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Research paper

Market timing with moving averages for fossil fuel and renewable energy stocks[☆,☆☆]

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ABSTRACT

The paper examines whether the Moving Average (MA) technique can outperform random market timing in the energy sector, compiled of fossil and renewable energy producers. According to the Capital Asset Pricing Model, random timing is a superior trading strategy in the long run. However, the MA technique may be more successful, if there are predictable stochastic trends in the price series. In the paper, eight representative firms are selected for both fossil and renewable portfolios with actually tradable stocks in order to create two Exchange-Traded Funds (ETF). The paper finds that MA timing outperforms random timing for the ETF of renewable energy companies, but not for the ETF of fossil energy companies.

1. Introduction

Gartley's (1935) seminal idea was to introduce the Moving Average (MA) technique to detect predictable stochastic trends in non-stationary price series. This is to say that investors might benefit from trend chasing. For example, Ilomäki et al. (2018) uses Dow Jones stocks data and finds that it is possible to obtain higher returns with equal volatility by reducing the frequency used in the MA rules. Using the largest sample size in every frequency produces the best results, on average.

This paper aims to investigate, if the MA technique would be beneficial in the energy sector, consisting of fossil and renewable energy producers. Hence, the paper provides useful information for large investors (such as pension funds) operating in the energy sector. Investigation of the energy sector is worthy in the context of market timing, especially because it is nowadays clearly divided into traditional (sunset) and newer (sunrise)

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branches. The relevance of the division is highlighted by the Paris Agreement (2015), which aims to reduce global greenhouse gas (GHG) emissions in order to control the rise of global average temperature.

As the use of fossil energy produces most of GHG, the Agreement aims to switch investments from oil, coal and gas companies to renewable energy firms. Moreover, the EU aims to reduce GHG emissions by 80%–95% in 2050 from 1990 levels by replacing the production of fossil energy by renewable alternatives, such as solar, wind, wave, water, bio-mass, bio-ethanol and hydrogen. The goal is to cover 97% of electricity consumption by renewable energy in 2050 (Energy Roadmap 2050).

The paper is inspired by Chang et al. (2018a), which finds predictable stochastic trends in the European renewable energy stock index, but not in the European fossil fuel stock index. However, since stock indices are not fully tradable, this paper tests whether similar conclusions hold for actually tradable energy stocks. For this purpose, we create two self-made Exchange-Traded Funds (ETF) for both branches as benchmarks, one with equal weights and the other with market-value weights. This issue does not seem to have been considered previously in the literature.

The fossil fuel energy companies have a long history, and their stocks have been publicly traded over the last fifty years. On the other hand, almost all renewable energy companies have been publicly traded only over the last 10–15 years. For this reason, the time span of the study starts from 2004. We consider US investors, but use also foreign (to US investors) renewable stocks, and convert share prices to US dollars. It is assumed that country-specific risk premia are taken into account in the changes in exchange rates. We construct two ETF stock portfolios, with equal weights and with market-value weights, which include eight prominent companies from fossil energy and renewable energy branches. The fossil fuel energy branch includes oil, gas, and coal companies, while the renewable energy branch includes wind, solar, wave, water, bio-mass, bio-ethanol, and fuel cell companies.

The paper proceeds as follows. Section 2 presents the literature review. Section 3 specifies the models and the data. Section 4 presents the empirical analysis. Some discussion and concluding comments are given in Section 5.

2. Literature review

The literature concerning the market development of fossil fuel energy (especially oil and gas) producers' stock prices is extensive. For example, Boyer and Filion (2007) reports that the changes in crude oil prices are positively correlated with Canadian oil stocks. El-Sharif et al. (2005) draws the same conclusion for UK oil stocks, as well as Arouri (2011) within the European oil sector. Elyasiani et al. (2011) notes that an increase in crude oil prices have a positive effect on US oil and gas stock returns. Fang et al. (2018) finds a significantly positive relation between oil price changes and oil stock ratings in China.

The renewable energy branch is an emerging one, and research in this area has grown rapidly. For example, Henriques and Sadorsky (2008) observes that the US renewable energy stocks correlate rather with US technology stocks than with changes in crude oil prices. This suggests that the renewable energy companies have more in common with technology companies than with fossil fuel energy companies. Sadorsky (2012) supports this finding by stating that renewable energy stock returns are negatively correlated with oil price changes, but positively correlated with technology stocks. Kumar et al. (2012) finds that positive changes in oil prices increase the volatility of renewable energy stocks.

However, Reboredo (2015) finds that high oil prices encourage investments to move toward the renewable energy industry, and vice versa. This suggests that the fossil fuel and renewable energy sectors boom and crash hand in hand, and that oil price changes create a significant systematic risk for the renewable energy industry. Best (2017) reports from 1998–2013 data that developed countries have shifted toward renewable energy investments, but developing countries have continued to invest in coal energy. Tietjen et al. (2016) notes that the renewable energy branch has higher capital expenditures, but lower operating expenditures than to the fossil fuel energy branch. For these reasons, the Paris Agreement should thus push the energy industry toward capital-intensive production.

Bohl et al. (2013) identifies the possibility of a speculative bubble among German renewable energy stocks between 2004–2008 and, as a consequence, a furious escape after that. Wen et al. (2014) finds that renewable energy stocks have been more volatile than fossil fuel energy stocks in Chinese stock markets from August 2006 to September 2012. Zhang and Du (2017) finds co-movements in renewable energy stocks and high technology stocks in China, while fossil fuel energy stocks are more stable due to government interventions. Trinks et al. (2018) finds no differences, regardless of whether fossil fuel energy stocks are included or not in US stock portfolios, arguing that fossil fuel divestments make no difference in the performance of the portfolios.

Malkiel (2003) states that, in efficient markets, an investor can produce average returns only by accepting above average risk. Thus, buy and hold should be a superior strategy, when the rest of wealth is invested in the risk-free assets, according to the risk tolerance of an investor. Another strategy is to try to predict when the stock market outperforms or underperforms the risk-free rate in time. The idea is to determine when to buy stocks and when to sell them, and then switch to the risk-free rate. Merton (1981) calls this *market timing*, and notes that, in efficient markets, it does not beat random market timing performance in the returns to volatility context. However, Shiller (2014) argues that evidence of returns predictability in the long run is due to rational investors' time-varying risk premia, or to behavioral biases.

To date, the literature has not found significant evidence about the performance of market timing among mutual fund managers (see, for example, Graham and Harvey, 1996; Daniel et al., 1997; Kacperczyk and Seru, 2007; Kacperczyk et al., 2014). However, Ilomäki et al. (2018) reports that, with lower frequencies in MA calculations, market timing with MA produces superior financial results than random timing, on average. Zhu and Zhou (2009) shows that MA rules add value for a risk averse investor if stock returns are partly predictable. Neely et al. (2014), Ni et al. (2015), and Ilomäki (2018) report that MA rules are useful for risk averse investors, but Hudson et al. (2017) and Yamamoto (2012) note that MA rules are useless in high frequency trading.

Chang et al. (2018b) uses the Dow Jones index and finds that the performance of MA rules improves when the size of the rolling window is expanded, which implies that stock returns are more predictable in the long run. Moreover, Chang et al. (2018a) finds that the MA technique outperforms random timing in the European renewable energy stock index, but not in the European fossil fuel stock index.

3. Models and data

The theoretical model follows Ilomäki et al. (2018) and Chang et al. (2018a,b). The context is an overlapping generation economy with a continuum of young and old investors [0,1]. A young risk-averse investor j invests her initial wealth w_t^j in infinitely lived risky assets $i = 1, 2, 3, \ldots, I$, and in risk-free assets that produce the risk-free rate of return, r^f. A risky asset i pays dividend $D_t{}^i$, and has $x_i{}^s$ outstanding. Assuming exogenous processes throughout, the aggregate dividend is D_t. A young investor j maximizes their utility from old age consumption through optimal allocation of initial resources w_t^j between risky and risk-free assets:

$$\max x_t^j \left(\frac{E_t(P_{t+1} + D_{t+1})}{P_t} - (1 + r^f) \right) - \frac{\nu^j}{2} x^{j^2} \sigma^2$$
$$s.t.$$
$$x_t^j P_t \leq w_t^j$$

where E_t is the expectations operator, P_t is the price of one share of aggregate stock, ν^j is a constant risk-aversion parameter for investor j, σ^2 is the variance of returns for the aggregate stock, and x_t^j is the demand of risky assets for an investor j.

From the first-order condition, optimal demand for the risky assets is given by:

$$x_t^j = \frac{E_t\left((P_{t+1} + D_{t+1})/P_t\right) - (1 + r^f)}{\nu^j \sigma^2}.$$

Suppose that an investor j uses MA rules for market timing and allocates her initial wealth, w_t^j, between risky stocks and risk-free assets according to their MA rule forecast about the return of the portfolio of stocks. Then, the investor invests in the individual stock only if the numerator on the right-hand side is positive, that is if

$$E_t\left((P_{t+1}^i + D_{t+1}^i)/P_t^i\right) > (1 + r^f).$$

This condition states that, for the next investment period, the stock yield is expected to be higher than the risk-free yield. The same procedure is repeated for every stock in the portfolio, with equal weights and with market-value weights for every stock, thereby producing two ETF portfolios for period t + 1. With the assistance of Thomson Reuters Datastream, all international stock prices are converted to US dollars on daily basis before any calculations.

The comparative data are restricted by the fact that the stocks of the renewable energy companies have been publicly traded far more recently than those of the fossil fuel energy companies. Therefore, the time span of the data set is between 1 January 2004 and 6 August 2018, which amounts to 3808 observations in the sample for each stock. In the renewable energy portfolios, there are only three US based companies, because they are the only ones that have been traded over the time span under investigation. As the USA has decided to withdraw from the Paris Agreement, an international portfolio may also reflect better the general considerations of investors about the climate issue.

The branch of fossil fuel energy companies is presented according to equally weighted and market-value weighted portfolios of eight US based, but mostly internationally operating firms. The data are from NYSE provided by Thomson Reuters Datastream. The portfolio includes the four largest (in terms of market capital) oil and gas companies: ExxonMobil, Chevron, ConocoPhillips and Marathon Oil; one coal company: NACCO Industries; and three oil and gas exploration and storage companies: Chesapeake Energy, EOG Resources, and Devon Energy.

The branch of renewable energy companies is presented by equally weighted and market-value weighted portfolios of eight companies. The data are from Thomson Reuters Datastream. The portfolio includes three US based companies: Ballard Power Systems (fuel cell), Brookfield Renewable Energy Partners (solar), and Valero (bioethanol); two German companies: Energiekontor (wind), and Nordex (wind); one company from Australia (wave): Carnegie Wave Energy; one company from Canada: Synex International (water); and one company from Taiwan: Motech Industries (solar).

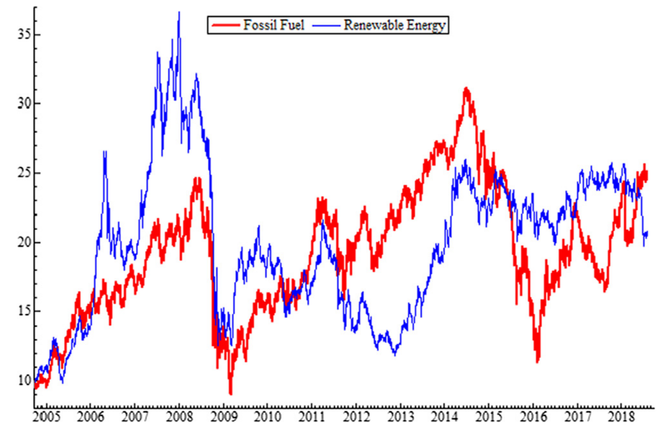

Fig. 1. Market development of fossil and renewable energy ETFs (equally weighted portfolios of buy and hold with dividends) from 7 Oct 2004 to 6 Aug 2018. . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

In the equally weighted portfolios, the weight of each energy source is 25% as the maximum. For the market-value weighted portfolios, we calculate the portfolio performances according to the average market values of the companies. For the fossil energy portfolio, the weights are as follows: ExxonMobil: 0.46, Chevron: 0.23, ConocoPhillips: 0.14, Marathon Oil: 0.03, NACCO Industries: 0.0001, Chesapeake: 0.06, EOG Resources: 0.05 and Devon Energy: 0.03. For the renewable energy portfolio, the weights are as follows: Ballard Power Systems: 0.03, Brookfield Renewable Energy Partners: 0.17, Valero: 0.67, Energiekontor: 0.005, Nordex: 0.06, Carnegie Wave Energy: 0.003, Synex: 0.0006 and Motech Industries: 0.06.

Fig. 1 shows the market development of the two select energy portfolios of equal weights. The fossil fuel energy portfolio includes stocks of Exxon, Chevron, ConocoPhillips, Marathon Oil, NACCO Industries, Chesapeake Energy, EOG Resources, and Devon Energy, while the renewable energy portfolio includes stocks of Energiekontor, Carnegie Wave Energy, Nordex, Brookfield Renewable Energy Partners, Ballard Power Systems, Synex International, Motech Industries, and Valero. In the portfolios, the stocks have equal weights, and dividends are reinvested. Thus, we interpret both portfolios as self-made ETFs.

Fig. 1 shows the equally weighted renewable energy ETF (thin blue line) and the equally weighted fossil energy ETF (thick red line). The figure also shows that \$10,000 invested in the fossil (renewable) energy ETF on 7 October 2004 has grown to \$24,900 (\$20,500) by 6 August 2018. The correlation between the returns ETFs is 0.90. The annualized volatility for the fossil energy ETF returns is 0.31, and for the renewable energy ETF is 0.23, while the correlation between the absolute returns of these series is 0.31.

The augmented Dickey–Fuller (ADF) (see Dickey and Fuller, 1979, 1981) tests confirm that the equally weighted portfolio of fossil (renewable) energy companies has a unit root, The t-value is −2.55 (−2.31), while the critical value is −3.41 at the 5% significance level. Moreover, Dickey and Fuller (1981) suggest a test as to whether there exists a statistically significant deterministic trend in the non-stationary series. The null hypothesis is that a statistically significant deterministic trend does not exist. The test statistic follows the F distribution with m and $n - k$ degrees of freedom:

$$F = \frac{(RSS_R - RSS_U)/m}{RSS_U/(n - k)},$$

where m is the number of restrictions in the restricted regression, n is the number of observations, k is the number of estimated

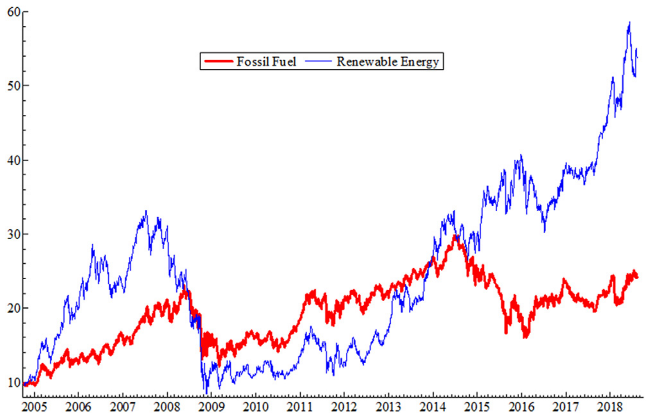

Fig. 2. Market development of fossil and renewable energy ETFs (market-value weighted portfolios of buy and hold with dividends) from 7 Oct 2004 to 6 Aug 2018. . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

parameters in the unrestricted regression, RSS_R is the residual sum of squares in the restricted (null) regression, and RSS_U is the residual sum of squares in the unrestricted (alternative) regression. The test reports that we cannot reject the null hypothesis for the fossil (renewable) energy portfolio with p-value of 0.32 (0.87). Therefore, deterministic trends do not exist. Furthermore, by the Johansen (1995) co-integration test, we cannot reject the null hypothesis of no cointegration in the trace test with p-value of 0.16, so there is no co-integration between the two price series.

Table A.1 in the Appendix reports the ADF and F test results for individual stock price series, revealing that all price series (column 1) are non-stationary I(1) processes, as the relative price change series (log returns) are stationary (column 2). The KPSS test (Kwiatkowski et al., 1992) is not reported here, but the results confirm the I(1) process for prices and I(0) process for returns. Table A.1 also shows that there are statistically significant deterministic trends in some fossil energy stock prices (Chevron, Chesapeake, and EOG), and in some renewable energy stock prices (Energiekontor, Brookfield, and Motech).

Fig. 2 shows the market development of fossil and renewable energy portfolios using market-value weights. The market-value weighted renewable energy ETF (thin blue line) has been more profitable than the market-value weighted fossil energy ETF (thick red line). The figure also shows that \$10,000 invested in the fossil (renewable) energy ETF on 7 October 2004 has grown to \$24,400 (\$53,700) by 6 August 2018. The correlation between the ETF returns is 0.66. The annualized volatility for the fossil energy ETF returns is 0.26, and for the renewable energy ETF is 0.30, while the correlation between the absolute returns of these series is 0.59.

The ADF tests confirm that the market-value weighted portfolio of fossil (renewable) energy companies has a unit root, with t-value −2.69 (−0.81), while the critical value is −3.41 at the 5% significance level. By the F-test, we cannot reject the null hypothesis of no deterministic trends in the fossil (renewable) energy portfolio, with p-value 0.11 (0.19). Therefore, there are no deterministic trends in the price series. Furthermore, the Johansen co-integration test shows that we cannot reject the null hypothesis of no cointegration, with p-value of 0.59. Thus, there is no co-integration between the two price series.

The trading data (daily closing prices) covers about 14 years from 7 October 2004 to 6 August 2018. The risk-free rate data has been collected from the website of the US Department of the Treasury. We use log returns in all performance calculations, and assume 0.1% cost per transaction of a stock, while the transactions of the risk-free asset are assumed costless.

4. Empirical analysis

The rolling window is 200 trading days, so that the sample size of each portfolio of eight companies sums to $3606 * 8 = 28848$. We calculate the empirical results with seven frequencies for the MA rules. When the MA turns lower (higher) than the current daily closing price, we invest the stock (three-month US Treasury Bills) at the closing price of the next trading day. Therefore, the trading rule provides a market timing strategy whereby we invest all wealth either in stocks (separately every stock included in the portfolio), or to the risk-free asset (three-month US Treasury bill), where the MA rule advises on the timing.

The 1st frequency rule is to calculate MA for every trading day; the 2nd frequency takes into account every 5th trading day (proxy for a weekly rule); the 3rd frequency is for every 22nd trading day (proxy for a monthly rule); the 4th rule is for every 44th trading day (proxy for every 2nd month); the 5th rule is for every 66th trading day (proxy for every 3rd month); the 6th rule is for every 88th trading day (proxy for every 4th month); and the 7th rule takes into account every 110th trading day (proxy for every 5th month).

For both portfolios, the MA rules produce $28848 * 9 = 259632$ daily returns for the 1st three frequencies, $28848 * 4 = 115392$ daily returns for the 4th rule, $28848 * 3 = 86544$ daily returns for the 5th rule, $28848 * 2 = 57696$ daily returns for the 6th rule, and 28 848 daily returns for the last rule. At the 1st frequency (every trading day), we calculate daily returns for MA200, MA180, MA160, MA140, MA120, MA100, MA80, MA60, and MA40.

For instance, MA200 is calculated as:

$$\left(\frac{P_{t-1} + P_{t-2} + \cdots + P_{t-200}}{200}\right) = X_{t-1}.$$

At the lowest frequency, where every 110th daily observation is counted, MAC2 is calculated as:

$$\left(\frac{P_{t-1} + P_{t-110}}{2}\right) = X_{t-1}$$

. If $X_{t-1} < P_{t-1}$, we buy the stock at the closing price P_t, and the daily return is:

$$R_{t+1} = \ln\left(\frac{P_{t+1}}{P_t}\right).$$

Table A.2 in Appendix shows that the annualized average buy and hold returns with equal weights are +**0.046** for the fossil fuel energy portfolio, and +**0.033** for the renewable energy portfolio before dividends. For robustness checks, Table A.2 reports the annualized average buy and hold returns **0.040** with market-value weights for the fossil energy portfolio, and **0.094** for the renewable energy portfolio before dividends.

Tables A.2–A.8 together show that the annualized average log returns after transaction costs and before dividends for MA200–MA40 are **0.021** for the equally weighted, and −**0.007** for the market-value weighted fossil energy portfolios; and +**0.032** for the equally weighted, and **0.067** for the market-value weighted renewable energy portfolios. The respective log returns for the weekly MAW40–MAW8 are **0.023** and −**0.007** for fossil energy portfolios; and **0.053** and **0.064** for renewable energy portfolios; for (monthly) MA10–MA2 **0.031** and **0.014** for fossil energy portfolios, and **0.060** and **0.082** for the renewable energy portfolios; for (every other month) MAD5–MAD2 **0.039** and **0.030** for the fossil energy portfolios, and **0.042** and **0.085** for the renewable energy portfolios; for (every 3rd month) MAT4–MAT2 **0.019** and **0.020** for the fossil energy portfolios, and **0.055** and **0.093** for the renewable energy portfolios; for (every 4th month) MAQ3–MAQ2 **0.031** and **0.018** for the fossil energy portfolios, and **0.023** and **0.099** for the renewable energy portfolios; and for (every 5th

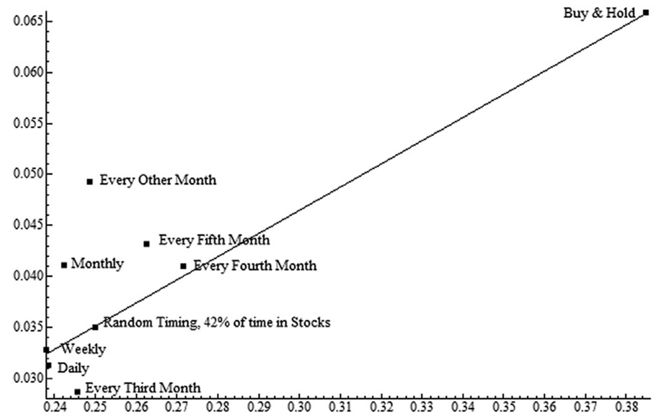

Fig. 3. Returns to volatility ratios in equally weighted fossil energy portfolios with dividends from 7 Oct 2004 to 6 Aug 2018 calculated daily, weekly, monthly, every other month, every 3rd month, every 4th month, and every 5th month, and the theoretical random timing efficient line.

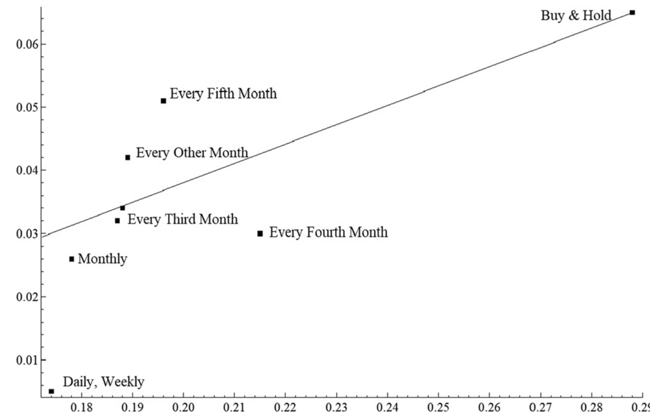

Fig. 4. Returns to volatility ratios in market-value weighted fossil energy portfolios with dividends from 7 Oct 2004 to 6 Aug 2018 calculated daily, weekly, monthly, every 2nd month, every 3rd month, every 4th month, and every 5th month, and the theoretical random timing efficient line.

month) MAC2 **0.033** and **0.039** for the fossil energy portfolios, and **0.034** and **0.083** for the renewable energy portfolios after transaction costs and before dividends.

Table A.9 in Appendix shows that, for the fossil energy, the buy and hold strategy produces the average annualized volatility **0.385** for the equally weighted portfolio, and **0.288** for the market-value weighted portfolio. For renewable energy, the average annualized volatility is **0.503** for the equally weighted portfolio, and **0.394** for the market-value weighted portfolio. However, Tables A.9–A.15 together suggest that the average volatility of the MA rule returns is **0.250** for the equally weighted fossil energy portfolio, and **0.188** for the market-value weighted portfolio thus indicating a **35%** reduction compared to the buy and hold performance in both cases. In the testing period, the average annualized three-month US Treasury bill yield has been +**0.012** with annualized average volatility **0**.

Consider first the volatility of the fossil energy portfolio. Note also that the average annualized dividend yield for a buy and hold portfolio has been +**0.020** for the equally weighted portfolio, and +**0.025** for the market-value weighted portfolio during the study period. The MA rule reduction in the volatility implies that, from 7 October 2004, we invest **42%** of the time in the equally weighted or the market-value weighted portfolio, and **58%** in the risk-free alternative. This is because $1 - \sqrt{0.42} = 0.352$, which implies that, according to the theoretical efficient security line, volatility **0.25** produces **+0.035** returns annually in random market timing procedure, as:

$$0.42 * (0.020 + 0.046) + 0.58 * 0.012 = 0.035$$

with equal weights, and:

$$0.42 * (0.025 + 0.040) + 0.58 * 0.012 = 0.034$$

with market-value weights. Together with these calculations, the buy and hold performances (i.e. returns with dividends +**0.066** and volatility **0.385** for equal weights, and +**0.065** and **0.288** with market-value weights) construct the efficient frontier in the return to volatility space, if market timing is useless. Fig. 3 illustrates the findings with equal weights.

In Fig. 3, the straight line represents the return to volatility ratio of portfolios, where wealth is randomly invested in combinations of the three-month Treasury Bill (risk-free rate) and equally weighted fossil fuel energy portfolio with dividends between 7 October 2004 and 6 August 2018. The black squares represent the average return/volatility points calculated in the 200-40-day rolling window, with the following frequencies: daily (MA200–MA40), weekly (MAW40–MAW8), monthly (MA10–MA2), every other month (MAD5–MAD2), every 3rd month (MAT4–MAT2), every 4th month (MAQ3–MAQ2), and every 5th month (MAC2). If

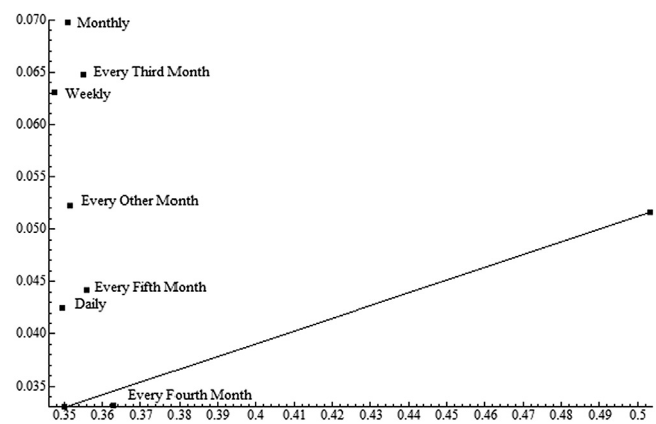

Fig. 5. Returns to volatility ratios in equally weighted renewable energy portfolios with dividends from 7 Oct 2004 to 6 Aug 2018 calculated daily, weekly, monthly, every 2nd month, every 3rd month, every 4th month, and every 5th month, and the theoretical random timing efficient line.

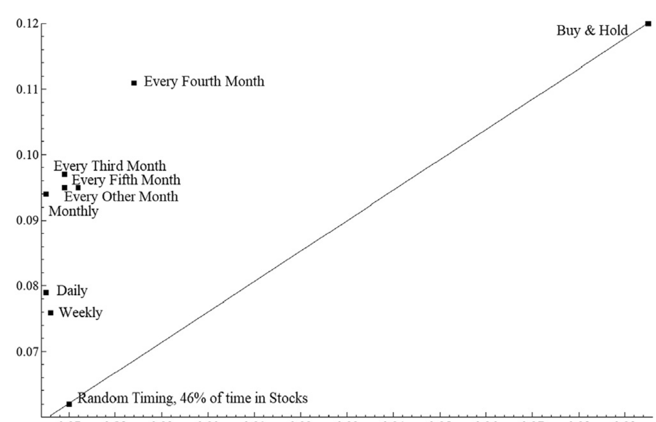

Fig. 6. Returns to volatility ratios in market-value weighted renewable energy portfolios with dividends from 7 Oct 2004 to 6 Aug 2018 calculated daily, weekly, monthly, every 2nd month, every 3rd month, every 4th month, and every 5th month, and the theoretical random timing efficient line.

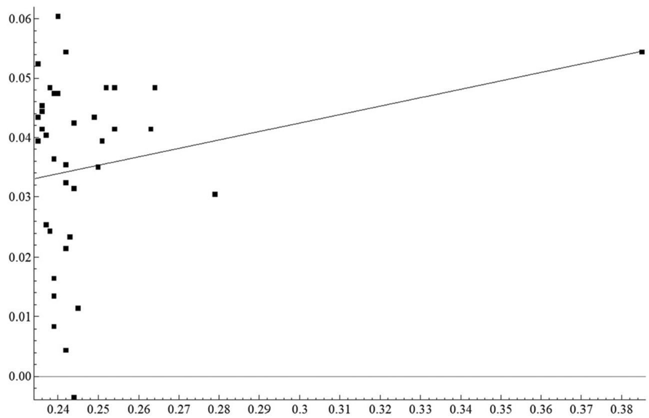

Fig. 7. Returns to volatility ratios in equally weighted fossil energy portfolios with dividends from 7 Oct 2004 to 6 Aug 2018 calculated daily (9 portfolios), weekly (9 portfolios), monthly (9 portfolios), every other month (4 portfolios), every 3rd month (3 portfolios), every 4th month (2 portfolios), and every 5th month (1 portfolio) indicating total 37 returns/volatility dots, and the theoretical random timing efficient line.

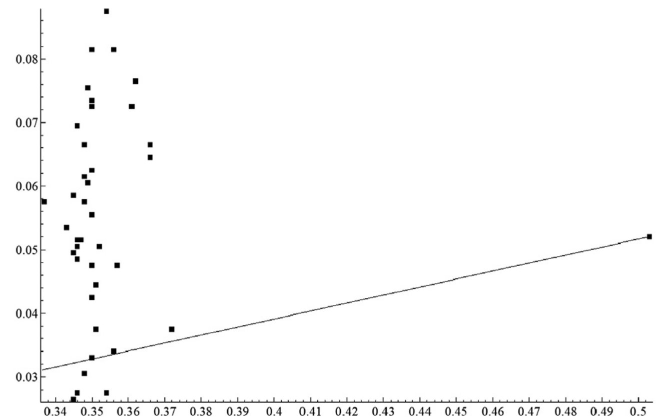

Fig. 9. Returns to volatility ratios in equally weighted renewable energy portfolios with dividends from 7 Oct 2004 to 6 Aug 2018 calculated daily (9 portfolios), weekly (9 portfolios), monthly (9 portfolios), every other month (4 portfolios), every 3rd month (3 portfolios), every 4th month (2 portfolios), and every 5th month (1 portfolio) indicating total 37 returns/volatility dots, and the theoretical random timing efficient line.

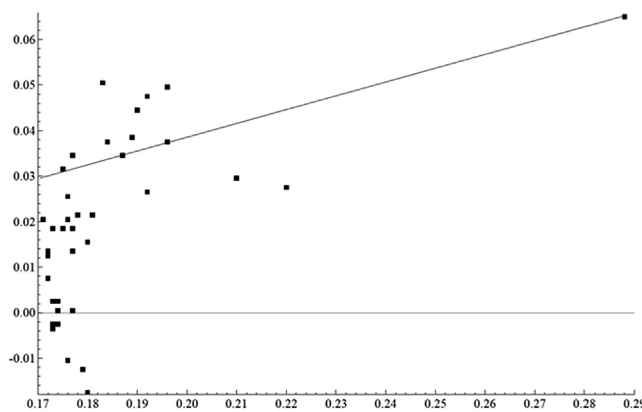

Fig. 8. Returns to volatility ratios in market-value weighted fossil energy portfolios with dividends from 7 Oct 2004 to 6 Aug 2018 calculated daily (9 portfolios), weekly (9 portfolios), monthly (9 portfolios), every other month (4 portfolios), every 3rd month (3 portfolios), every 4th month (2 portfolios), and every 5th month (1 portfolio) indicating total 37 returns/volatility dots, and the theoretical random timing efficient line.

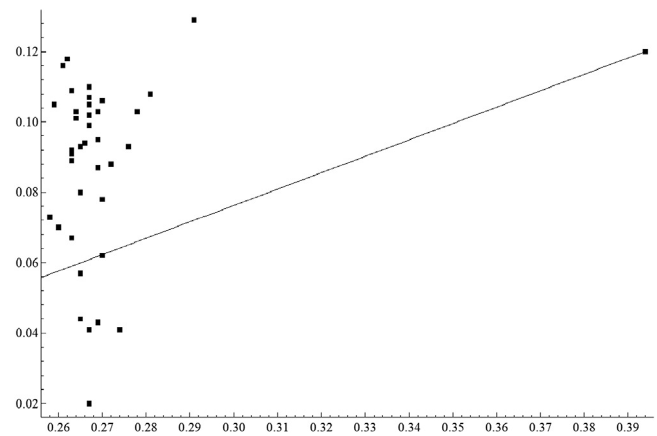

Fig. 10. Returns to volatility ratios in market-value weighted renewable energy portfolios with dividends from 7 Oct 2004 to 6 Aug 2018 calculated daily (9 portfolios), weekly (9 portfolios), monthly (9 portfolios), every other month (4 portfolios), every 3rd month (3 portfolios), every 4th month (2 portfolios), and every 5th month (1 portfolio) indicating total 37 returns/volatility dots, and the theoretical random timing efficient line.

we invest randomly in time 42% in the fossil fuel energy portfolio and 58% in the risk-free rate, it produces the average annualized returns **0.035** with volatility **0.25**.

In the equally weighted portfolio, market timing with the MA rules gives an average performance of +0.038 with dividends and with average volatility **0.25**, implying a **9%** increase from the theoretical random timing returns, on average. However, volatilities vary between 0.235 and 0.279, implying a **19%** increase from the smallest to the largest volatility. Thus, we can conclude that market timing with MA rules has not added value to the fossil fuel energy portfolio over the last 14 years. The Sharpe ratio is calculated as $[r_i - 0.012]/\sigma_i = SR_i$, where r_i is the average annualized returns with dividends and σ_i is the average annualized daily volatility of returns for portfolio *i*. It measures the risk adjusted performance of trading strategy. The Sharpe ratio for random timing is **0.09** and that for MA rules is **0.10**. Thus, these strategies produce practically similar performances.

Fig. 4 presents the results for the market-value weighted portfolio. The straight line represents the return to volatility ratio of portfolios, where wealth is randomly invested in combinations of the three-month Treasury Bill (risk-free rate) and market-value weighted fossil energy portfolio with dividends, between 7 October 2004 and 6 August 2018. The black squares represent the average return/volatility points calculated in the 200-40-day rolling window, with the following frequencies: daily (MA200–MA40), weekly (MAW40–MAW8), monthly (MA10–MA2), every other month (MAD5–MAD2), every 3rd month (MAT4–MAT2), every 4th month (MAQ3–MAQ2), and every 5th month (MAC2).

If we invest randomly over time **42%** in the fossil energy portfolio and **58%** in the risk-free rate, it produces the average annualized returns **0.034**, with volatility **0.19**. Market timing with the MA rules gives an average performance of **0.020** with dividends, with average volatility of **0.19**. Therefore, we can conclude that market timing with MA rules would have reduced the value of the fossil energy portfolio over the last 14 years. The Sharpe ratio for random timing is **0.12**, and for MA rules is **0.04**.

With the renewable energy portfolio, Tables A.9–A.15 together show that the average volatility of the MA rule returns of the equally weighted renewable energy portfolio reduces **29%** (to 0.350), and that of the market-value weighted portfolio reduces **32%** (to 0.270) compared to the buy and hold performance. This to say that half of the time is randomly invested in the risk-free rate and half of the time in the equally weighted portfolio,

Table A.1
Detailed analysis of data.

	ADF test of I(1) process (stochastic trend) in prices, critical value at 5% level is −3.41	ADF test of I(1) process (stochastic trend) in returns, critical value at 5% level is −3.41	p-value for no deterministic trend (5% critical level)
Exxon	−2.82	**−26.23**	0.254
Chevron	−2.96	**−24.97**	**0.020**
ConocoPhillips	−2.44	**−25.02**	0.406
Marathon Oil	−2.09	**−24.64**	0.458
NACCO Industries	−1.27	**−22.60**	0.053
Chesapeake	−2.66	**−24.07**	**0.018**
EOG Resources	−2.90	**−25.28**	**0.005**
Devon Energy	−2.78	**−23.90**	0.091
Ballard	−3.38	**−24.99**	0.459
Nordex	−1.97	**−25.35**	0.649
Energiekontor	−2.64	**−24.63**	**0.010**
Carnegie Wave Energy	−2.61	**−25.93**	0.277
Brookfield	−2.82	**−27.64**	**0.005**
Synex	−2.66	**−29.23**	0.151
Motech	−2.72	**−24.46**	**0.015**
Valero	−0.45	**−24.54**	0.221

Note: The first column reports the test results, where the null hypothesis is that the stock price series is a non-stationary I(1) process, indicating that the respective returns series is a stationary I(0) process. The first column suggests that all price series are non-stationary, so that stochastic trends exist in all price series. The second column confirms that all returns series are stationary. The third column reports the p-values of F-tests for the non-existence of deterministic trends in the price series. The test suggests that if the p-value is low (at the 5% significance level), there exist both stochastic and deterministic trends in the price series. The second row reports that there are three prices series (Chevron, Chesapeake, and EOG) in the fossil energy group, and also three price series (Energiekontor, Brookfield, and Motech) in the renewable energy group, where deterministic trends have also been identified.

Table A.2
Annualized daily returns of MA40–MA200, average annualized returns.

	B&H	MA200	MA180	MA160	MA140	MA120	MA100	MA80	MA60	MA40	
Exxon	0.034	−0.008	−0.010	−0.012	−0.028	−0.032	−0.041	−0.022	−0.045	−0.044	
Chevron	0.058	0.002	0.009	0.003	−0.003	−0.008	−0.005	−0.024	−0.017	−0.029	
ConocoPhillips	0.054	0.016	0.013	−0.003	0.009	0.008	0.018	0.019	0.032	0.032	
Marathon Oil	0.034	0.058	0.063	0.055	0.045	0.055	0.038	0.014	0.056	0.061	
NACCO Industries	0.122	0.073	0.086	0.067	0.105	0.091	0.050	0.002	−0.014	0.040	
Chesapeake	−0.088	0.048	0.041	0.008	0.031	0.002	−0.030	−0.069	−0.075	−0.040	
EOG Resources	0.141	0.081	0.083	0.089	0.099	0.089	0.055	0.034	0.026	−0.022	
Devon Energy	0.011	0.017	0.026	0.045	0.042	0.053	0.049	0.042	0.007	0.025	
Average of equal weight	**0.046**	**0.036**	**0.039**	**0.031**	**0.037**	**0.032**	**0.017**	**0.000**	**−0.004**	**0.003**	**0.021**
Average of market value	**0.040**	**0.008**	**0.008**	**0.003**	**−0.003**	**−0.008**	**−0.014**	**−0.013**	**−0.021**	**−0.023**	**−0.007**
	B&H	MA200	MA180	MA160	MA140	MA120	MA100	MA80	MA60	MA40	
Ballard	−0.068	−0.050	−0.030	−0.030	−0.090	−0.002	0.012	0.032	0.150	0.142	
Nordex	0.020	0.090	0.096	0.130	0.101	0.125	0.121	0.133	0.140	0.148	
Energiekontor	0.181	0.096	0.125	0.153	0.197	0.174	0.113	0.087	0.114	0.158	
Carnegie Wave Energy	−0.017	0.028	0.013	0.037	0.031	0.065	−0.056	0.008	0.042	−0.007	
Brookfield	0.057	−0.014	−0.017	−0.027	−0.039	−0.026	−0.032	−0.037	−0.042	−0.073	
Synex	−0.002	−0.029	−0.035	−0.048	−0.060	−0.104	−0.105	−0.139	−0.148	−0.173	
Motech Industries	−0.037	0.030	0.033	−0.045	−0.008	0.028	0.050	0.046	0.018	0.006	
Valero	0.127	0.116	0.115	0.111	0.096	0.065	0.043	0.035	0.043	0.109	
Average of equal weight	**0.033**	**0.033**	**0.038**	**0.035**	**0.028**	**0.041**	**0.018**	**0.021**	**0.040**	**0.039**	**0.032**
Average of market value	**0.094**	**0.091**	**0.090**	**0.089**	**0.081**	**0.068**	**0.029**	**0.032**	**0.045**	**0.082**	**0.067**

Note: The rows show the average annualized returns before dividends for different rolling windows (from 200 to 40 daily observations) for daily observations. The first column presents the buy and hold returns before dividends. The row **Average** presents the average returns before dividends for the fossil energy companies with equal and market-value weighted portfolios, and for renewable energy companies with equal and market value weighted portfolios. The last column in the **Average** row reports the average of the average MA returns before dividends for both portfolios. The same procedure is repeated when the annualized average volatilities are presented in Table A.9.

while the time shares are **54%** and **46%** in the case of the market-value weighted portfolio. This is because $1-\sqrt{0.50} = 0.293$ and $1-\sqrt{0.46} = 0.322$. Furthermore, the average annualized dividend yield in the equally (market-value) weighted buy and hold portfolio has been +**0.019** (+**0.026**). The theoretical efficient market line implies that:

$$0.50 * (0.019 + 0.034) + 0.50 * 0.012 = 0.033$$

for the equally weighted portfolio, and:

$$0.46 * (0.026 + 0.094) + 0.54 * 0.012 = 0.062$$

for the market-value weighted portfolio. Thus, the performance with the equally weighted portfolio is **0.033** in returns with dividends with volatility **0.35**, while the respective figures with the market-value weighted portfolio are **0.062** and **0.27**.

In Fig. 5, the straight line represents the return to the volatility ratio of renewable energy portfolios, when wealth is randomly invested in combinations of the three-month Treasury Bill (risk-free rate) and equally weighted renewable energy stocks with dividends, between 7 October 2004 and 6 August 2018.

Again, the black squares plot the average return to volatility ratios calculated from 200 to 40 day rolling windows, with the following frequencies: daily (MA200–MA40), every five days (MAW40–MAW8), every 22 days (MA10–MA2), every 44 days (MAD5–MAD2), every 66 days (MAT4–MAT2), every 88 days (MAQ3–MAQ2), and every 110 days (MAC2).

Table A.3
Annualized daily (every 5th trading day) returns of MAW8–MAW40 (W = number of weeks), average annualized returns.

	B&H	MAW40	MAW36	MAW32	MAW28	MAW24	MAW20	MAW16	MAW12	MAW8	
Exxon	0.034	−0.011	−0.015	−0.016	−0.036	−0.040	−0.021	−0.014	−0.020	−0.044	
Chevron	0.058	0.004	0.017	−0.003	−0.011	−0.023	−0.031	−0.031	−0.033	−0.009	
ConocoPhillips	0.054	0.029	0.019	0.007	0.015	0.017	0.032	0.008	0.031	−0.003	
Marathon Oil	0.034	0.038	0.063	0.066	0.075	0.083	0.056	0.058	0.056	0.010	
NACCO Industries	0.122	0.077	0.087	0.068	0.075	0.085	0.066	0.059	0.042	0.061	
Chesapeake	−0.088	0.037	0.030	0.017	0.020	0.018	−0.057	−0.110	−0.048	−0.106	
EOG Resources	0.141	0.098	0.118	0.096	0.083	0.080	0.052	0.055	0.056	0.016	
Devon Energy	0.011	0.004	0.033	0.047	0.040	0.034	0.035	0.038	0.032	−0.023	
Average of equal weight	**0.046**	**0.035**	**0.044**	**0.035**	**0.033**	**0.032**	**0.016**	**0.008**	**0.015**	**−0.012**	**0.023**
Average of market value	**0.040**	**0.008**	**0.010**	**0.002**	**−0.008**	**−0.013**	**−0.010**	**−0.013**	**−0.010**	**−0.028**	**−0.007**
	B&H	MAW40	MAW36	MAW32	MAW28	MAW24	MAW20	MAW16	MAW12	MAW8	
Energiekontor	0.181	0.141	0.168	0.181	0.216	0.208	0.168	0.216	0.195	0.234	
Carnegie Wave Energy	−0.017	0.092	0.091	0.085	0.059	0.055	0.090	0.080	0.128	0.077	
Nordex	0.020	0.134	0.135	0.134	0.138	0.154	0.171	0.170	0.104	0.120	
Brookfield	0.057	0.011	0.018	0.007	−0.003	−0.010	−0.027	−0.033	−0.051	−0.075	
Ballard	−0.068	−0.039	−0.030	−0.054	−0.029	−0.121	−0.091	0.041	0.107	0.005	
Synex	−0.002	−0.038	−0.028	−0.047	−0.055	−0.062	−0.067	−0.078	−0.078	−0.113	
Motech Industries	−0.037	0.018	0.029	−0.042	−0.015	0.023	0.036	0.086	0.075	0.047	
Valero	0.127	0.137	0.124	0.108	0.102	0.107	0.100	0.028	0.003	0.045	
Average of equal weight	**0.033**	**0.057**	**0.063**	**0.046**	**0.052**	**0.044**	**0.048**	**0.064**	**0.060**	**0.042**	**0.053**
Average of market value	**0.094**	**0.104**	**0.097**	**0.080**	**0.077**	**0.079**	**0.075**	**0.031**	**0.008**	**0.029**	**0.064**

Note: The rows show the average annualized returns before dividends for different rolling windows (from 40 to 8 weekly observations) for every 5th trading day. The first column presents the buy and hold returns before dividends. The row **Average** presents the average returns before dividends for the fossil energy companies with equal and market-value weighted portfolios, and for renewable energy companies with equal and market-value weighted portfolios. The last column in the **Average** row reports the average of the average MA returns before dividends for both portfolios. The same procedure is repeated where the annualized average volatilities are presented in Table A.10.

Table A.4
Annualized daily (every 22nd trading day) returns of MA2–MA10, average annualized returns.

	B&H	MA10	MA9	MA8	MA7	MA6	MA5	MA4	MA3	MA2	
Exxon	0.034	0.000	0.000	−0.006	−0.008	−0.002	0.000	−0.002	−0.005	0.003	
Chevron	0.058	0.016	0.023	0.007	−0.005	−0.006	−0.013	−0.008	0.026	0.025	
ConocoPhillips	0.054	0.049	0.051	0.039	0.035	0.046	0.063	0.038	0.030	0.045	
Marathon Oil	0.034	0.097	0.098	0.066	0.059	0.043	0.000	0.022	0.003	0.091	
NACCO Industries	0.122	−0.007	0.010	0.003	0.003	0.016	0.042	0.039	0.045	−0.009	
Chesapeake	−0.088	0.025	0.046	0.017	−0.012	−0.012	−0.017	−0.107	−0.064	0.039	
EOG Resources	0.141	0.112	0.113	0.122	0.105	0.103	0.078	0.087	0.095	0.081	
Devon Energy	0.011	0.031	0.028	0.064	0.048	0.024	0.037	0.036	0.053	0.044	
Average of equal weight	**0.046**	**0.040**	**0.046**	**0.039**	**0.028**	**0.027**	**0.024**	**0.013**	**0.023**	**0.040**	**0.031**
Average of market value	**0.040**	**0.021**	**0.024**	**0.015**	**0.008**	**0.011**	**0.010**	**0.003**	**0.011**	**0.024**	**0.014**
	B&H	MA10	MA9	MA8	MA7	MA6	MA5	MA4	MA3	MA2	
Energiekontor	0.181	0.141	0.168	0.181	0.216	0.208	0.168	0.216	0.195	0.234	
Carnegie Wave Energy	−0.017	0.106	0.086	0.107	0.093	0.077	0.044	0.089	0.040	0.045	
Nordex	0.020	0.142	0.119	0.119	0.104	0.103	0.104	0.061	0.060	0.037	
Brookfield	0.057	0.041	0.031	0.020	0.028	0.026	0.017	0.018	0.014	0.014	
Ballard	−0.068	0.011	0.001	0.024	0.026	−0.033	−0.057	−0.036	0.008	−0.027	
Synex	−0.002	0.019	0.019	0.018	0.006	0.013	0.010	0.000	0.002	−0.020	
Motech Industries	−0.037	0.035	−0.014	−0.056	−0.017	0.010	−0.007	−0.030	−0.054	0.020	
Valero	0.127	0.129	0.092	0.120	0.122	0.128	0.132	0.077	0.074	0.081	
Average of equal weight	**0.033**	**0.078**	**0.063**	**0.067**	**0.072**	**0.066**	**0.051**	**0.049**	**0.042**	**0.048**	**0.060**
Average of market value	**0.094**	**0.106**	**0.076**	**0.091**	**0.095**	**0.098**	**0.098**	**0.058**	**0.055**	**0.061**	**0.082**

Note: The rows show the average annualized returns before dividends for different rolling windows (from 10 to 2 monthly observations) for every 22nd trading day. The first column presents the buy and hold returns before dividends. The row **Average** presents the average returns before dividends for the fossil energy companies with equal and market-value weighted portfolios, and for renewable energy companies with equal and market-value weighted portfolios. The last column in the **Average** row reports the average of the average MA returns before dividends for both portfolios. The same procedure is repeated where the annualized average volatilities are presented in Table A.11.

According to Tables A.8–A.14 in Appendix, average volatility of all MA rule returns is 0.35. Market timing with the MA rules gives average returns of +0.053 with dividends, as compared with the theoretical random timing returns +0.033. The averages +0.053 and 0.35 come from 548 112 daily observations. This indicates a **61%** rise in average annualized returns compared with random market timing, while volatility varies between 0.337 and 0.372, indicating a **10%** increase from the smallest to the largest. Thus, we can conclude that market timing with MA rules has significantly added value to the renewable energy portfolio of a risk averse investor over the last 14 years. The Sharpe ratio for random timing is **0.06** and that for MA rules is **0.12** suggesting that the MA rules produces two times better performance than random timing in the period.

In Fig. 6, the straight line represents the return to the volatility ratio of market-value weighted renewable energy portfolios, when wealth is randomly invested in combinations of the three-month Treasury Bill (risk-free rate) and renewable energy stocks with dividends, between 7 October 2004 and 6 August 2018. The black squares plot the average return to volatility ratios calculated from 200 to 40 day rolling windows, with the following frequencies: daily (MA200–MA40), every five days (MAW40–MAW8), every 22 days (MA10–MA2), every 44 days (MAD5–MAD2), every 66 days (MAT4–MAT2), every 88 days (MAQ3–MAQ2), and every 110 days (MAC2).

Table A.5
Annualized daily (every other month) returns of MAD2–MAD5 (D = every other month, 5, 4, 3, 2, are the numbers of observations in the rolling window), average annualized returns.

	B&H	MAD5	MAD4	MAD3	MAD2	
Exxon	0.034	0.015	0.026	0.010	−0.011	
Chevron	0.058	0.047	0.045	0.047	0.018	
ConocoPhillips	0.054	0.049	0.012	−0.007	0.035	
Marathon Oil	0.034	0.112	0.086	0.016	0.038	
NACCO Industries	0.122	−0.054	−0.081	−0.045	−0.050	
Chesapeake	−0.088	0.083	0.066	0.074	0.058	
EOG Resources	0.141	0.123	0.111	0.158	0.138	
Devon Energy	0.011	0.041	0.054	0.025	0.018	
Average of equal weight	**0.046**	**0.052**	**0.040**	**0.035**	**0.031**	**0.039**
Average of market value	**0.040**	**0.040**	**0.037**	**0.028**	**0.016**	**0.030**
	B&H	MAD5	MAD4	MAD3	MAD2	
Energiekontor	0.181	0.073	0.069	−0.001	0.053	
Carnegie Wave Energy	−0.017	0.080	0.108	0.103	−0.021	
Nordex	0.020	0.096	0.118	0.142	0.009	
Brookfield	0.057	0.046	0.047	0.057	0.066	
Ballard	−0.068	−0.086	−0.080	−0.095	−0.065	
Synex	−0.002	0.038	0.026	0.007	0.005	
Motech Industries	−0.037	0.074	0.055	0.004	0.010	
Valero	0.127	0.102	0.116	0.112	0.081	
Average of equal weight	**0.033**	**0.053**	**0.057**	**0.041**	**0.017**	**0.042**
Average of market value	**0.094**	**0.087**	**0.096**	**0.093**	**0.066**	**0.085**

Note: The rows show the average annualized returns before dividends for different rolling windows (from 5 to 2 observations in every other month) for every 44th trading day. The first column presents the buy and hold returns before dividends. The row **Average** presents the average returns before dividends for the fossil energy companies with equal and market-value weighted portfolios, and for renewable energy companies with equal and market-value weighted portfolios. The last column in the **Average** row reports the average of the average MA returns before dividends for both portfolios. The same procedure is repeated where the annualized average volatilities are presented in Table A.12.

Table A.6
Annualized daily (every 3rd month) returns of MAT2–MAT4 (T = every third month, and 4, 3, 2, are the numbers of observations in the rolling window), average annualized returns.

	B&H	MAT4	MAT3	MAT2	
Exxon	0.034	0.022	0.019	0.009	
Chevron	0.058	0.031	0.053	−0.005	
ConocoPhillips	0.054	0.028	0.005	0.000	
Marathon Oil	0.034	0.043	0.013	−0.047	
NACCO Industries	0.122	0.076	0.079	0.025	
Chesapeake	−0.088	0.003	0.029	0.022	
EOG Resources	0.141	0.095	0.088	0.073	
Devon Energy	0.011	−0.023	−0.025	−0.037	
Average of equal weight	**0.046**	**0.034**	**0.033**	**0.005**	**0.019**
Average of market value	**0.040**	**0.027**	**0.027**	**0.005**	**0.020**
	B&H	MAT4	MAT3	MAT2	
EnergieKontor	0.181	0.044	0.070	0.056	
Carnegie Wave Energy	−0.017	0.036	0.012	0.076	
Nordex	0.020	0.165	0.129	0.020	
Brookfield	0.057	0.036	0.041	0.024	
Ballard	−0.068	0.059	0.033	−0.013	
Synex	−0.002	−0.002	0.005	−0.032	
Motech Industries	−0.037	0.132	0.040	0.048	
Valero	0.127	0.102	0.107	0.126	
Average of equal weight	**0.033**	**0.072**	**0.055**	**0.038**	**0.055**
Average of market value	**0.094**	**0.094**	**0.091**	**0.093**	**0.093**

Note: The rows show the average annualized returns before dividends for different rolling windows (from 4 to 2 observations in every 3rd month) for every 66th trading day. The first column presents the buy and hold returns before dividends. The row **Average** presents the average returns before dividends for the fossil energy companies with equal and market-value weighted portfolios, and for renewable energy companies with equal and market-value weighted portfolios. The last column in the **Average** row reports the average of the average MA returns before dividends for the both portfolios. The same procedure is repeated where the annualized average volatilities are presented in Table A.13.

Table A.7
Annualized daily (every 4th month) returns of MAQ2–MAQ3 (Q = every fourth month, 3, 2, are the numbers of observations in the rolling window), average annualized returns.

	B&H	MAQ3	MAQ2	
Exxon	0.034	0.015	0.017	
Chevron	0.058	0.009	0.020	
ConocoPhillips	0.054	0.017	−0.004	
Marathon Oil	0.034	0.089	0.026	
NACCO Industries	0.122	0.077	0.032	
Chesapeake	−0.088	0.006	−0.013	
EOG Resources	0.141	0.093	0.086	
Devon Energy	0.011	0.013	0.013	
Average of equal weight	**0.046**	**0.040**	**0.022**	**0.031**
Average of market value	**0.040**	**0.019**	**0.017**	**0.018**
	B&H	MAQ3	MAQ2	
Energiekontor	0.181	0.044	0.049	
Carnegie Wave Energy	−0.017	−0.122	−0.064	
Nordex	0.020	0.047	0.059	
Brookfield	0.057	0.055	0.062	
Ballard	−0.068	−0.019	−0.035	
Synex	−0.002	0.031	0.031	
Motech Industries	−0.037	0.009	−0.034	
Valero	0.127	0.101	0.156	
Average of equal weight	**0.033**	**0.018**	**0.028**	**0.023**
Average of market value	**0.094**	**0.081**	**0.117**	**0.099**

Note: The rows show the average annualized returns before dividends for different rolling windows (from 3 to 2 observations in every 4th month) for every 88th trading day. The first column presents the buy and hold returns before dividends. The row **Average** presents the average returns before dividends for the fossil energy companies with equal and market-value weighted portfolios, and for renewable energy companies with equal and market-value weighted portfolios. The last column in the **Average** row reports the average of the average MA returns before dividends for the both portfolios. The same procedure is repeated where the annualized average volatilities are presented in Table A.14.

Table A.8
Annualized daily (every 5th month) returns of MAC2 (C = every fifth month, 2 is the numbers of observations in the rolling window), average annualized returns.

	B&H	MAC2	
Exxon	0.034	0.030	
Chevron	0.058	0.033	
ConocoPhillips	0.054	0.064	
Marathon Oil	0.034	0.081	
NACCO Industries	0.122	−0.072	
Chesapeake	−0.088	−0.016	
EOG Resources	0.141	0.121	
Devon Energy	0.011	0.024	
Average of equal weight	**0.046**	**0.033**	**0.033**
Average of market value	**0.040**	**0.039**	**0.039**
	B&H	MAC2	
Energiekontor	0.181	0.058	
Carnegie Wave Energy	−0.017	0.093	
Nordex	0.020	0.039	
Brookfield	0.057	0.030	
Ballard	−0.068	−0.187	
Synex	−0.002	−0.022	
Motech Industries	−0.037	0.157	
Valero	0.127	0.106	
Average of equal weight	**0.033**	**0.034**	**0.034**
Average of market value	**0.094**	**0.083**	**0.083**

Note: The rows show the average annualized returns before dividends for different rolling windows (only 2 observations in every 5th month) for every 110th trading day. The first column presents the buy and hold returns before dividends. The row **Average** presents the average returns before dividends for the fossil energy companies with equal and market-value weighted portfolios, and for the renewable energy companies with equal and market-value weighted portfolios. The last column in the **Average** row reports the average of the average MA returns before dividends for the both portfolios. The same procedure is repeated where the annualized average volatilities are presented in Table A.15.

According to Tables A.8–A.14 in Appendix, the average volatility of all MA rule returns is **0.27**. Market timing with the MA rules gives average returns of **0.092** with dividends. Compared with the theoretical random timing returns **0.062**, this indicates a **48%** rise in average annualized returns. Volatility varies between 0.258 and 0.291, which indicates a **13%** increase from the smallest to the largest. Therefore, we conclude that market timing with MA rules has significantly added value to the renewable energy portfolio of a risk averse investor over the last 14 years. The Sharpe ratio for random timing is **0.16** and that for MA rules is **0.27**, suggesting that the MA rules produce almost twice as good a performance than random timing for the sample period.

In Figs. 7–10, the returns/volatility measures are plotted for every calculated MA frequency for all the cases examined. The figures show 37 returns/volatility dots and the theoretical random timing efficient line, thereby revealing differences in the performance of MA rules when applied to fossil and renewable energy ETFs.

Comparison of Figs. 7 and 8 shows that, with the equally weighted fossil energy portfolio, there are 14/37 (37%) dots below the theoretical random timing efficient line, and 26/37 (70%) dots below the efficient line with the market-value weighted portfolio. This observation suggests that the MA trading rules perform at least as well as random timing with the equally weighted portfolio, but perform worse than random timing with the market-value weighted portfolio. Therefore, the MA rules do not seem to outperform random timing when applied to fossil energy portfolios, in general.

However, Figs. 9 and 10 tell a different story. They show that there are only 4/37 (11%) dots below the theoretical random timing efficient line in the case of the equally weighted renewable energy portfolio, and 6/37 (16%) dots below the efficient line in the case of the market-value weighted portfolio. This observation suggests quite consistent behavior by the MA trading rules for the renewable energy ETFs, whereby the MA rules seem to generally outperform random timing in both portfolios.

Moreover, the plots display seems very similar to the equally and market-value weighted renewable energy portfolios. It is worth noting that, even though the (buy and hold benchmark) market capital weighted portfolio has shown strong performance from 2012 (see Fig. 2), there are only two more dots below the theoretical random timing efficient line than in the equally weighted portfolio, where the performance of the buy and hold portfolio has been less impressive (see Fig. 1).

5. Concluding remarks

The paper examined the performance of Moving Average (MA) market timing rules in the context of fossil and renewable energy stocks. Note that the MA rules detect positive and negative trends in the price series. Self-constructed Exchange-Traded Funds (ETF) were composed as equally weighted and market-value weighted portfolios. The fossil energy ETF included stocks of oil, gas,

Table A.9
Annualized daily volatility of MA40–MA200, average annualized volatility.

	B&H	MA200	MA180	MA160	MA140	MA120	MA100	MA80	MA60	MA40	
Exxon	0.237	0.141	0.142	0.139	0.142	0.143	0.143	0.144	0.144	0.147	
Chevron	0.259	0.157	0.158	0.156	0.156	0.155	0.156	0.155	0.157	0.163	
ConocoPhillips	0.311	0.193	0.195	0.190	0.189	0.188	0.187	0.187	0.186	0.188	
Marathon Oil	0.418	0.258	0.262	0.258	0.255	0.254	0.249	0.256	0.255	0.255	
NACCO Industries	0.513	0.349	0.349	0.343	0.352	0.356	0.358	0.358	0.353	0.357	
Chesapeake	0.571	0.295	0.304	0.302	0.303	0.307	0.312	0.320	0.333	0.334	
EOG Resources	0.380	0.258	0.262	0.256	0.255	0.255	0.252	0.252	0.264	0.266	
Devon Energy	0.391	0.234	0.239	0.237	0.236	0.240	0.239	0.241	0.243	0.249	
Average of equal weight	**0.385**	**0.236**	**0.239**	**0.235**	**0.236**	**0.237**	**0.237**	**0.239**	**0.242**	**0.245**	**0.238**
Average of market value	**0.288**	**0.173**	**0.175**	**0.172**	**0.172**	**0.173**	**0.173**	**0.174**	**0.176**	**0.179**	**0.174**
	B&H	MA200	MA180	MA160	MA140	MA120	MA100	MA80	MA60	MA40	
Energiekontor	0.491	0.397	0.405	0.396	0.394	0.395	0.385	0.372	0.363	0.362	
Carnegie Wave Energy	0.797	0.573	0.579	0.559	0.564	0.567	0.547	0.561	0.551	0.561	
Nordex	0.598	0.391	0.401	0.399	0.397	0.399	0.397	0.393	0.390	0.380	
Brookfield	0.206	0.156	0.158	0.155	0.154	0.152	0.152	0.153	0.153	0.151	
Ballard	0.726	0.482	0.498	0.496	0.501	0.523	0.511	0.524	0.522	0.522	
Synex	0.323	0.214	0.216	0.207	0.202	0.186	0.183	0.189	0.189	0.195	
Motech Industries	0.483	0.323	0.330	0.328	0.333	0.328	0.328	0.326	0.327	0.331	
Valero	0.403	0.266	0.268	0.263	0.265	0.266	0.269	0.267	0.266	0.268	
Average of equal weight	**0.503**	**0.350**	**0.357**	**0.351**	**0.351**	**0.352**	**0.346**	**0.348**	**0.345**	**0.346**	**0.350**
Average of market value	**0.394**	**0.264**	**0.267**	**0.264**	**0.265**	**0.265**	**0.267**	**0.265**	**0.265**	**0.266**	**0.265**

Table A.10
Annualized daily (every 5th trading day) volatility of MAW8–MAW40 (W = number of weeks), average annualized volatility.

	B&H	MAW40	MAW36	MAW32	MAW28	MAW24	MAW20	MAW16	MAW12	MAW8	
Exxon	0.237	0.142	0.140	0.139	0.144	0.144	0.145	0.142	0.147	0.152	
Chevron	0.259	0.157	0.156	0.157	0.156	0.158	0.158	0.159	0.160	0.160	
ConocoPhillips	0.311	0.192	0.188	0.190	0.190	0.192	0.186	0.185	0.183	0.189	
Marathon Oil	0.418	0.255	0.257	0.257	0.257	0.254	0.253	0.259	0.255	0.259	
NACCO Industries	0.513	0.351	0.347	0.342	0.351	0.353	0.363	0.362	0.356	0.353	
Chesapeake	0.571	0.297	0.301	0.305	0.304	0.307	0.309	0.312	0.333	0.331	
EOG Resources	0.380	0.258	0.256	0.254	0.251	0.249	0.255	0.252	0.264	0.262	
Devon Energy	0.391	0.232	0.233	0.237	0.236	0.238	0.235	0.244	0.248	0.248	
Average of equal weight	**0.385**	**0.235**	**0.235**	**0.235**	**0.236**	**0.237**	**0.238**	**0.239**	**0.243**	**0.244**	**0.238**
Average of market value	**0.288**	**0.173**	**0.171**	**0.172**	**0.174**	**0.174**	**0.174**	**0.173**	**0.177**	**0.180**	**0.174**
	B&H	MAW40	MAW36	MAW32	MAW28	MAW24	MAW20	MAW16	MAW12	MAW8	
Energiekontor	0.491	0.399	0.405	0.396	0.395	0.392	0.390	0.383	0.357	0.363	
Carnegie Wave Energy	0.797	0.570	0.562	0.561	0.554	0.545	0.564	0.562	0.564	0.579	
Nordex	0.598	0.386	0.387	0.386	0.384	0.396	0.396	0.398	0.396	0.382	
Brookfield	0.206	0.156	0.154	0.152	0.151	0.149	0.151	0.151	0.153	0.151	
Ballard	0.726	0.472	0.488	0.497	0.494	0.477	0.497	0.515	0.509	0.493	
Synex	0.323	0.215	0.211	0.208	0.201	0.185	0.184	0.190	0.188	0.196	
Motech Industries	0.483	0.324	0.327	0.337	0.338	0.333	0.329	0.327	0.329	0.329	
Valero	0.403	0.261	0.264	0.264	0.265	0.265	0.272	0.271	0.269	0.282	
Average of equal weight	**0.503**	**0.348**	**0.350**	**0.350**	**0.348**	**0.343**	**0.348**	**0.350**	**0.346**	**0.347**	**0.348**
Average of market value	**0.394**	**0.261**	**0.263**	**0.263**	**0.263**	**0.263**	**0.269**	**0.269**	**0.267**	**0.274**	**0.266**

Table A.11
Annualized daily (every 22nd trading day) volatility of MA2–MA10, average annualized volatility.

	B&H	MA10	MA9	MA8	MA7	MA6	MA5	MA4	MA3	MA2	
Exxon	0.237	0.142	0.142	0.144	0.144	0.142	0.143	0.142	0.154	0.153	
Chevron	0.259	0.163	0.164	0.167	0.167	0.167	0.162	0.165	0.160	0.174	
ConocoPhillips	0.311	0.194	0.199	0.188	0.193	0.195	0.194	0.200	0.185	0.195	
Marathon Oil	0.418	0.260	0.268	0.266	0.258	0.255	0.259	0.262	0.264	0.267	
NACCO Industries	0.513	0.363	0.365	0.357	0.352	0.356	0.360	0.350	0.354	0.364	
Chesapeake	0.571	0.289	0.296	0.302	0.309	0.330	0.328	0.322	0.336	0.354	
EOG Resources	0.380	0.263	0.265	0.257	0.255	0.254	0.244	0.243	0.250	0.267	
Devon Energy	0.391	0.230	0.236	0.237	0.236	0.240	0.244	0.251	0.248	0.243	
Average of equal weight	**0.385**	**0.238**	**0.242**	**0.240**	**0.239**	**0.242**	**0.242**	**0.242**	**0.244**	**0.252**	**0.242**
Average of market value	**0.288**	**0.175**	**0.177**	**0.176**	**0.177**	**0.178**	**0.176**	**0.177**	**0.181**	**0.187**	**0.178**
	B&H	MA10	MA9	MA8	MA7	MA6	MA5	MA4	MA3	MA2	
Energiekontor	0.491	0.409	0.410	0.405	0.406	0.385	0.373	0.358	0.361	0.338	
Carnegie Wave Energy	0.797	0.563	0.568	0.560	0.563	0.551	0.554	0.533	0.533	0.550	
Nordex	0.598	0.404	0.411	0.417	0.414	0.410	0.409	0.407	0.399	0.402	
Brookfield	0.206	0.158	0.164	0.157	0.158	0.153	0.155	0.153	0.153	0.141	
Ballard	0.726	0.479	0.487	0.510	0.508	0.499	0.505	0.501	0.501	0.479	
Synex	0.323	0.236	0.236	0.232	0.196	0.197	0.197	0.214	0.214	0.174	
Motech Industries	0.483	0.320	0.338	0.348	0.337	0.327	0.332	0.336	0.342	0.355	
Valero	0.403	0.260	0.272	0.267	0.265	0.268	0.268	0.258	0.262	0.258	
Average of equal weight	**0.503**	**0.354**	**0.361**	**0.362**	**0.356**	**0.349**	**0.349**	**0.345**	**0.346**	**0.337**	**0.351**
Average of market value	**0.394**	**0.262**	**0.272**	**0.269**	**0.267**	**0.267**	**0.267**	**0.260**	**0.263**	**0.258**	**0.265**

Table A.12
Annualized daily (every other month) volatility of MAD2–MAD5 (D = every other month, 5, 4, 3, 2, are the numbers of observations in rolling window), average annualized volatility.

	B&H	MAD5	MAD4	MAD3	MAD2	
Exxon	0.237	0.151	0.158	0.159	0.162	
Chevron	0.259	0.173	0.178	0.172	0.166	
ConocoPhillips	0.311	0.203	0.217	0.202	0.213	
Marathon Oil	0.418	0.260	0.281	0.287	0.283	
Nacco Industries	0.513	0.337	0.353	0.332	0.319	
Chesapeake	0.571	0.283	0.314	0.329	0.354	
EOG Resources	0.380	0.269	0.277	0.259	0.259	
Devon Energy	0.391	0.246	0.250	0.253	0.254	
Average of equal weight	**0.385**	**0.240**	**0.254**	**0.249**	**0.251**	**0.249**
Average of market value	**0.288**	**0.183**	**0.192**	**0.189**	**0.192**	**0.189**
	B&H	MAD5	MAD4	MAD3	MAD2	
Energiekontor	0.491	0.413	0.416	0.390	0.396	
Carnegie Wave Energy	0.797	0.538	0.561	0.530	0.508	
Nordex	0.598	0.389	0.418	0.413	0.405	
Brookfield	0.206	0.158	0.167	0.159	0.159	
Ballard	0.726	0.491	0.522	0.492	0.487	
Synex	0.323	0.215	0.219	0.201	0.192	
Motech Industries	0.483	0.324	0.345	0.327	0.342	
Valero	0.403	0.269	0.282	0.254	0.271	
Average of equal weight	**0.503**	**0.350**	**0.366**	**0.346**	**0.345**	**0.352**
Average of market value	**0.394**	**0.267**	**0.281**	**0.259**	**0.270**	**0.269**

Table A.13
Annualized daily (every 3rd month) volatility of MAT2–MAT4 (T = every third month, and 4, 3, 2, are the numbers of observations in the rolling window), average annualized volatility.

	B&H	MAT4	MAT3	MAT2	
Exxon	0.237	0.148	0.163	0.153	
Chevron	0.259	0.164	0.176	0.159	
ConocoPhillips	0.311	0.219	0.223	0.207	
Marathon Oil	0.418	0.250	0.273	0.294	
NACCO Industries	0.513	0.328	0.331	0.319	
Chesapeake	0.571	0.318	0.332	0.272	
EOG Resources	0.380	0.291	0.298	0.247	
Devon Energy	0.391	0.235	0.238	0.257	
Average of equal weight	**0.385**	**0.244**	**0.254**	**0.239**	**0.246**
Average of market value	**0.288**	**0.184**	**0.196**	**0.180**	**0.187**
	B&H	MAT4	MAT3	MAT2	
EnergieKontor	0.491	0.397	0.408	0.387	
Carnegie Wave Energy	0.797	0.552	0.574	0.547	
Nordex	0.598	0.391	0.406	0.408	
Brookfield	0.206	0.164	0.170	0.157	
Ballard	0.726	0.469	0.494	0.502	
Synex	0.323	0.243	0.244	0.201	
Motech Industries	0.483	0.309	0.349	0.330	
Valero	0.403	0.274	0.278	0.267	
Average of equal weight	**0.503**	**0.350**	**0.366**	**0.350**	**0.355**
Average of market value	**0.394**	**0.270**	**0.278**	**0.267**	**0.272**

and coal companies listed in the USA, while the renewable energy portfolio included stocks of wind, solar, wave, water, biomass, bio-ethanol, and fuel cell companies in the USA, Germany, Australia, Canada, and Taiwan.

Non-American firms were used because of the lack of data from equally large US companies over the sample period 2004–2018. All stock prices were converted to US dollars, assuming that the changes in exchange rates take into account the foreign country risk premia. The four self-made ETFs served as benchmarks as buy and hold portfolios.

The main finding was that, within the renewable energy portfolio, the MA market timing produced a significantly better performance than random market timing for both equally weighted and market-value weighted portfolios. However, the MA market timing produced quite similar performance to random market timing with the equally weighted fossil energy portfolio, and a worse performance than random market timing with the market-value weighted fossil energy portfolio.

It is now widely understood that it is essential to reduce reliance on the use of fossil energy sources, namely coal, oil and gas, in order to reduce global greenhouse gas emissions. The results of this paper suggest that the MA trading rules do not help in predicting the returns of fossil energy companies, whereas those of renewable energy companies are more predictable according to MA rules. This may be useful in guiding investments from fossil energy to renewable energy companies, thereby reducing carbon emissions and improving the physical and social environment.

That returns predictability clearly exists within renewable energy stocks may be due to the existence of predictable risk premium effects, or behavioral biases in market pricing within the energy sector. These explanations are to be scrutinized in future research. By Zhu and Zhou (2009), MA rules add value for a risk averse investor simply if returns are predictable. This still unknown theoretical mechanism should also be investigated in future research. In addition, it seems that forecastable stochastic trends in stock prices appear in the renewable energy branch when MA rules are used, irrespective of data frequency.

Note that stochastic trends develop naturally in non-stationary time series, and that deterministic trend may also appear. However, on the basis of the statistical tests, there has not been any significant deterministic trends in any ETF price series during the

Table A.14
Annualized daily (every 4th month) volatility of MAQ2–MAQ3 (Q = every 4th month, and 3, 2, are the numbers of observations in the rolling window), average annualized volatility.

	B&H	MAQ3	MAQ2	
Exxon	0.237	0.182	0.187	
Chevron	0.259	0.196	0.205	
ConocoPhillips	0.311	0.217	0.239	
Marathon Oil	0.418	0.266	0.302	
NACCO Industries	0.513	0.334	0.362	
Chesapeake	0.571	0.334	0.352	
EOG Resources	0.380	0.299	0.308	
Devon Energy	0.391	0.279	0.279	
Average of equal weight	**0.385**	**0.264**	**0.279**	**0.271**
Average of market value	**0.288**	**0.210**	**0.220**	**0.215**
	B&H	MAQ3	MAQ2	
Energiekontor	0.491	0.416	0.422	
Carnegie Wave Energy	0.797	0.513	0.558	
Nordex	0.598	0.404	0.452	
Brookfield	0.206	0.164	0.167	
Ballard	0.726	0.458	0.481	
Synex	0.323	0.230	0.230	
Motech Industries	0.483	0.366	0.377	
Valero	0.403	0.278	0.293	
Average of equal weight	**0.503**	**0.354**	**0.372**	**0.363**
Average of market value	**0.394**	**0.276**	**0.291**	**0.284**

Table A.15
Annualized daily (every 5th month) volatility of MAC2 (C = every fifth month, and 2 is the number of observations in the rolling window), average annualized volatility.

	B&H	MAC2	
Exxon	0.237	0.139	
Chevron	0.259	0.205	
ConocoPhillips	0.311	0.252	
Marathon Oil	0.418	0.260	
NACCO Industries	0.513	0.363	
Chesapeake	0.571	0.386	
EOG Resources	0.380	0.267	
Devon Energy	0.391	0.231	
Average of equal weight	**0.385**	**0.263**	**0.263**
Average of market value	**0.288**	**0.196**	**0.196**
	B&H	MAC2	
Energiekontor	0.491	0.400	
Carnegie Wave Energy	0.797	0.549	
Nordex	0.598	0.453	
Brookfield	0.206	0.157	
Ballard	0.726	0.467	
Synex	0.323	0.233	
Motech Industries	0.483	0.321	
Valero	0.403	0.268	
Average of equal weight	**0.503**	**0.356**	**0.356**
Average of market value	**0.394**	**0.269**	**0.269**

sample period. As MA market timing produced a better performance in the renewable energy ETFs than with random timing, it can be concluded that forecastable stochastic trends exist in both the equally weighted and in the market value weighted renewable energy ETFs. On the other hand, the fossil energy ETFs do not have forecastable stochastic trends, as MA market timing produced a similar and a worse performance than random market timing, respectively.

CRediT authorship contribution statement

Chia-Lin Chang: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing - review & editing. **Jukka Ilomäki:** Conceptualization, Data curation, Funding acquisition, Investigation, Project administration, Resources, Software, Validation, Visualization, Writing - original draft. **Hannu Laurila:** Conceptualization, Funding acquisition, Investigation, Project administration, Resources, Validation, Visualization, Writing - original draft. **Michael McAleer:** Conceptualization, Formal analysis, Investigation, Methodology, Resources, Validation, Visualization, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Tables A.1–A.15.

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