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Abstract

We examine the weak-form efficiency status of the European carbon market over periods of sustained volatility, uncertainty, complexity and ambiguity (VUCA). We use 1,035 daily spot price data observations from the Phase II European Union Emissions Trading Scheme (EU ETS) from 2008-2012, along with random walk and trading rule profitability tests. To establish the evolution of weak-form efficiency, the time period under investigation is further divided into two distinct crisis periods, i.e. global financial crisis (GFC) period and European sovereign debt crisis (ESDC) period. *Period 1* random walk test findings provide limited support for price return predictability in the European carbon market during the GFC. *Period 2* results show that price return predictabilities became non-existent during the ESDC. Trading rule profitability findings reveal that after applying simple trading rules (that account for risk and transaction costs), price return predictabilities cannot be manipulated to profit above a naïve buy-and-hold strategy in the European carbon market. Despite ongoing market volatility, economic uncertainty and complexity, and global climate change policy ambiguity, it appears that the EU ETS is becoming more weak-form efficient.

Keywords: Capital markets, socially responsible investment, sustainability

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1 Introduction

In recent times, global financial markets have encountered heightened volatility, uncertainty, complexity and ambiguity (VUCA). The global financial crisis (GFC) (2008-2010) and European sovereign debt crisis (ESDC) (2010-2012) are classic examples of such VUCA[2]. Driven by the United States (U.S.) housing bubble in 2007-08, the GFC rapidly consumed leveraged entities and wreaked havoc on the real economy[3]. In response to this unprecedented crisis, the U.S. and other Western economies simultaneously manufactured massive economic bailout packages to assist financially crippled banks, insurance companies, financial service providers and multinational corporations, in an attempt to thwart a collapse of the global financial system. With the realisation that not only had the GFC paralysed the global financial system but government balance sheets as well, the GFC manifested into the ESDC in early 2010. This dangerous new phase of the crisis resulted in numerous stimulus packages, quantitative easing and government bond purchases being coordinated by the European central bank (ECB) and directed towards distressed Euro-zone economies (i.e. Portugal, Italy, Ireland, Greece and Spain) in the hope that such actions would: (i) reduce sovereign risk; (ii) bolster domestic demand/economic growth; (iii) prevent further increases in bond yields; and (iv) strengthen the broader European economy.

Whether the above mentioned policy responses have solved the problems associated with the GFC and ESDC remains a moot point. Nevertheless, the myriad of capital injected into the global financial system since the onset of the GFC has led to burgeoning Western government expenditures and intergenerational debt. For instance, drastic fiscal policy measures have added to already staggering debt/budget deficit levels for the U.S. and most of Europe (Klepsch & Wollmershäuser 2011). Other consequences brought about by these financial crises include, but are not limited to, the write-down of "toxic" sub-prime mortgage assets and the collapse of major banks, availability of credit, weakening consumer/business confidence, falling housing starts and manufacturing output, asset illiquidity and devaluation, historically low interest rates, rising bankruptcies and unemployment, stagnant economic growth, and social unrest (Maydybura & Andrew 2011; McNicholas & Windsor 2011). Although these events are comparable to previous meltdowns, few have anticipated the depth and severity of the current financial puzzle (Klein et al. 2009).

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[2] The GFC and ESDC are considered to be among the most destructive and controversial crisis events since the Great Depression.

[3] The GFC (or sub-prime crisis, global credit crisis, liquidity crisis, etc) was primarily caused by both the securitisation of the U.S. mortgage market, i.e. bundling of sub-prime mortgages into derivatives and synthetic products, and excessive financial leverage and risk taking.

The ongoing crises represent a serious threat to the stability of capital markets and the global economy (Liebreich et al. 2009). Arguably, the inability to price risk effectively has resulted in heightened economic uncertainty and price volatility (Maydybura & Andrew 2011). During the GFC, and more recently the ESDC, global markets have demonstrated significant price falls, witnessing a growing connection between financial and commodity markets (particularly energy markets) (Koch 2011). This is consistent with the notion that asset returns from capital markets exhibit higher dependence during periods of economic or market downturns, thus challenging the usefulness of portfolio diversification (Gronwald et al. 2011). Given this phenomenon, the price behaviour of new or "emerging" markets and whether they can be considered viable investment alternatives during such periods, has become of particular interest to market participants.

The European Union Emissions Trading Scheme (EU ETS) is a recent example of an emerging environmental market. While the greenhouse gas (GHG) or "carbon" market is relatively undeveloped it is growing rapidly in scale, scope and complexity. The possibility of low price return correlation with other asset classes, together with market infrastructure growth supporting liquidity, have further increased the attractiveness of carbon as a potential investment market (Abraham 2007; Benz & Hengelbrock 2008). Moreover, carbon market players now have the ability to hedge, invest or speculate in allowances, transforming the price behaviour and dynamics of carbon into an issue of major importance in the financial arena (Miclăus et al. 2008).

Despite the phenomenal growth and the investment potential of the carbon market, the global climate change politics involved are both complex and controversial. A lack of binding international agreements, policy uncertainty, and the ongoing financial/economic crises all threaten to undermine the overall objective (that is to mitigate the economic, social and environmental effects of climate change) of the emerging market. Further, it is questionable how carbon as a "stand-alone" asset class will hold up against the long-term financial constraints currently hampering the global economy. The failure of recent valuations of global asset prices due to the GFC and ESDC is indeed a concern for the price return characteristics of the carbon market. The operation of the carbon market has also been condemned by critics on issues such as poor verification, compliance and permit allocation standards, government intervention and inadequate market regulation, lack of market transparency, market manipulation, price instability, and market illiquidity (Egenhoffer 2007; Taylor 2007; Willis & Fitz-Gerald 2007).

It is possible that policy governing the carbon market has inhibited market growth, confined the flow of information, and led to the materialisation of price return predictability in the carbon market. Under such circumstances, quoted prices become less reliable or "efficient". Furthermore, without efficient pricing mechanisms or signals, markets simply cannot serve their purpose as effective resource allocators. If this is the case, it is possible the carbon market may be inefficient or even fail – an outcome that may have unfavourable long-term environmental, social and economic consequences. The uncertainty surrounding the informational efficiency status of the carbon market therefore deserves greater academic scrutiny.

The aim of this paper is to investigate the informational or "weak-form" efficiency of the European carbon market over crisis periods. The theoretical lens is the weak-form efficient market hypothesis (EMH). A time-series approach is employed using 1,035 daily spot price data observations from Phase II (2008-2012) of the EU ETS, and random walk hypothesis (RWH) procedures such as unit root, serial correlation coefficient, runs and variance ratio tests are carried out. Trading rule profitability tests are also employed. To establish the evolution of weak-form efficiency, the time period under investigation is further divided into two distinct crisis periods, namely the GFC period and ESDC period. The remainder of this paper is organised as follows: Section 2 contains a review of the literature. Section 3 outlines the data and methodology required to carry out the analysis. Empirical results are presented in Section 4. The paper is concluded in Section 5.

2 Literature review

In the context of financial markets, randomness and informational efficiency are intrinsically related. The analogy of the problem for locating a "drunkard" abandoned in the centre of a large field was raised by Pearson (1905) in the early twentieth century. If the drunkard stumbles in an erratic manner, he or she is probably going to end up closer to where they had been left than to any other point on the field. In finance (and other related disciplines), this analogy has been applied to price series whose successive returns are unpredictable or "random" (Dimson & Mussavian 1998), known as the RWH. With earlier studies (Bachelier 1900; Cootner 1964; Cowles & Jones 1937; Kendall & Hill 1953; Working 1934) clearly supporting the RWH, Fama's (1965) research on stock price behaviour in developed markets confirmed the hypothesis. The conclusion reached by Fama (1965) was that future security prices are no more predictable than a series of randomly calculated numbers, demonstrating that the past cannot be used to make meaningful predictions of the future. With a more informed understanding of price formation because of this research, the

RWH came to be seen as the empirical foundation for examining informational efficiency or the EMH (Dimson & Mussavian 1998).

Fama's (1970, 1991, 1998) EMH affirms that financial markets are efficient because prices incorporate <u>all</u> available information, and change instantaneously to reflect any new information. Therefore market participants cannot consistently outperform the market by using homogeneous information, and capital market performance can only be matched in a passive "buy-and-hold" portfolio that is completely reflective of the market itself. Fama also hypothesised classifications of market efficiency according to three different information sets available to market participants. The three sub-sets of the hypothesis are: (i) weak-form efficiency (historical information); (ii) semi-strong form efficiency (historical and public information); and (iii) strong-form efficiency (historical, public and private information).

The jury, however, is still out on whether markets are actually considered efficient. Providing reinterpretations of his work in the light of subsequent research (Lo & MacKinlay 1988) refuting the EMH, Fama (1991, 1998) defends his work on the basis that inefficiencies or "return predictability" discovered in markets are "one-off" anomalies in the data that cannot be repeated to obtain above average profits over the long-run (particularly after risk and transaction costs are taken into consideration). Further, whether statistical evidence of market anomalies actually indicates informational inefficiency still remains a point of controversy in the literature. Even Fama (1998) concedes that much work remains to be done in this area.

Empirical evidence indicates that developed markets, with some variation, exhibit informational efficiency (Smith 2007). Past prices do not predict future returns, and asset prices adjust quickly to the release of new information. But what about emerging markets? Since it is generally believed that developed markets are more efficient and less volatile than less developed and emerging markets, naturally the question arises whether a new market becomes more efficient as it evolves (Gu & Finnerty 2002). Consequently, the efficiency status of emerging markets in the weak-form sense is of particular interest. Weak-form market efficiency is dependent upon conditions such as sound accounting and market regulations, the organisation of markets affecting information transmission, rigid information disclosure requirements, low transaction costs, and high volume trading. Low volume and/or infrequent trading in emerging markets make it difficult for traders to quickly react to new information, allowing large traders to substantially influence prices (Barnes 1986). In many cases, emerging market trading volume/activity is considerably lower than more developed

markets, thus hampering price-information transmission. El-Erian & Kumar (1995) and Antoniou & Ergul (1997) argue that low volume or "thin" trading introduces bias in observed returns and may actually contribute to weak-form inefficiency in emerging markets.

The less-developed nature of emerging markets, alleged infrequent and thin trading during certain periods, and the problems related to information disclosure and transmission have all been suggested by Bailey (1994), Gilmore & McManus (2003), and Worthington & Higgs (2004) as potential reasons for the somewhat less-efficient nature of emerging markets. Observations of occasional market run-ups followed by run-downs, and long-standing perceptions of general instability, have resulted in the characterisation of emerging market price patterns as highly volatile, and thus, not appropriate for adequate resource allocation (Errunza 1997). Notwithstanding this evidence, Darrat & Zhong (2000), Laurence et al. (1997), and Smith & Ryoo (2003) have indicated that large price volatility in emerging markets has, at times, translated to predictable return behaviour or weak-form inefficiency. Similarly, Harvey (1993, 1995) finds that emerging market returns are more predictable than developed market returns and are potentially unstable, concluding that predictability could indeed be influenced by market inefficiencies.

It is clear from the literature (Guidi et al. 2011; Gupta & Basu 2007) that a plethora of empirical work has been undertaken to challenge the weak-form EMH in emerging markets. However, modest academic attention has been paid to the emerging carbon market, despite being a major policy response to what is believed to be one of the most significant global environmental challenges humankind has ever encountered. The EU established the first multi-country, multi-sector cap-and-trade carbon trading scheme (the EU ETS) on 1 January 2005. The significance of this scheme is that the EU economy is the only economy to be constrained by a mandatory carbon trading mechanism (Taberner et al. 2005).

The EU ETS is a market-based mechanism whereby companies operating under the scheme can fluently trade carbon emissions. This forms an alternative to imposing absolute emission limits on individual companies, allowing for a more flexible determination on how and where emissions are reduced (Alberola et al. 2008). The EU ETS operates by determining a price on carbon emissions, placing a value on the mitigation of such emissions, and promoting trade of a limited number of carbon allowances (World Bank 2008), called European Union Allowances (EUAs). Under this mandatory "cap-and-trade" carbon trading scheme, the number of carbon allowances is based on a maximum quantity of emissions that may be discharged over a fixed time period, set by the regulator. The allowances represent a

cap on participants' emissions. Participants who cannot keep their emissions under their cap can fulfil their scheme obligations by purchasing allowances from participants who have been able to reduce their emissions.

Whether the carbon market can be considered informationally efficient remains a moot point. Do carbon prices contain *all* available information? Are carbon price signals allowing the efficient allocation of resources throughout the carbon economy? These questions of market efficiency are of upmost importance to carbon stakeholders for two primary reasons: (i) the aim of carbon trading schemes such as the EU ETS is to regulate polluting companies via economically efficient climate change policy - a policy approach which assumes that the market is *prima facie* "weak-form efficient" (Abeysekera 2001); and (ii) an efficient carbon market, or otherwise, will shape policy, influence regulation, drive investment in clean or "green" technologies and promote emissions abatement (Albrecht et al. 2006).

Following the establishment of the EU ETS, policy makers have been greatly concerned about its operational efficiency (Chevallier 2011). A notable feature of the performance of the EU ETS since inception has been the volatility of prices for EUAs. This price volatility could be attributable to (i) a decrease in industrial production, energy demand and market confidence due to unforeseen market events (e.g. GFC and ESDC); (ii) an increase in funding needs of companies; (iii) energy prices; (iv) weather patterns; and/or (v) the implementation of policy measures, regulatory changes and government intervention (e.g. yearly compliance events and growing uncertainties in post-Kyoto international agreements) (Chevallier 2011; Gronwald et al. 2011; Koch 2011; Maydybura & Andrew 2011). The Phase I over-allocation of EUAs has also been an ongoing contributor to carbon market volatility since the resultant price crash (Chevallier 2011). All of these underlying drivers provide the impetus to sell emissions allowances, and as such, can promote poor price signals for emissions abatement (Silverstein 2010). Further, large price volatility is problematic in the efficient functioning of the EU ETS because it increases actors' uncertainty and potentially discourages long-term investment into environmentally sound technologies (Borghesi 2010). Given these constraints, it is questionable whether the EU ETS meets the assumptions of an informationally efficient market.

The uncertainty surrounding the efficiency status of the carbon market has prompted empirical investigations. Some studies have discovered short and long-run dynamic relationships in the European carbon market, suggesting joint price discovery is occurring between spot and forward prices (Alberola 2006; Benz & Hengelbrock 2008; Boutaba 2009;

Chevallier 2010; Milunovich & Joyeux 2007; Uhrig-Homburg & Wagner 2009). These findings suggest that the carbon market is already liquid, transparent, useful for investment, hedging and risk mitigation purposes, and displaying a reasonable degree of informational efficiency.

Other studies have specifically explored the weak-form efficiency status of the EU ETS. The results generally indicate that Phase I (2005-2007) price patterns are non-random (Lu & Wang 2010; Montagnoli & de Vries 2010; Charles et al. 2011; Daskalakis & Markellos 2008; Feng et al. 2011). The price return predictabilities found suggest that abnormally large returns could have been derived through active trading. Indeed, Daskalakis & Markellos (2008) confirmed that, based on 2005-2006 spot and forward European carbon returns, basic technical trading strategies could have been employed to generate substantial risk-adjusted profits. Feng et al. (2011) also show that the Phase I carbon price displays evidence of short-term memory and is mildly chaotic. Lu & Wang (2010) found that the latter half of Phase I allowances had considerably less robust rejection against the RWH compared to other periods. Such a finding could be attributable to the EU ETS allowance over-allocation announcement on 26 April 2006 and subsequent policy responses. Results related to Phase II show signs that the European carbon market may be weak-form efficient (Lu & Wang 2010; Montagnoli & de Vries 2010; Charles et al. 2011). Montagnoli & de Vries (2010) find signs of random walk price behaviour in Phase II and Charles et al. (2011) find that spot and forward price changes in Phase II are random. Lu & Wang (2010) also find that Phase II allowances display weaker rejection against the RWH than in Phase I.

The general conclusion from this research is that the European carbon market appears to be demonstrating greater levels of weak-form efficiency as it develops. However, the limited data samples employed in carbon market efficiency studies thus far (i.e. Phase I and up to 2010 in Phase II) limits the conclusions that can be drawn, particularly in light of extreme volatility displayed in financial markets due to the GFC and ESDC and ongoing climate change policy uncertainty. It is therefore appropriate to empirically examine the weak-form efficiency status of the Phase II EU ETS for a longer time period.

3 Data & Methodology

3.1 Data

In this study, we employ 1,035 daily closing spot Phase II[4] EUA price and volume data observations from 2008- 2012. The sample is further divided into two sub-samples covering *Period 1* (25 February 2008 to 12 February 2010 – 515 observations) and *Period 2* (15 February 2010 to 10 February 2012 – 520 observations). The price variable under investigation is categorised as *EUAS*. Daily prices are utilised as intra-daily, weekly and monthly data were unavailable at the time of testing. Forward EUAs are omitted from the analysis because the literature (Alberola 2006; Benz & Hengelbrock 2008; Boutaba 2009; Chevallier 2010; Milunovich & Joyeux 2007; Uhrig-Homburg & Wagner 2009) statistically confirms that EU ETS forward markets are already operating as efficient unbiased estimators of the future spot price. If efficient price formation is occurring between spot and forward carbon markets then it is only necessary to include the spot market in Phase II weak-form efficiency analyses.

Monthly 10-year German government bond yields are considered to be the most appropriate risk-free rate (*RFR*) reference, and are averaged across the periods examined. *EUAS* price and volume data are collected from "BlueNext[5]", while *RFR* data are obtained from the ECB. Log returns of the price series are derived using the continuously compounded formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{1}$$

where *Pt* is the price series at time *t*, *ln* is the natural logarithm, and *Rt* represents the log return series. Note: *Rt = ln(Pt) – ln(Pt-1) = ΔlnPt*. The statistical software used to analyse this data is EViews 7.2.

3.2 Unit root tests

To test for mean reversion, it is appropriate to consider unit root tests. Most financial time-series have trends implying that the stationarity assumption (that the underlying time series process has a constant mean or does not follow a random walk) is violated (Elam &

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[4] Phase II of the EU ETS runs from February 2008 to December 2012.

[5] BlueNext is a European environmental trading exchange and was founded by NYSE EuroNext and Caisse des Depots in December 2007. Spot and derivative products (including EUAs) are traded on the exchange. An historical price database is freely available and can be accessed at www.bluenext.eu/statistics/downloads.php.

Dixon 1988). The augmented Dickey & Fuller (ADF) (1981) test forms a parametric correction for higher-order correlation by assuming that the y series follows an $AR(\rho)$ process and including ρ lagged difference terms of the dependent variable y to the right-hand side of the test regression:

$$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + ... + \beta_\rho \Delta y_{t-\rho} + v_t. \tag{2}$$

The Phillips & Perron (PP) (1988) unit root test is also considered. The test is a nonparametric method for controlling serial correlation when determining whether a price series contains a unit root. The PP test is based on the statistic:

$$t_\alpha = \hat{t}_\alpha \left(\frac{y_0}{f_0}\right)^{\frac{1}{2}} - \frac{T(f_0 - y_0)(se(\alpha(\hat{\alpha}))}{2f_0^{\frac{1}{2}}s}, \tag{3}$$

where $\hat{\alpha}$ is the estimate, and t_α the t-ratio of α, $se(\hat{\alpha})$ is coefficient standard error, and s is the standard error of the test regression. y_0 is a consistent estimate of the error variance (calculated as $(T-k)s^2/T$, where k is the number of regressors), and f_0 is an estimator of the residual spectrum at frequency zero.

3.3 Serial correlation coefficient tests

A serial correlation coefficient is estimated from two observations of the same time-series at different dates. A statistically significant positive coefficient indicates that a trend exists in prices, whereas a statistically significant negative coefficient confirms the existence of a reversal in prices. Both the significant trend and reversal of prices can be used to help predict price return movement. Furthermore, this test of the random walk may be based on the serial correlation coefficients themselves or more powerful tests may be constructed from the sum of squared serial correlations (i.e. the Ljung & Box (1978) test). The model for the individual serial correlations coefficient of series Y at lag k is:

$$\tau_k = \frac{\sum_{t=k+1}^{T}((Y_t - \overline{Y})(Y_{t-k} - \overline{Y}_{t-k}))/(T-K)}{\sum_{t=1}^{T}(Y_t - \overline{Y})^2/T}, \tag{4}$$

where $\overline{Y}$ is the sample mean of Y and is the correlation coefficient for values of the series k periods apart. If τ_k is non-zero, it indicates that the series is serially correlated. If τ_k falls

geometrically with increasing lags, it suggests that the series obeys a low-order AR process. If τ_k reduces to zero after a small number of lags, this infers that the series obey a low-order moving average (MA) process.

To check the joint hypothesis that all the serial correlation coefficients τ_k are simultaneously equal to zero, the Ljung & Box (LB) (1978) Q-statistic is utilised. The LB Q-statistic at lag k tests for no autocorrelation up to order k and is computed as:

$$Q_{LB} = T(T+2)\sum_{j=1}^{k}\frac{\tau^2_{j}}{T-J},$$ (5)

where τ_j is the j-th autocorrelation, T is the number of observations, and k is the maximum lag length.

3.4 Runs tests

The non-parametric runs test is created to establish whether the changes between observations are random or 'non-random'. A 'run' is classified as series of successive observations with the same signs: for instance, '+' symbolises a positive return, '-' represents a negative return, and '0' stands for a zero or unchanged return. The runs test presumes that if the price changes are random, the actual number of runs should approximately equal the expected number of runs. Consequently, too many or too few actual runs are inconsistent with randomness. Wallis & Roberts (1956) illustrate the expected number of runs (M), and the standard error of runs (S_M) of the runs test:

$$M = \frac{t(t-1) - \sum_{i=1}^{3}\eta^2_i}{t}$$ (6)

$$S_M = \left\{\frac{[\sum_{i=1}^{3}\eta^2_i\left\langle\sum_{i=1}^{3}\eta^2_i + t(t+1)\right\rangle - 2t\sum_{i=1}^{3}\eta^3_i - t^3]}{t^2(t-1)}\right\}^{1/2},$$ (7)

where t signifies the number of observations, $i = 1, 2$ and 3 denotes the signs of plus, minus, and no change respectively, and η_i represents the total numbers of changes of each type of signs. However, only positive and negative returns changes, not unchanged returns, are considered in this testing (Geary 1970; Mood 1940). The standard normal statistic in the runs test of the actual number of runs (A_c) being equal to the expected number of runs (M) is:

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$$z = \frac{A_c - M \pm (\frac{1}{2})}{S_M} \quad \overset{a}{\sim} \quad t(0,1),$$ (8)

where ½ is the correction factor for continuity adjustment, in which the sign of the continuity adjustment is positive if $A_c \leq M$, and negative if $A_c \geq M$ (Wallis & Roberts 1956).

3.5 Variance ratio tests

The Lo & MacKinlay (LOMAC) (1988) variance ratio test compares variances of differences of returns calculated over different intervals in order to establish the predictability of asset prices. The basis of the test is that the variance estimated from q-period returns should be q times as large as the variance approximated from one-period returns. LOMAC construct two variance ratio test statistics for random walk properties. Firstly, an assumption is made that the ε_t are i.i.d Gaussian with variance σ^2. This assumption is referred to as the i.i.d or "homoskedastic" hypothesis. Alternatively, the i.i.d assumption can be weakened to allow for general forms of heteroskedasticity and dependence. This assumption is termed the martingale difference sequence (m.d.s) or "heteroskedastic" hypothesis. Estimators for the mean of first difference and the scaled variance of the q-th difference are defined as:

$$\hat{\mu} = \frac{1}{T} \sum_{t=1}^{T} (Y_t - Y_{t-1})$$ (9)

$$\hat{\sigma}^2(q) = \frac{1}{Tq} \sum_{t=1}^{T} (Y_t - Y_{t-q} - q\hat{\mu})^2,$$ (10)

where the corresponding variance ratio is:

$$VR(q) = \hat{\sigma}^2(q) / \hat{\sigma}^2(1).$$ (11)

A variance ratio of less than one implies that price returns of short intervals tend toward mean reversion over a longer interval. Conversely, a variance ratio exceeding one implies that price returns of short intervals are inclined to trend over a longer interval. The variance estimators may also be adjusted for bias by replacing T in Equations (9) and (10) with $(T - q + 1)$ in the no-drift case, or with $(T - q + 1)(1 - q/T)$ in the drift case. The variance ratio z-statistic:

$$z(q) = (VR(q) - 1) \cdot [\hat{a}^2(q)]^{-\frac{1}{2}},$$ (12)

is asymptotically $N(0,1)$, where $\hat{a}^2(q)$ is the appropriate choice of estimator. Under the *i.i.d* hypothesis the estimator is:

$$\hat{a}^2(q) = \frac{2(2q-1)(q-1)}{3qT}, \tag{13}$$

while under the *m.d.s* assumption the kernel estimator is:

$$\hat{a}^2(q) = \sum_{j=1}^{q-1}\left(\frac{2(q-j)}{q}\right)^2 \cdot \hat{\delta}_j, \tag{14}$$

where,

$$\hat{\delta}_j = \left\{\sum_{t=j+1}^{T}(y_{t-j} - \hat{\mu})^2(y_t - \hat{\mu})^2\right\} \Big/ \left\{\sum_{t=j+1}^{T}(y_{t-j} - \hat{\mu})^2\right\}^2. \tag{15}$$

Since the variance ratio restriction holds for every $q > 1$, it is appropriate to evaluate the *z*-statistic at several selected values of q. Chow & Denning (CHODE) (1993) propose a joint *z*-statistic that examines the maximum absolute value of a set of multiple variance ratio *z*-statistics. The *p*-value for the CHODE joint maximum *z*-statistic using m variance ratio *z*-statistics is bounded by the probability for the Studentized Maximum Modulus (SMM) distribution with parameter m and T degrees-of-freedom. This bound is approximated using the asymptotic $(T = \infty)$ SMM distribution. To provide more robust findings, Wright (2000) modifies the individual and joint variance ratio *z*-statistics using standardised ranks of the increments ΔY_t. Allowing $r(\Delta Y_t)$ to be the rank of the ΔY_t, among all T values, the standardized rank is:

$$r_{1t} = \left(r(\Delta Y_t) - \frac{T+1}{2} \Big/ \sqrt{\frac{(T-1)(T+1)}{12}}\right). \tag{16}$$

Where there are tied ranks, the denominator in r_{1t} is modified by averaging the tie. Under the *i.i.d* null hypothesis, the exact sampling distribution of the test *z*-statistics is approximated using a permutation bootstrap.

3.6 Trading rule profitability tests

Like Daskalakis & Markellos' (2008) study, basic trading rules are applied in an attempt to determine carbon market return profitability and confirm previous random walk testing. If

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the market in question is weak-form efficient then the technical trading rules employed should <u>not</u> generate risk-adjusted profits (net of transaction costs) larger than those of a buy-and-hold (BH) approach (Fama 1970, 1991, 1998). In this paper, 15-day exponential moving averages (EMAs), random walk (RW) predictions, and a buy-and-hold (BH) strategy are examined. The EMA trading rule assumes that a buy/sell signal is produced when the price rises above/falls below a nominated moving average. For example, an investor takes a long/short position every time the price is above/below the 15-day moving average. The RW trading rule states that the price today is the best indicator of the price in the future. Therefore, a buy/sell signal is produced when the price today is above/below the price yesterday. Finally, the BH rule makes the assumption that prices will always rise, so the investor continuously holds a long position throughout the trading period (Daskalakis & Markellos 2008). Note: mean reversion is assumed for the EMA and RW trading rules in this testing only.

Buy-sell signals from the trading rules are used to generate daily profits or losses. The profitability of each rule is determined by calculating the profitability index, profit factor, average daily return and cumulative return (both before and after transactions costs). OLS regressions are further carried out to establish whether trading rule net returns are statistically different to BH net returns. OLS regressions are estimated using the following functional forms:

$$EMA(15) = \alpha + \beta_1 BH + \beta_2 RW + \varepsilon_t \tag{17}$$

$$RW = \alpha + \beta_1 BH + \beta_2 EMA(15) + \varepsilon_t \tag{18}$$

A positive/negative statistically significant *t*-statistic for alpha (α), at either the 5% or 1% significance levels, indicates that the trading rule has outperformed/underperformed the BH approach.

The profitability index is the ratio of winning days over the total number of trading days. The profit factor is calculated as the gross profit from the cumulative winning days divided by the gross loss from the cumulative losing days. It is desirable that a trading strategy has a profit factor larger than one and a profitability index exceeding 50% (Daskalakis & Markellos 2008). In order to establish the risk/reward trade-off for each trading rule, the standard deviation and the Sharpe ratio are also estimated. The standard deviation indicates the total risk of the trading rule. The Sharpe ratio is a measure of the excess return of the

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trading rule over the risk free rate, which in this paper, is assumed to be an average of monthly 10-year German government bond yields (over specified periods) per unit of total risk. Therefore, a low/high Sharpe ratio implies a high/low risk trading strategy.

To carry out the trading rule profitability tests effectively, a few assumptions and limitations of the analysis should be observed. First, due to the data set only consisting daily closing price observations, long or short trading positions are executed at the end of the day. Second, brokerage and other trading costs are referred to as "transaction costs" and equate to one (1) percent per trade (Daskalakis & Markellos 2008; Shambora & Rossiter 2007). For example, transaction costs are incurred every time a buy (long) and sell (short) signal is generated and a new position is taken (including the reversal of the old position). Finally, short sales are not permissible in the EU ETS spot market. However, for the purpose of this investigation, it is assumed that they can be carried out in over-the-counter (OTC) transactions with other EU ETS market participants (Daskalakis & Markellos 2008).

4 Results

The European carbon price series shows a decrease in trading volume from *Period 1* to *Period 2* (see Summary statistics in Figure 1 and Table 1 below). The significant fall in volume in *Period 2* suggests that economic uncertainty due to both the GFC and ESDC may have had a material effect on economic growth and trading activity in general. It also appears that investment and speculation activity in carbon has become less desirable for market participants during the crisis periods. Nominal price return underperformance is also evident across the periods. Large negative annualised returns reveal poor investability, which are more than likely attributable to the ongoing economic crises. Price volatility is also evident in the carbon market, albeit with lower levels of volatility in *Period 2* (which is somewhat surprising given the economic turmoil surrounding the ESDC, but less so when trading volumes are taken into consideration). Carbon investments clearly demonstrate a larger degree of risk during *Period 1*, with market immaturity, climate change policy uncertainty and the GFC all likely drivers of such volatility. The investment characteristics observed are not an unusual phenomenon however. Emerging markets, like carbon, tend to display similar price behaviour during their early stages of growth (Abeysekera 2001).

The ADF and PP unit root null hypotheses are accepted at both the 5% and 1% significance levels for log level price series across all periods examined. Test statistics become less robust from *Period 1* to *Period 2*, which suggest increasing non-stationarity and

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non-mean reverting price behaviour. Moreover, the unit root test findings provide preliminary evidence of random walk activity in the Phase II EU ETS.

[Insert Figure 1 here]

[Insert Table 1 here]

The individual serial correlation coefficient test results show that the European carbon price returns exhibit statistically significant serial correlation coefficients mainly at short-order lag lengths (see serial correlation coefficient test results in Table 2 below). In *Period 1*, serial correlation coefficients are significantly different from zero at the 5% level for lags 1, 2, 18 and 19. In *Period 2*, serial correlation coefficients are significantly different from zero at the 5% level for lags 10 and 19. Across *Combined Periods*, serial correlation coefficients are significantly different from zero at the 5% level for lag 1 and at the 1% level for lag 2. Note: coefficients at larger lag intervals, while significant, may be evidence of white noise in the data and should be treated with caution.

The findings show that the European carbon price series displays a small degree of return predictability in first and second order serial correlation coefficients in *Period 1* and *Combined Periods* but not in *Period 2*. Specifically, there is trend in first order and reversal in second order price returns (as indicated by the significant positive and negative coefficients, respectively). However, it is uncertain whether these correlation coefficients would provide investors with large risk-adjusted returns after trading costs. For instance, the largest correlation coefficient discovered, being 0.110 in *Period 1* "lag 2", only has an R^2 of 1.21%. The disappearance of statistically significant first and second order serial correlation coefficients in *Period 2* could also be considered further evidence of random walk behaviour.

To confirm whether all the serial correlations coefficients between the lags of one and twenty are simultaneously equal to zero, joint LB Q-statistics are investigated. The joint test leads to the rejection of the null hypothesis at the 5% significance level for *Period 1* only. This suggests that correlation coefficients are simultaneously <u>not</u> equal to zero. However, this does not hold for *Period 2* and *Combined Periods,* implying that the European carbon market appears to be following a random walk.

[Insert Table 2 here]

The runs test null hypothesis is rejected at the 5% level for *Period 1* and *Combined Periods* but not for *Period 2* (see nonparametric runs test results in Table 3 below). The

findings indicate that actual runs of first differenced returns are less than their expected runs, and *z*-statistics show trend patterns for *Period 1* and *Combined Periods*. The departure from randomness in one-day returns suggests an element of return predictability in both *Period 1* and *Combined Periods*, albeit with less magnitude in the *Combined Periods*. Again, the lack of price return predictability in *Period 2* supports the previous serial correlation coefficient findings. Overall, the runs tests mostly reject the RWH in the European carbon market.

[Insert Table 3 here]

LOMAC variance ratio findings show that the European carbon price return series rejects the null hypothesis at the 1% significance level in *Period 1* and the 5% significance level in *Combined Periods* (see variance ratio results in Table 4 below). The joint CHODE results reject the null hypothesis at the 5% significance level in *Period 1* only. Conversely, *Period 2* variance ratio results are far less robust. In this period, LOMAC and joint CHODE findings show that European carbon price returns fail to reject the null hypothesis at either the 5% or 1% significance levels. Thus, the LOMAC evidence suggests that European carbon price returns did <u>not</u> initially follow a random walk in *Period 1* but did so in *Period 2* and *Combined Periods*.

WRIGHT results reveal that the European carbon price return series rejects the null hypothesis at the 5% significance level in *Period 1* only. The joint CHODE results do <u>not</u> reject the null hypothesis at either the 5% or 1% significance levels in this period. *Period 2* and *Combined Period* WRIGHT and joint CHODE testing do not provide any evidence of return predictability. In contrast to the LOMAC testing, the more robust WRIGHT findings suggest that European carbon price returns did follow a random walk in *Period 1*. Therefore, the lack of reported return predictability across all periods investigated in the WRIGHT testing is an indication of random walk behaviour and weak-form market efficiency in the European carbon market. However, to confirm the weak-form efficiency status of the Phase II EU ETS, it is necessary to carry out trading rules and compare to a buy-and-hold (BH) approach over the periods in question.

[Insert Table 4 here]

Period 1, *Period 2* and *Combined Period* trading rule profitability findings demonstrate that of the trading rules employed, only the BH approach was able to consistently generate a higher net cumulative return over its counterparts (see trading rule profitability results in Table 5 below). The BH yields the highest net cumulative return, while the RW produces the

lowest net cumulative return. OLS regressions reveal that the EMA (15) trading rule failed to reject the null hypothesis across all periods. This suggests that the EMA (15) trading rule neither statistically under- or outperformed the BH approach. On the other hand, OLS regressions showed that the RW trading rule rejected the null hypothesis at the 1% significance level across all periods. Significant negative t-statistics across all periods examined implies that the RW trading rule statistically underperformed the BH approach. The nominal outperformance of the BH approach over the remaining trading rules also highlights the impact of frequent trading and transaction costs on return performance. Note: EMA (15) and RW comprehensively defeated BH before trading costs were taken into consideration. Similar deductions can be drawn if risk is taken into account. Standard deviations indicate that the variability of the BH approach is the lowest. The Sharpe ratios suggest that the BH approach yielded the highest risk-adjusted return, while the RW trading rule delivered the lowest risk-adjusted return. The application of trading rules shows that large risk-adjusted profits (net of transaction costs) are <u>not</u> possible across all periods under investigation, inferring that the European carbon market is increasingly behaving in a manner which is consistent with the weak-form EMH.

[Insert Table 5 here]

5 Conclusions

This paper has revealed limited evidence of non-random walk behaviour over the Phase II EU ETS. *Period 1* random walk tests support some degree of price return predictability in the European carbon market during the GFC. In contrast, random walk testing in *Period 2* demonstrated non-stationary price return behaviour during the ESDC. As such, return predictabilities became non-existent during this period. Despite the phenomenon of sustained market volatility due to the ESDC and lower EUA trading volumes, it seems that the EU ETS followed a random walk over these periods. This is important for profit seeking investors as it shows that variation in carbon market returns may <u>not</u> be explained by the returns of preceding days, even during global-centric crisis events and periods of extreme market volatility. Arguably, the ability of policy makers to overcome earlier design mishaps (i.e. Phase I EUA over-allocation), learn from past experiences, and create more resilient policies may have contributed to such findings. Moreover, these results add to the growing body of carbon market efficiency literature (Charles et al. 2011; Lu & Wang 2010; Montagnoli & de Vries 2010) that suggest the EU ETS is becoming more efficient over time.

To confirm any reported return predictabilities, along with the weak-form efficiency status of the Phase II EU ETS, trading rules were applied. Across all periods examined, the results showed that after applying simple trading rules (that account for risk and transaction costs), return predictabilities cannot be manipulated to profit above a naïve buy-and-hold strategy in the European carbon market. This finding has ramifications for those who challenge or question the validity of weak-form EMH theory. Overall, it appears that the EU ETS is achieving a greater level of weak-form efficiency. If the EU ETS is becoming more weak-form efficient despite significant economic crisis events, and can continue to do so without being hampered by further policy and regulatory mistakes, the cap-and-trade mechanism may prove to be an effective global climate change policy tool over time. Nevertheless, the promotion of transparent price signals for long-term investment into environmentally friendly technologies and emissions abatement must surely remain the policy focus of such trading schemes.

References

Abeysekera, S.P. (2001). Efficient markets hypothesis and the emerging capital market in Sri Lanka: Evidence from the Colombo stock exchange - a note. *Journal of Business Finance & Accounting,* 28(1-2), 249-261.

Abraham, A. (2007). Is carbon the new asset class? *Infinance,* 121, 37-39.

Alberola, E. (2006). The informational efficiency of the EU ETS: An empirical evaluation on the spot and futures prices. Working Paper, France: University of Paris.

Alberola, E., Chevallier, J., & Chèze, B. (2008). Price drivers and structural breaks in European carbon prices 2005-2007. *Energy Policy,* 36(2), 787-797.

Albrecht, J., Verbeke, T., & De Clercq, M. (2006). Informational efficiency of the U.S. SO_2 permit market. *Environmental Modelling & Software,* 21(10), 1471-1478.

Antoniou, A., & Ergul, N. (1997). Market efficiency, thin trading and non-linear behaviour: Evidence from an emerging market. *European Financial Management,* 3, 175-190.

Bachelier, L. (1900). Theory of speculation, in Cootner, P.H. (1964). The random character of stock market prices. Massachusetts Institute of Technology Press, Cambridge, Massachusetts, U.S.

Bailey, W. (1994). Risk and return on China's new stock markets: Some preliminary evidence. *Pacific-Basin Finance Journal,* 2(2-3), 243-260.

Barnes, P. (1986). Thin trading and stock market efficiency: The case of the Kuala Lumpur stock exchange. *Journal of Business Finance & Accounting,* 13(4), 609-617.

Benz, E.A., & Hengelbrock, J. (2008). Liquidity and price discovery in the European CO_2 futures market: An intraday analysis. Paper presented at the 21st Australasian Finance

and Banking Conference; 16-18 December, The University of New South Wales, Sydney, Australia.

Borghesi, S. (2010). The European emission trading scheme and renewable energy policies: Credible targets for incredible results? Working Paper, Fondazione Eni Enrico Mattei, Italy: University of Siena. Accessed 20 February 2012. Available online: http://www.bepress.com/feem/paper529.

Boutaba, M.A. (2009). Dynamic linkages among European carbon markets. *Economics Bulletin,* 29(2), 499-511.

Box, G.E.P., & Pierce D.A. (1970). Distribution of residual autocorrelations in autoregressive integrated moving average time series models. *Journal of the American Statistical Association,* 65(332), 1509-1526.

Charles, A., Darné, O., & Fouilloux, J. (2011). Testing the martingale difference hypothesis in CO_2 emission allowances. *Economic Modelling,* 28(1-2), 27-35.

Chevallier, J. (2010). A note on cointegrating and vector autoregressive relationships between CO_2 allowances spot and futures prices. *Economics Bulletin,* 30(2), 1564-1584.

Chevallier, J. (2011). Detecting instability in the volatility of carbon prices. *Energy Economics*, 33, 99-110.

Chow, V.K., & Denning, K.D. (1993). A simple multiple variance ratio test. *Journal of Econometrics,* 58(3), 385-401.

Cootner, P.H. (1964). The random character of stock market prices. Massachusetts Institute of Technology Press, Cambridge, Massachusetts, U.S.

Cowles, A.C. 3rd, & Jones, H.E. (1937). Some a posteriori probabilities in stock market action. *Econometrica,* 5(3), 280–294.

Darrat, A.F., & Zhong, M. (2000). On testing the random walk hypothesis: A model-comparison approach. *The Financial Review,* 35(3), 105-124.

Daskalakis, G., & Markellos, R. (2008). Are the European carbon markets efficient? *Review of Futures Markets,* 17(2), 103-128.

Dickey, D.A., & Fuller, W.A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica,* 49(4), 1057-1072.

Dimson, E., & Mussavian, M. (1998). A brief history of market efficiency. *European Financial Management,* 4(1), 91-103.

Egenhoffer, C. (2007). The making of the EU ETS: Status, prospects and implications for business. *European Management Journal,* 25(6), 453-463.

Elam, E., & Dixon, B.L. (1988). Examining the validity of a test of futures market efficiency. *Journal of Futures Markets,* 8(3), 365-372.

El-Erian, M., & Kumar, M.S. (1995). Emerging equity markets in the Middle Eastern countries. *IMF Staff Papers,* 42, 313-343.

Errunza, V.R. (1997). Research on emerging markets: Past, present, and future. *Emerging Markets Quarterly,* 1(3), 5-18.

Fama, E.F. (1965). The behaviour of stock market prices. *Journal of Business,* 38(1), 34-105.

Fama, E.F. (1970). Efficient capital markets: A review of theory and empirical work. *Journal of Finance,* 25(2), 383-417.

Fama, E.F. (1991). Efficient capital markets: II. *Journal of Finance,* 46(5), 1575-1617.

Fama, E.F. (1998). Market efficiency, long-term returns, and behavioural finance. *Journal of Financial Economics,* 49(3), 283-306.

Feng, Z.H., Zou, L.L., & Wei, Y.M. (2011). Carbon price volatility: Evidence from EU ETS, *Applied Energy*, 88, 590-598.

Geary, R.C. (1970). Relative efficiency of count of sign changes for assessing residual autocorrelation in least squares regression. *Biometrika,* 57, 123-127.

Gilmore, C.G., & McManus, G.M. (2003). Random walk and efficiency tests of central European equity markets. *Managerial Finance,* 29(4), 42-61.

Gu, A.Y., & Finnerty, J. (2002). The evolution of market efficiency: 103 years daily data of the Dow. *Review of Quantitative Finance & Accounting,* 18(3), 219-237.

Guidi, F., Gupta, R., & Maheshwari, S. (2011). Weak-form market efficiency and calendar anomalies for Eastern Europe Equity Markets. *Journal of Emerging Market Finance*, 10(3), 337-389.

Gupta, R., & Basu, P.K. (2007). Weak-form efficiency in Indian stock markets. *International Business and Economics Research Journal*, 6(3), 57-64.

Gronwald, M., Ketterer, J., & Trück, S. (2011). The Relationship between Carbon, Commodity and Financial Markets: A Copula Analysis. *The Economic Record*, 87, 105-124.

Harvey, C. (1993). Portfolio investment using emerging markets and conditioning information. Working Paper, World Bank, Washington DC, U.S.

Harvey, C. (1995). Predictable risk and returns in emerging markets. *Review of Financial Studies,* 8(3), 773-816.

Kendall, M.G., & Hill, A.B. (1953). The analysis of economic time-series-part I: Prices. *Journal of the Royal Statistical Society,* 116(1), 11-34.

Klein, R.W., Ma, G., Ulm, E.R., Wang, S., Xiangjing, W., & Zanjani, G. (2009). The financial crisis and lessons for insurers. Report, Society of Actuaries.

Klepsch, C., & Wollmershäuser, T. (2011). Yield spreads on EMU government bonds – How the financial crisis has helped investors to rediscover risk. *Intereconomics*, 3, 169-176.

Koch, N. (2011). Co-movements between carbon, energy and financial markets. Working Paper, Accessed 20 February 2012, Available online: http://ssrn.com/abstract=1975749.

Laurence, M., Cai, F., & Qian, S. (1997). Weak-form efficiency and causality tests in Chinese stock markets. *Multinational Finance Journal,* 1(4), 291-307.

Liebreich, M., Greenwood, C., von Bismarck, M., & Gurung, A. (2009). Green investing: Towards a clean energy infrastructure. Report, World Economic Forum, 1-54.

Ljung, G.M., & Box, G.E.P. (1978). On a measure of lack of fit in time series models. *Biometrika,* 65(2), 297-303.

Lo, A.W., & MacKinlay, C.A. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test. *The Review of Financial Studies,* 1(1), 41-66.

Lu W., & Wang, W. (2010). Weak-form efficiency of European Union emission trading scheme: Evidence from variance ratio tests. *International Journal of Green Economics* 4(2), 183-196.

Maydybura, A., & Andrew, B. (2011). A study of the determinants of emissions unit allowance price in the European union emissions trading scheme. *Australasian Accounting Business & Finance Journal*, 5(4), 123-142.

McNicholas, P., & Windsor, C. (2011). Can the financialized atmosphere be effectively regulated and accounted for? *Accounting, Auditing & Accountability Journal*, 24(8), 1071-1096.

Miclăus, P.G., Lupu, R., Dumitrescu, S.A., & Bobircă, A. (2008). Testing the efficiency of the European carbon futures market using event-study methodology. *International Journal of Energy & Environment,* 2(2), 121-128.

Milunovich, G., & Joyeux, R. (2007). Market efficiency and price discovery in the EU carbon futures market. Discussion Paper, Australia: Division of Economic and Financial Studies, Macquarie University.

Montagnoli, A., & de Vries, F.P. (2010). Carbon trading thickness and market efficiency. *Energy Economics,* 32(6), 1331-1336.

Mood, A.M. (1940). The distribution theory of runs. *The Annals of Mathematical Statistics,* 11(4), 367-392.

Newey, W.K., & West, K.D. (1994). Automatic lag selection in covariance matrix estimation. *The Review of Economic Studies,* 61(4), 631-653.

Pearson, K. (1905). The problem of the random walk. *Nature,* 72(1865), 294.

Phillips, P.C.B., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika* ,75(2), 335-346.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics,* 6(2), 461-464.

Shambora, W.E., & Rossiter, R. (2007). Are there exploitable inefficiencies in the futures market for oil? *Energy Economics,* 29, 18-27.

Silverstein, D.N. (2010). A method to finance a global climate fund with a harmonized carbon tax. *MPRA Paper No. 27121,* Accessed 20 February 2012, Available online: http://mpra.ub.uni-muenchen.de/27121/.

Smith, G. (2007). Random walks in Middle Eastern stock markets. *Applied Financial Economics,* 17(7), 587-596.

Smith, G., & Ryoo, H.J. (2003). Variance ratio tests of the random walk hypothesis for European emerging stock markets. *The European Journal of Finance,* 9(3), 290-300.

Taberner, J., Taubman, A., & Burns, S. (2005). European Union emissions trading scheme. *Australian Environment Review, 20,* 3-5.

Taylor, R. (2007). Catching up with the new carbon cycle. *ECOS,* 138, 12-15.

Uhrig-Homburg, M., & Wagner, M.W. (2009). Futures price dynamics of CO_2 emission certificates - An empirical analysis. *Journal of Derivatives,* 17(2), 73-88.

Wallis, W., & Roberts, H. (1956). Statistics: A New Approach, Glencoe, Illinois: Free Press.

Willis, M., & Fitz-Gerald, L. (2007). Carbon Credits: The New Currency, Accessed 21 April 2008, Available online: http://www.wme.com.au/categories/emissions/feb5_07.php.

Working, H. (1934). A random-difference series for use in the analysis of time series. *Journal of the American Statistical Association,* 29(185), 11-24.

World Bank. (2008). State and Trends of the Carbon Market. World Bank Institute, Washington DC, U.S.

Worthington, A.C., & Higgs, H. (2004). Random walks and market efficiency in European equity markets. *Global Journal of Finance & Economics,* 1(1), 59-78.

Wright, J.H. (2000). Alternative variance-ratio tests using ranks and signs. *Journal of Business and Economic Statistics,* 18(1), 1–9.

Table 1 Summary statistics

EUAS	Period 1	Period 2	Combined Periods
Observations	515	520	1,035
Volume (mil)	1,458.97	281.16	1,740.13
Avg. Daily Volume (mil)	2.83	0.54	1.68
Min. Return (%)	-10.29	-10.38	-10.38
Max. Return (%)	10.55	20.38	20.38
Mean	-0.0009	-0.0019	-0.0014
Annualised Return (%)	-21.63	-47.50	-34.88
Standard Deviation (%)	2.68	2.41	2.55
Skewness	-0.218	0.789	0.216
Kurtosis	4.592	14.397	8.550
JB	58.441**	2,868.012**	1,336.200**
ADF	-1.676	-1.557	-1.563
PP	-1.716	-1.519	-1.684

Notes: * Statistical significance at 5% level. ** Statistical significance at 1% level. JB is Jarque-Bera, ADF is Augmented Dickey-Fuller and PP is Phillips-Perron. ADF lag lengths chosen by Schwarz information criterion (SIC). PP lag lengths chosen by Newey-West bandwidth. PP spectral estimation method is Bartlett-Kernel. Tests include a constant and trend. * Statistical significance at 5% level. ** Statistical significance at 1% level.

Table 2 Serial correlation coefficient tests

| | EUAS | | |
| | | | Combined |
Lag	Period 1	Period 2	Periods
1	0.091*	0.004	0.066*
2	-0.110*	-0.018	-0.084**
3	0.054	0.056	0.055
4	0.079	-0.014	0.051
5	-0.013	-0.022	-0.013
6	-0.035	0.011	-0.021
7	-0.040	-0.044	-0.041
8	0.044	0.032	0.041
9	-0.010	0.057	0.006
10	0.062	-0.092*	0.019
11	-0.027	0.030	-0.013
12	-0.039	0.032	-0.017
13	-0.012	0.037	-0.000
14	0.039	0.021	0.036
15	0.014	0.020	0.018
16	-0.013	0.037	0.003
17	0.058	0.047	0.056
18	0.090*	-0.063	0.043
19	0.086*	-0.109*	0.032
20	-0.015	0.005	-0.009
Q-stat	32.323*	22.671	30.974

Notes: LB *Q*-statistics are computed using twenty lags. * Statistical significance at 5% level. ** Statistical significance at 1% level.

Table 3 Runs tests

EUAS	Act	Exp	Std Error	z-stat
Period 1	232	257.984	11.324	-2.295*
Period 2	254	260.283	11.370	-0.553
Combined Periods	486	517.843	16.065	-1.982*

Notes: The price series are differenced once. 'Act' is actual runs, 'Exp' is expected runs, 'Std' is standard, and z-statistic is (actual runs - expected runs)/standard error of runs. * Statistical significance at 5% level. ** Statistical significance at 1% level.

EUAS	Act	Exp	Std Error	z-stat

Table 4 Variance ratio tests

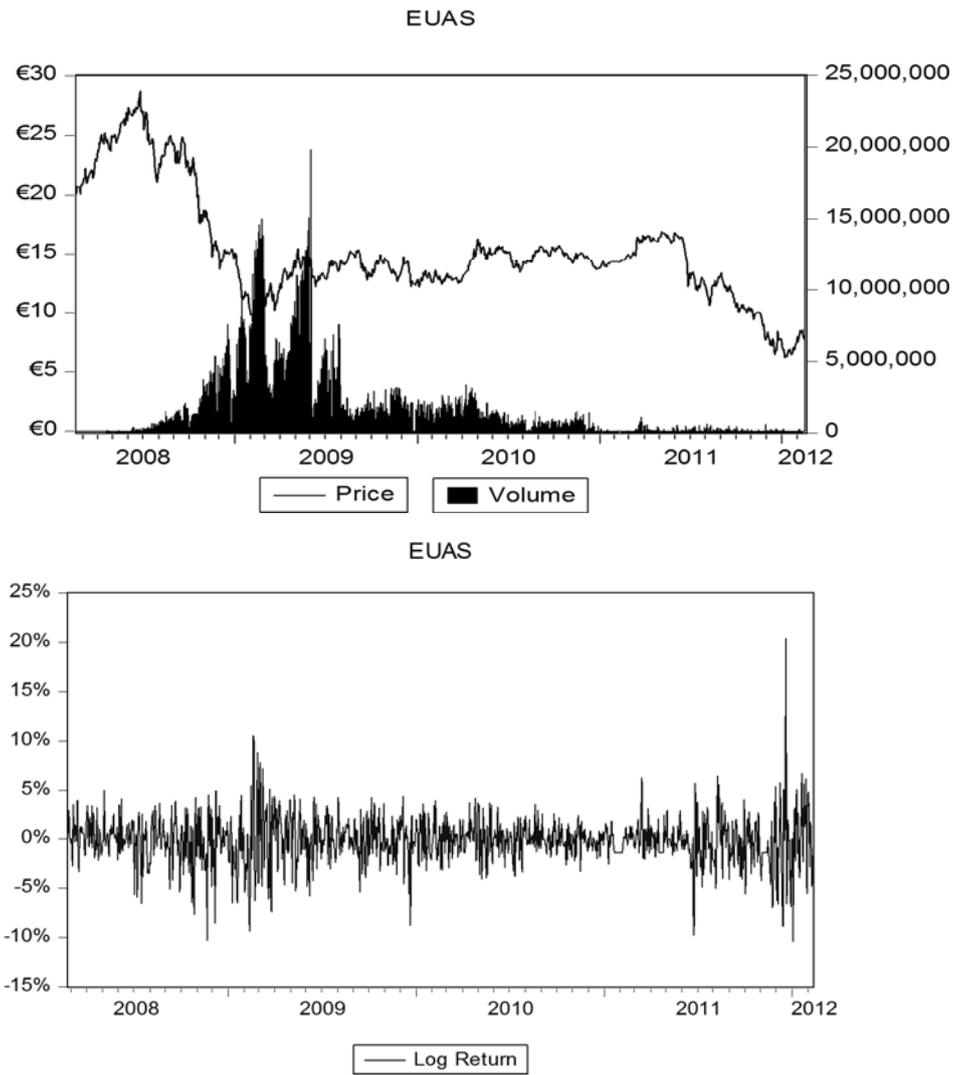| EUAS	Vector	LOMAC VR	LOMAC z-stat	CHODE Joint z-stat	WRIGHT VR	WRIGHT z-stat	CHODE Joint z-stat
Period 1	2	1.119	2.687**	2.687*	1.100	2.165*	2.165
	5	1.110	1.148		1.067	0.696	
	10	1.148	0.992		1.082	0.550	
	30	1.161	0.593		1.119	0.437	
Period 2	2	1.011	0.245		0.980	-0.453	-0.453
	5	0.985	-0.158		0.973	-0.284	
	10	0.946	-0.364		0.978	-0.150	
	30	0.859	-0.521	-0.521	0.950	-0.186	
Combined Periods	2	1.070	2.268*	2.268	1.051	1.633	1.633
	5	1.055	0.810		1.031	0.452	
	10	1.059	0.565		1.043	0.406	
	30	1.028	0.144		1.046	0.238	

Notes: LOMAC and WRIGHT are the individual variance ratio (VR) tests of Lo & MacKinlay (1988) and Wright (2000), respectively. CHODE Joint *z*-statistic is the variance ratio test of Chow & Denning (1993). Vectors match Wright's (2000) study. LOMAC tests are computed with log first differences, drift, no unbiased variance corrections, no heteroskedastic robust standard errors, and asymptotic normal approximations. WRIGHT tests are computed with log first differences, ranks, and permutation bootstrap approximations (with 5,000 replications, a Knuth generator, a seed for the random number generator of 1,000, and averaged tied ranks). CHODE joint *z*-statistics are bound by the individual *z*-statistics and SMM distribution. * Statistical significance at 5% level. ** Statistical significance at 1% level.

Table 5 Trading rule profitability tests in the Phase II EU ETS spot market

EUAS	Period 1			Period 2			Combined Periods		
	EMA (15)	RW	BH	EMA (15)	RW	BH	EMA (15)	RW	BH
Trading Days	501	515	515	506	520	520	1021	1035	1035
# Buy Signals	31	118	1	34	130	1	66	247	1
# Sell Signals	30	117	1	33	129	1	65	246	1
# Winning Days	266	281	262	265	260	264	534	541	527
Cumulative Winning Days (%)	532.906	622.663	498.296	420.086	415.296	392.008	960.081	1038.959	891.631
# Losing Days	235	234	253	241	260	256	487	494	508
Cumulative Losing Days (%)	-587.849	-866.659	-527.026	-504.730	-915.232	-430.776	-1120.679	-1784.218	-955.802
Profitability Index	0.531	0.546	0.509	0.524	0.500	0.508	0.523	0.523	0.509
Profit Factor	0.907	0.718	0.945	0.832	0.454	0.910	0.857	0.582	0.933
Average Daily Return (%)	-0.110	-0.474	-0.056	-0.167	-0.961	-0.075	-0.157	-0.720	-0.062
Gross Cumulative Return (%)	65.057	224.004	-26.730	47.356	16.064	-36.768	99.402	238.741	-62.171
Transaction Costs (%)	-120.000	-468.000	-2.000	-132.000	-516.000	-2.000	-260.000	-984.000	-2.000
Net Cumulative Return (%)	-54.943	-243.996	-28.730	-84.644	-499.936	-38.768	-160.598	-745.259	-64.171
	(-0.281)	(-2.709**)	-	(-1.012)	(-6.239**)	-	(-0.876)	(-6.475**)	-
Standard Deviation (%)	3.006	3.440	2.673	2.751	3.157	2.426	2.879	3.310	2.550
Sharpe Ratio	-19.541	-72.029	-12.166	-31.889	-159.347	-17.252	-56.854	-226.106	-26.374

Notes: EMA, RW and BH refer to the exponential moving average, random walk and buy-and-hold trading rules, respectively. ** Statistical significance at 1% level.

Figure 1 Phase II EU ETS price, volume & volatility

Source: BlueNext