ICAE
Instituto Complutense de Análisis Económico

Market Timing with Moving Averages for Fossil Fuel and Renewable Energy Stocks

Chia-Lin Chang
Department of Applied Economics
Department of Finance
National Chung Hsing University, Taiwan

Jukka Ilomäki
Faculty of Management University of Tampere, Finland

Hannu Laurila
Faculty of Management University of Tampere, Finland

Michael McAleer
Department of Finance Asia University, Taiwan and
Discipline of Business Analytics University of Sydney Business School, Australia
And Econometric Institute, Erasmus School of Economics
Erasmus University Rotterdam, The Netherlands and
Department of Economic Analysis and ICAE
Complutense University of Madrid, Spain and
Institute of Advanced Sciences Yokohama National University, Japan

Abstract

The paper examines whether the moving average (MA) technique can beat random market timing in traditional and newer branches of an industrial sector. The sector considered is the energy sector, divided into balanced stock portfolios of fossil and renewable energy companies. Eight representative firms are selected for both portfolios. The paper finds that MA timing outperforms random timing with the portfolio of renewable energy companies, whereas the result is less clear with the portfolio of fossil energy companies. Thus, there seems to be more forecastable stochastic trends in sunrise branches than in sunset branches.

Keywords Moving averages, market timing, industrial sector, energy sector, fossil fuels, renewable energy, random timing, sunrise branches, sunset branches.

JEL Classification C22, C32, L71, L72, Q16, Q42, Q47.

Working Paper nº 1824
September, 2018

UNIVERSIDAD
COMPLUTENSE
MADRID

ISSN: **2341-2356**
WEB DE LA COLECCIÓN: http://www.ucm.es/fundamentos-analisis-economico2/documentos-de-trabajo-del-icae

Market Timing with Moving Averages for Fossil Fuel and Renewable Energy Stocks *

Chia-Lin Chang
Department of Applied Economics
Department of Finance
National Chung Hsing University, Taiwan

Jukka Ilomäki
Faculty of Management
University of Tampere, Finland

Hannu Laurila **
Faculty of Management
University of Tampere, Finland

Michael McAleer
Department of Finance
Asia University, Taiwan
and
Discipline of Business Analytics
University of Sydney Business School, Australia
and
Econometric Institute, Erasmus School of Economics
Erasmus University Rotterdam, The Netherlands
and
Department of Economic Analysis and ICAE
Complutense University of Madrid, Spain
and
Institute of Advanced Sciences
Yokohama National University, Japan

September 2018

* For financial support, the first author wishes to acknowledge the Ministry of Science and Technology (MOST), Taiwan, and the fourth author is grateful to the Australian Research Council and Ministry of Science and Technology (MOST), Taiwan.
** Corresponding author: hannu.laurila@uta.fi

Abstract

The paper examines whether the moving average (MA) technique can beat random market timing in traditional and newer branches of an industrial sector. The sector considered is the energy sector, divided into balanced stock portfolios of fossil and renewable energy companies. Eight representative firms are selected for both portfolios. The paper finds that MA timing outperforms random timing with the portfolio of renewable energy companies, whereas the result is less clear with the portfolio of fossil energy companies. Thus, there seems to be more forecastable stochastic trends in sunrise branches than in sunset branches.

Keywords: Moving averages, market timing, industrial sector, energy sector, fossil fuels, renewable energy, random timing, sunrise branches, sunset branches.
JEL: C22, C32, L71, L72, Q16, Q42, Q47.

1. Introduction

Many technical traders use the Moving Average (MA) technique (Gartley 1936) in macroeconomic forecasting. For example, Ilomäki, Laurila and McAleer (2018) uses Dow Jones stocks data from 1 January 1988 to 31 December 2017, and find that a macro forecaster, who seeks to identify ups and downs in the market, can beat the buy-and-hold strategy. Moreover, it is possible to obtain higher returns with equal volatility by reducing the frequency used in the MA rules. Moreover, using the largest sample size in every frequency produces the best results, on average. Nevertheless, it would be unsurprising if the empirical results were to differ between sectors, and even between different branches within sectors.

The energy sector should be a very useful example to highlight such market timing, especially given its traditional (fossil) and newer (renewable) branches. The relevance of the division is highlighted by the Paris Agreement (2015), where 196 countries agreed in the United Nations Framework Convention on Climate Change to combat climate change, with the USA being the only major country not to have signed the Agreement. Its key target is to reduce global greenhouse gases (GHG) to keep the rise of global average temperature smaller than $+2^{o}$C, as compared with pre-industrial levels. 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. For example, 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 Paris Agreement reflects more general concerns, not only on climate change but also on the sustainability of fossil resources. The latter concern rose in the 1970’s due to the first and second oil price shocks, and promoted the production of energy from renewable resources. More recently, many countries have been divesting their nuclear energy production, replacing it with alternative renewable means. Thus, the energy sector has for long time been in a state of flux.

The primary purpose of the paper is to examine, whether the general findings of Ilomäki et al. (2018) concerning the performance of the MA technique apply for energy sector portfolios and, in particular, whether there are differences between branches within the sector. The branches to be considered are the fossil fuel energy and renewable energy branches. The former includes oil, gas, and coal companies, while the latter includes wind, solar, wave, water, bio-mass, bio-ethanol, and fuel cell companies. Nuclear energy producers are excluded. For both branches, we construct balanced stock portfolios that include eight prominent companies. The fossil fuel energy companies have a long history, and their stocks have been publicly traded over the last fifty years, whereas 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.

The remainder of 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 concluding comments are given in Section 5.

2. Literature Review

The literature concerning the market development of fossil fuel energy (especially oil and gas) producer stock prices is extensive. For example, Boyer and Filion (2007) report that the changes in raw oil prices are positively correlated with Canadian oil stocks. El-Sharif et al. (2005) draw the same conclusion for UK oil stocks, as well as Arouri (2011) within the European oil sector. Elyasiani et al. (2011) note that an increase in raw 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) observe that the US renewable energy stocks correlate with US technology stocks rather than with changes in raw 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) find 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 towards renewable energy investments, but developing countries have continued to invest in coal energy. Tietjen et al. (2016) note that the renewable energy branch has high capital expenditures, but low operating expenditures, as compared with the fossil fuel energy branch. For these reasons, the Paris Agreement should push the energy industry towards capital-intensive production.

Bohl et al. (2013) identify 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) find 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) find 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) find no differences, regardless of whether fossil fuel energy stocks are included 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 above 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.

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; and Kacperczyk et al. 2014). However, Ilomäki et al. (2018) report that, with lower frequencies in MA calculations, market timing with MA produces superior financial results than random timing, on average. Zhu and Zhou (2009) show 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. However, Hudson et al. (2017) and Yamamoto (2012) note that MA rules are useless in high frequency trading.

The test of the usefulness of MA rules is actually a test regarding market efficiency in time. The energy sector, with its sunrise and sunset branches, provides an interesting test subject. As far as we know, there have been no market efficiency comparisons between fossil fuel and renewable energy stocks using market timing procedure. One of the primary purposes of the paper is to fill in such a gap.

3. Models and Data

The theoretical model follows Ilomäki et al. (2018) closely. 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 $i = 1, 2, 3, ...I$, 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:

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

$$s.t.$$

$$x_t^j P_t \le w_t^j$$

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 ues 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 stocks only if the numerator on the right-hand side is positive, that is if:

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

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.

The branch of fossil fuel energy companies is presented by an equally weighted portfolio 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 an equally weighted portfolio of eight companies. The data are from Thomson Reuters Datastream. The portfolio includes 3 US based companies: Ballard Power Systems (fuel cell), Brookfield Renewable Energy Partners (solar), and Valero (bioethanol); 2 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).

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 not signed the Paris Agreement, an international portfolio may also reflect better the general considerations of investors about the climate issue. In the diversified portfolio, the weight of each energy source is 25% as the maximum. With the assistance of Thomson Reuters Datastream, all international stock prices are converted to US dollars on a daily basis before any calculations.

Figure 1 shows the market development of the two selected energy portfolios. 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.

Figure 1 shows that the renewable energy portfolio (the thin line) is more volatile than the fossil energy portfolio (the fat line). Moreover, the figure shows that $10,000 invested in the fossil (renewable) energy portfolio in 7 October 2004 has grown to $24,900 ($20,500) by 6 August

2018. The correlation between the returns portfolios is 0.90, but the Johansen co-integration test tells that 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 collected from the website of the US Department of the Treasury. We use log returns in all performance calculations.

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 U.S. 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 28848 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:

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

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

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

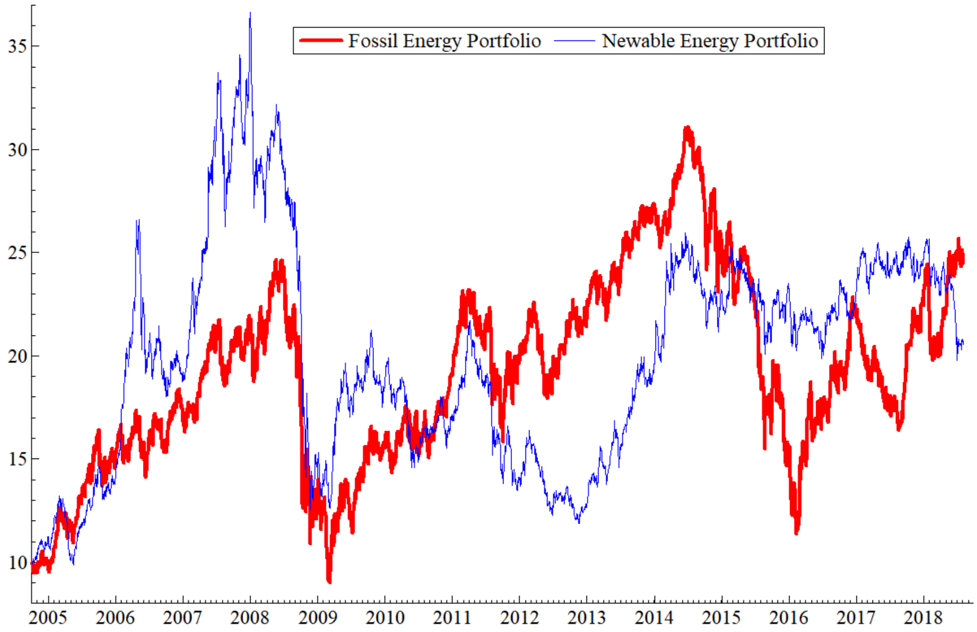

Figure 1

Market development of fossil and renewable energy portfolios with dividends from 7 October 2004 to 6 August 2018

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

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

Table A1 in Appendix A shows that the annualized average buy and hold returns are **+0.046** for the fossil fuel energy portfolio, and **+0.033** for the renewable energy portfolio before dividends. Tables A1-A7 together show that the annualized average log returns after transaction costs and before dividends for MA200-MA40 are **+0.021** for the fossil fuel energy portfolio, and **+0.032** for the renewable energy portfolio. The respective log returns for the weekly MAW40-MAW8 are **+0.023** and **+0.053;** for (monthly) MA10-MA2 **+0.031 and +0.060;** for (every other month) MAD5–MAD2 **+0.039** and **+0.042**; for (every 3rd month) MAT4–MAT2 **+0.019** and **+0.055**, for (every 4th month) MAQ3–MAQ2 **+0.031** and **+0.023**; and for (every 5th month) MAC2 **+0.033 and +0.034** after transaction costs and before dividends.

Table A8 in Appendix A shows that the buy and hold strategy produces the average annualized volatility of **0.385** for the fossil fuel energy portfolio, and **0.503** for the renewable energy portfolio. However, Tables A8-A14 together suggest that the average volatility of the MA rule returns in the fossil fuel (renewable) energy portfolio reduces to **0.250 (0.355),** indicating a reduction of **35% (29%)** compared with the buy and hold performance. In the testing period, the average annualized three-month US Treasury bill yield has been **+0.012** with annualized average volatility **0.000**.

Consider first the volatility of the fossil energy portfolio. Note also that the average annualized dividend yield has been **+0.020** in the buy and hold portfolio during the period. The MA rule reduction in the volatility implies that, from 7 October 2004, we invest **42%** of the time in the equally weighted portfolio, and **58%** in the risk-free rate. 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 $0.42*(0.020+0.046)+0.58*0.012=0.035$. The buy and hold performance (returns with dividends +0.066 and volatility 0.385), together with the above calculations, construct the efficient frontier in the return to volatility space, if market timing is useless.

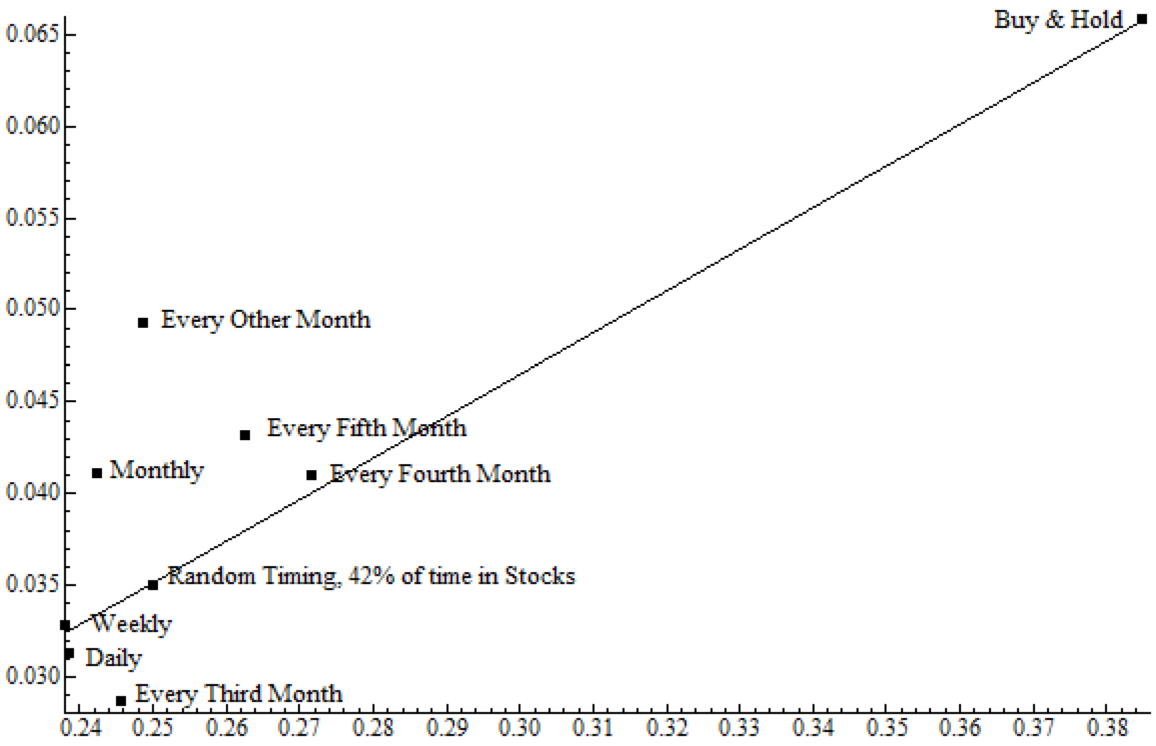

Figure 2

Returns to volatility ratios in equally weighted portfolios in eight fossil energy stocks with dividends from 7 October, 2004 to 6 August, 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

In Figure 2, 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 with 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 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 of **+0.035** with volatility **0.25**.

Market timing with the MA rules gives an average performance of **+0.038** with dividends and with average volatility of **0.25,** implying an increase of **9%** from the theoretical random timing returns, on average. However, volatilities vary between 0.235 and 0.264, implying an increase of **12%** 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.

With the renewable energy portfolio, the MA rule reduction in volatility implies that 50% of the time is randomly invested in the risk-free rate, and 50% in the equally weighted portfolio from 7 October 2004, as $1-\sqrt{0.50}=0.293$. Furthermore, the average annualized dividend yield in the buy and hold portfolio has been **+0.019**. The theoretical efficient market line implies that $0.50*(0.019+0.034)+0.50*0.012=0.033$, indicating a performance of **+0.033** in returns with dividends and volatility **0.35**, when we invest randomly half the time in stocks and half in the risk-free rate.

In Figure 3, 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).

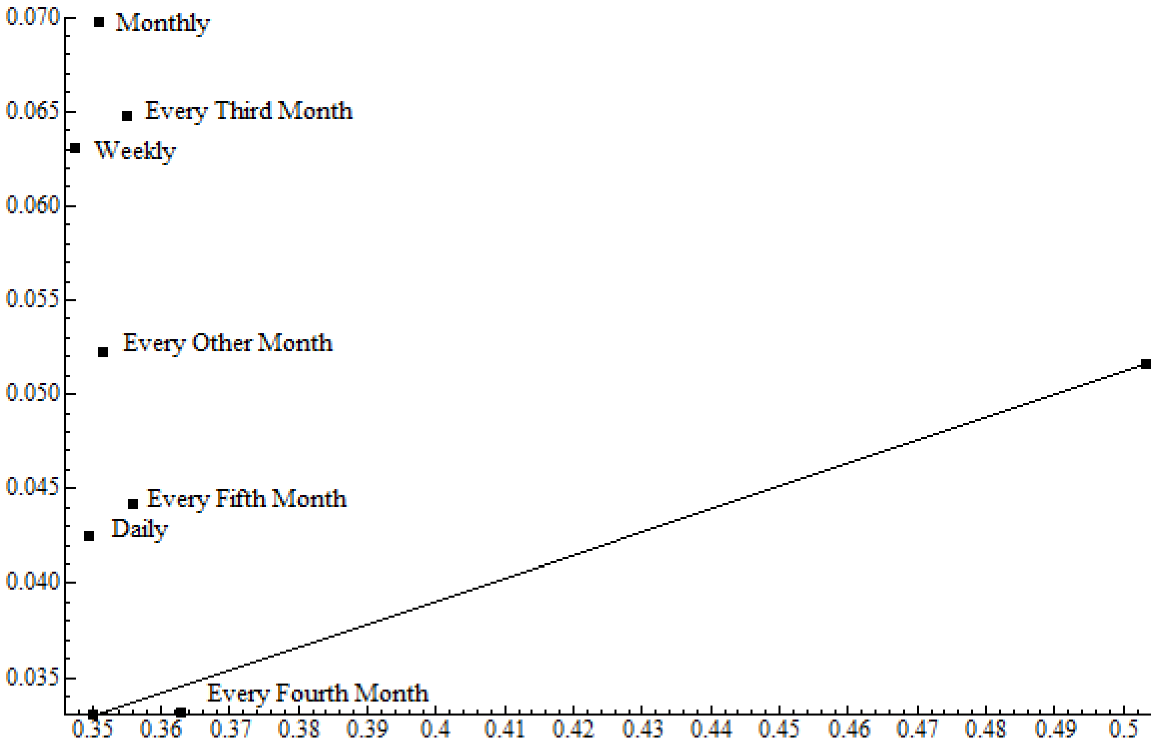

Figure 3

Returns to volatility ratios in equally weighted portfolios in eight renewable energy stocks with dividends from 7 October, 2004 to 6 August, 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

According to Tables A8-A14 in Appendix A, 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 548112 daily observations. This indicates a **61%** rise in average annualized returns compared with random market timing, while volatility varies between 0.348 and 0.363, indicating a **4%** 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.

Furthermore, Ilomäki et al. (2018) find that, by reducing the frequencies in calculating the moving averages produces better returns, while volatility remains virtually unchanged. However, Figures 2 and 3 clearly show that the present results contradict those findings, in both the fossil fuel and renewable energy portfolios, when all sample sizes are considered. The difference in the results concerning the effect of frequency reduction in the MA calculations is at least partly due to the fact that the earlier study uses DJIA stocks from 1 January 1988 to 31 December 2017, whereas this paper uses sectoral data from 7 October 2004 and 6 August 2018.

Figure 4 illustrates that, if only the largest sample size is taken into account for every frequency, the results change significantly in the fossil fuel energy portfolio (see also the second columns in Tables A1-A14 in Appendix A).

In Figure 4, only MA200 (200 days; daily), MAW40 (40 days every five days; weekly), MA10 (10 days every 22 days; monthly), MAD5 (5 days every 44 days; every 2nd month), MAT4 (4 days every 66 days; every 3rd month) MAQ3 (3 days every 88 days; every 4th month), and MAC2 (2 days every 110 days; every 5th month) are taken into account. These MA rules produce **+0.046** returns, on average, with average volatility **0.25**, while theoretical random timing produces **+0.035** with **0.25** volatility. Note that the averages +0.046 and 0.25 are based on 259632 daily observations.

This indicates a **31%** increase in returns, while volatility varies between 0.236 and 0.263, indicating an **11%** increase from the smallest to the largest. This suggest that, by using only the largest rolling windows (that is, the most information) at different frequencies, market timing with MA rules has significantly added value in the fossil fuel energy portfolio for a risk averse investor over the last 14 years. This result is in line with the findings in Ilomäki et al. (2018), showing that the largest sample at every frequency produces the best results.

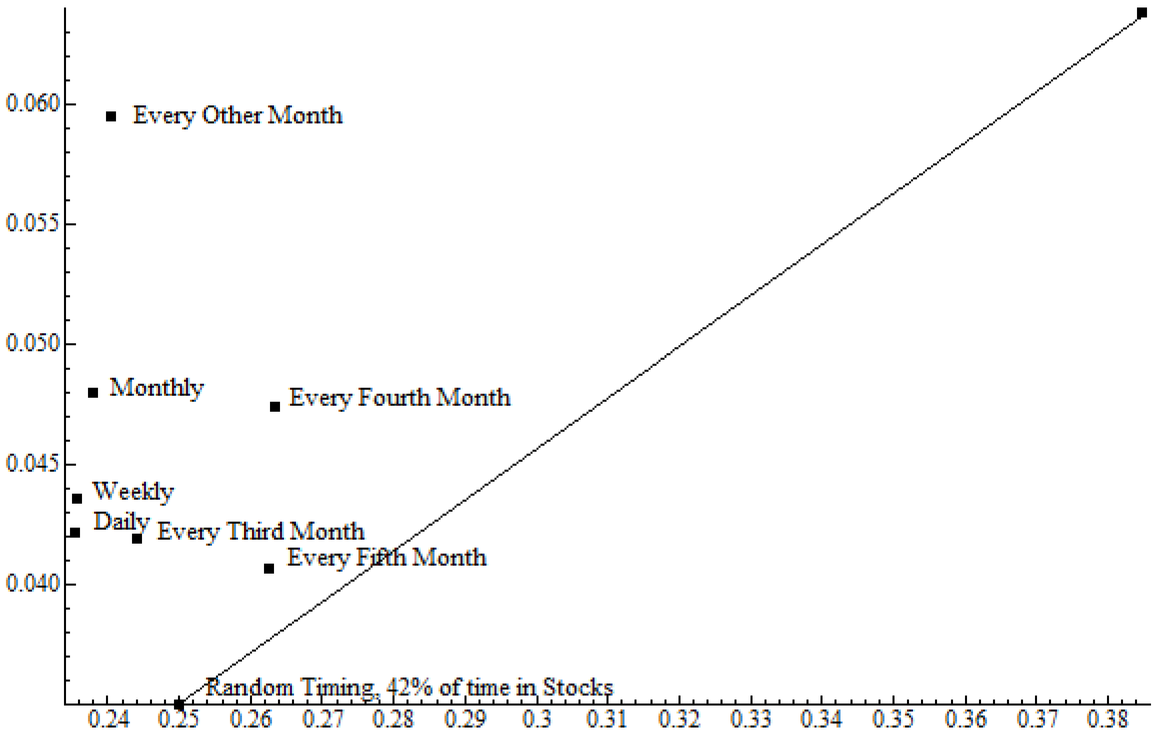

Figure 4
Returns to volatility ratios in equally weighted portfolios in eight fossil energy stocks with dividends from 7 October, 2004 to 6 August, 2018 calculated in MA200 (daily), MAW40 (weekly), MA10 (monthly), MAD5 (every other month), MAT4 (every 3rd month), MAQ3 (every 4th month), MAC2 (every 5th month), and the theoretical random timing efficient line

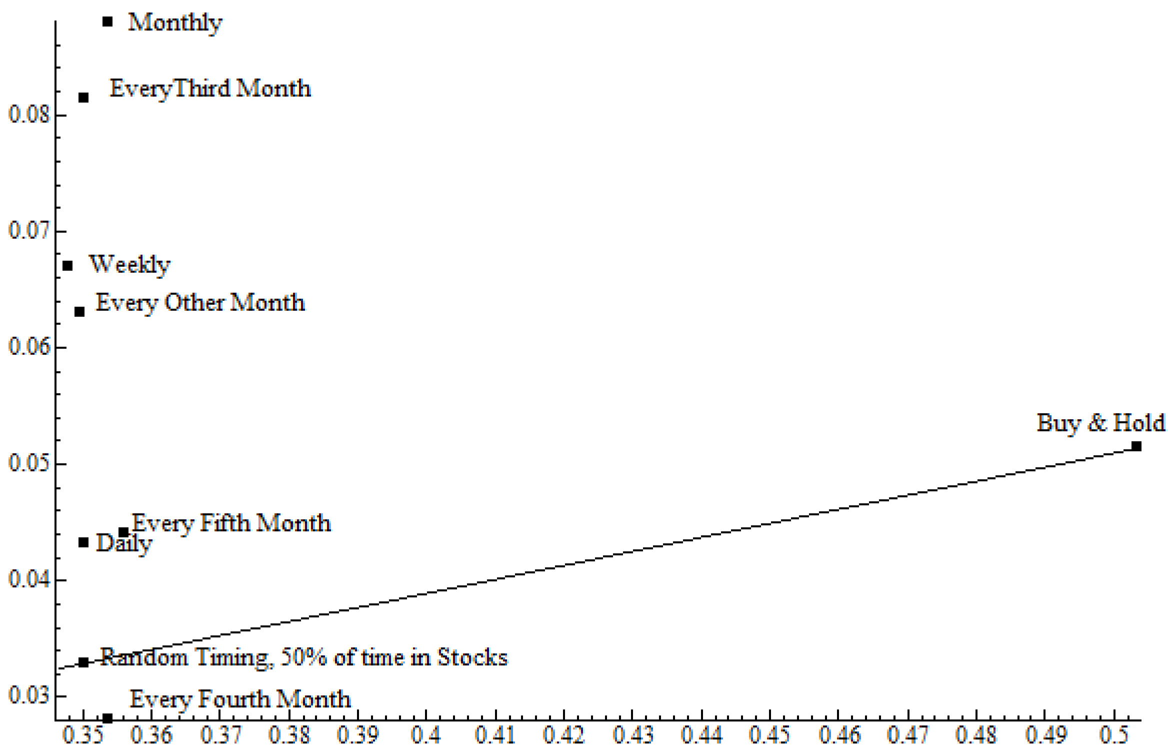

Figure 5

Returns to volatility ratios in equally weighted portfolios in eight renewable energy stocks with dividends from 7 October 2004 to 6 August 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

Figure 5 presents the case of the renewable energy portfolio, and shows that the rules MA200, MAW40, MA10, MAD5, MAT4, MAQ3, and MAC2 produce **+0.059** returns, on average, with average volatility of **0.35.** The theoretical random timing produces **+0.033** with **0.35** volatility. This indicates a **79%** increase in returns, on average, while volatility varies between 0.348 and 0.356, indicating a **2%** increase from the smallest to the largest. This suggest that, by using only the largest rolling windows at different frequencies, market timing with MA rules has significantly added value, on average, in the renewable energy portfolio of a risk averse investor over the last 14 years.

5. Concluding Remarks

Inspired by the apparent flux in the energy sector, and by the results in Ilomäki et al. (2018), the paper examined whether the MA technique was powerful with respect to portfolios of fossil fuel energy and renewable energy stocks. More precisely, the paper seeks possible differences of Moving Average (MA) performance between the sunset and sunrise branches of the energy industry. In essence, the paper tests whether there exist forecastable stochastic trends in price series. In the CAPM world, the performance of MA market timing should not differ from that of random market timing.

In this paper, the balanced portfolio of fossil fuel energy includes stocks of oil, gas, and coal companies that are listed in the USA. Renewable energy includes stocks of wind, solar, wave, water, bio-mass, bio-ethanol, and fuel cell companies in the USA, Germany, Australia, Canada, and Taiwan. The time span of the data is 2004-2018.

The paper found that, within the renewable energy portfolio, MA market timing produced significantly better performance than random market timing, in general. That is, forecastable stochastic trends in stock prices seem to appear in the renewable energy branch when MA rules are used, irrespective of data frequencies. Within the fossil fuel energy portfolio, MA market timing beat random market timing only if the whole sample size in the 200 days rolling windows were used.

Furthermore, it was found that the daily returns of the portfolios of fossil fuel energy and the renewable energy stocks have high positive correlation (at 0.90). The finding contradicts that of Sadorsky (2012), which uses US stocks between 2001-2010, and also differs from that of Zhang and Du (2017) for China, where government intervention can distort what is purported to be market behaviour.

References

Arouri, M. (2011) Does crude oil move stock markets in Europe? a sector investigation. *Economic Modelling* 28, 1716 – 1725.

Best, R. (2017) Switching towards coal or renewable energy? The effects of financial capital on energy transitions. *Energy Economics* 63, 75 – 83.

Bohl, M., Kaufmann, P., Stephan, P. (2013) From hero to zero: Evidence of performance reversal and speculative bubbles in German renewable stocks. *Energy Economics* 37, 40 – 51.

Boyer, M., Filion D. (2007) Common and fundamental factors in stock returns of Canadian oil and Gas companies. *Energy Economics* 29, 428 – 453.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R. (1997) Measuring mutual fund performance with characteristic based benchmarks. *Journal of Finance* 52, 1035 – 1058.

El-Sharif, I., Brown, D., Nixon, B., Russel, A. (2005) Evidence on the nature and extend of the relationship between oil and equity value in UK. *Energy Economics* 27, 819 – 930.

Elyasiani, E., Mansur, I., Odusami, B. (2011) Oil price shocks and industry returns. *Energy Economics* 33, 966 – 974.

European Commission (2012) *Energy Road Map 2050.* Luxembourg: Publication Office of the European Union.

Fang, S., Lu, X., Egan, P. (2018) Reinvestigating oil price-stock market nexus: Evidence from Chinese industry stock returns. *China & World Economy* 26, 43 – 62.

Gartley, H. (1935) *Profits in the Stock Markets.* Washington: Lambert-Gann Publishing.

Graham, J., Harvey, C. (1996) Market timing ability and volatility implied in investment newsletters' asset allocation recommendations. *Journal of Financial Economics* 42, 397 – 421.

Henriques, I., Sadorsky, P. (2008) Oil prices and the stock prices of alternative energy companies. *Energy Economics* 30, 998 – 1010.

Hudson, R., McGroarty, F., Urquhart, A. (2017) Sampling frequency and the performance of different types of technical trading rules. *Finance Research Letters* 22, 136 – 139.

Ilomäki, J. (2018) Risk and return of a trend chasing application in financial markets: An empirical test. *Risk Management* 20, 258 – 271.

Ilomäki, J., Laurila H., McAleer, M. (2018) Market timing with moving averages. *Sustainability,* 10 (7:2125), 2018, 1 – 25.

Kacperczyk, M., Seru, A. (2007) Fund manager use of public information: New evidence on managerial skills. *Journal of Finance* 62, 485 – 528.

Kacperczyk, M., van Nieuwerburgh, S., Veldkamp, L. (2014) Time-varying fund manager skill. *Journal of Finance* 69,1455 – 1484.

Kumar, S., Managi, S., Matsuda A. (2012) Stock prices of clean energy firms, oil, and carbon markets: A vector autoregressive analysis. *Energy Economics* 34, 215 – 226.

Malkiel, B. (2003) The efficient market hypothesis and its critics. *Journal of Economic Perspectives* 17, 59 – 82.

Merton, R. (1981) On market timing and investment performance. I. An equilibrium theory of value for market forecast. *Journal of Business* 54, 363 – 406.

Neely, C., Rapach, D., Tu, J., Zhou, G. (2014) Forecasting equity risk premium: The role of technical indicators. *Management Science* 66, 1772 – 1791.

Ni, Y., Liao, Y., Huang, P. (2015) MA trading rules, and stock market overreaction. *International Review of Economics and Finance* 39, 253 – 265.

Reboredo, J. (2015) Is there dependence and systemic risk between oil and renewable energy stock prices? *Energy Economics* 48, 32 – 45.

Sadorsky, P. (2012) Correaltions and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics* 34, 248 – 255.

Tietjen, O., Pahle, M., Fuss, S. (2016) Investment risks in power generation: A comparison of fossil fuel and renewable energy dominated markets. *Energy Economics* 58, 174 – 185.

Trinks, A., Scholtens, B., Mulder, M., Dam, L. (2018) Fossil fuel divestment and portfolio performance. *Ecological Economics* 146, 740 – 748.

United Nations (2015) UNFCCC. https://unfccc.int/files/meetings/paris_nov_2015/application/pdf/ paris_agreement_english_.pdf

Wen, X,, Guo, Y., Wei, Y., Huang, D. (2014) How do the stock prices of new energy and fossil fuel companies correlate? Evidence from China. *Energy Economics* 41, 63 – 75.

Zhang, G., Du, Z. (2017) Co-movements among the stock prices of new energy, high-technology and fossil fuel companies in China. *Energy* 135, 249 – 256.

Zhu, Y., Zhou, G. (2009) Technical analysis: An asset allocation perspective on the use of moving averages. *Journal of Financial Economics* 36, 519 – 544.

Yamamoto, R. (2012) Intraday technical analysis of individual stocks on the Tokyo Stock Exchange. *Journal of Banking and Finance* 16, 3033 – 3047.

Appendix A

Table A1

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	**0.046**	**0.036**	**0.039**	**0.031**	**0.037**	**0.032**	**0.017**	**0.000**	**-0.004**	**0.003**	**0.021**

	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	**0.033**	**0.033**	**0.038**	**0.035**	**0.028**	**0.041**	**0.018**	**0.021**	**0.040**	**0.039**	**0.032**

Table A2

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 Resourges	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	**0.046**	**0.035**	**0.044**	**0.035**	**0.033**	**0.032**	**0.016**	**0.008**	**0.015**	**-0.012**	**0.023**

	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	**0.033**	**0.057**	**0.063**	**0.046**	**0.052**	**0.044**	**0.048**	**0.064**	**0.060**	**0.042**	**0.053**

Table A3

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	**0.046**	**0.040**	**0.046**	**0.039**	**0.028**	**0.027**	**0.024**	**0.013**	**0.023**	**0.040**	**0.031**

	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	**0.033**	**0.078**	**0.063**	**0.067**	**0.072**	**0.066**	**0.051**	**0.049**	**0.042**	**0.048**	**0.060**

Table A4

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	**0.046**	**0.052**	**0.040**	**0.035**	**0.031**	**0.039**

	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	**0.033**	**0.053**	**0.057**	**0.041**	**0.017**	**0.042**

Table A5

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	**0.046**	**0.034**	**0.033**	**0.005**	**0.019**

	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	**0.033**	**0.072**	**0.055**	**0.038**	**0.055**

Table A6

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	**0.046**	**0.040**	**0.022**	**0.031**

	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	**0.033**	**0.018**	**0.028**	**0.023**

Table A7

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 Resouces	0.141	0.121	
Devon Energy	0.011	0.024	
Average	**0.046**	**0.033**	**0.033**

	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	**0.033**	**0.034**	**0.034**

Table A8

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	**0.385**	**0.236**	**0.239**	**0.235**	**0.236**	**0.237**	**0.237**	**0.239**	**0.242**	**0.245**	**0.238**

	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	**0.503**	**0.350**	**0.357**	**0.351**	**0.351**	**0.352**	**0.346**	**0.348**	**0.345**	**0.346**	**0.350**

Table A9

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	**0.385**	**0.235**	**0.235**	**0.235**	**0.236**	**0.237**	**0.238**	**0.239**	**0.243**	**0.244**	**0.238**

	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	**0.503**	**0.348**	**0.350**	**0.350**	**0.348**	**0.343**	**0.348**	**0.350**	**0.346**	**0.347**	**0.348**

Table A10

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	**0.385**	**0.238**	**0.242**	**0.240**	**0.239**	**0.242**	**0.242**	**0.242**	**0.244**	**0.252**	**0.242**

	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	**0.503**	**0.354**	**0.361**	**0.362**	**0.356**	**0.349**	**0.349**	**0.345**	**0.346**	**0.337**	**0.351**

Table A11

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	**0.385**	**0.240**	**0.254**	**0.249**	**0.251**	**0.249**

	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	**0.503**	**0.350**	**0.366**	**0.346**	**0.345**	**0.352**

Table A12

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	**0.385**	**0.244**	**0.254**	**0.239**	**0.246**

	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	**0.503**	**0.350**	**0.366**	**0.350**	**0.355**

Table A13

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	**0.385**	**0.264**	**0.279**	**0.271**

	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	**0.503**	**0.354**	**0.372**	**0.363**

Table A14

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 Volatility	**0.385**	**0.263**	**0.263**

	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 Volatilities	**0.503**	**0.356**	**0.356**