i.d. hypothesis for Phase I.

Table 5: BDSL test results for phase I and II

	Unadjusted returns						Adjusted returns					
	$\varepsilon = .5$		$\varepsilon = 1$		$\varepsilon = 2$		$\varepsilon = .5$		$\varepsilon = 1$		$\varepsilon = 2$	
Bootstr. dim.	I	II	I	II	I	II	I	II	I	II	I	II
2	.000	.127	.008	.421	.165	.779	.000	.239	.007	.184	.088	.626
3	.000	.249	.002	.312	.045	.418	.000	.437	.000	.181	.021	.676
4	.000	.178	.002	.179	.012	.338	.000	.488	.000	.116	.009	.620
Asympt. dim.												
2	.000	.128	.008	.471	.180	.814	.000	.269	.003	.199	.080	.661
3	.000	.284	.001	.386	.045	.484	.000	.498	.000	.197	.016	.708
4	.000	.207	.000	.214	.010	.393	.000	.569	.000	.135	.007	.664

Only p-values are reported under the null hypothesis that the time series is a serial i.i.d. process.

All calculations are done using the non-linear toolkit of Patterson and Ashley (2000).

4 Concluding remarks

This paper tests the efficiency of the EU ETS carbon market. Although market efficiency is generally important, it is particularly relevant when the market is relatively immature and in an emerging state. Assessing the behavior of market participants in the EU ETS, as reflected through the behavior of CO_2 spot price dynamics, is especially relevant for effective risk management and investment strategies. However, in the relatively young European carbon market the number of trades were very limited for the period in our sample. It is this infrequent or thin trading that has negative implications for both the gains from permit trade as well as the statistical inferences for testing the EMH.

For the sample periods 27 June 2005 to 28 December 2007 (Phase I) and 26 February 2008 to 4 April 2009 (Phase II) the EMH is tested through variance-ratio tests while adjusting for thin trading. The results show that the EU ETS was inefficient during Phase I but efficient during the first period of Phase II. This suggests that the carbon market shows the first signs of maturation after the learning and trial period in Phase I.

the correlation integral $C_{m,N} = (\varepsilon)$, it essentially "counts up the number of $m - histories$ that lie within a hypercube of size ε of each other" (Patterson and Ashley, 2000, p.41).

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