

ANALYSIS OF FOUR ALTERNATIVE ENERGY MUTUAL FUNDS

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To my pet cat.

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LIST OF SYMBOLS AND ABBREVIATIONS

CAPM	Capital asset pricing model
FAN	First Trust Global Wind Energy ETF
Future Contract 1	First-Month Future Contract
GARCH	Generalized autoregressive conditional heteroskedasticity
NBDI	PowerShares WilderHill Clean Energy Portfolio
NMCDI	Nominal Major Currency Dollar Index
NUCL	iShares S&P Global Nuclear Index ETF
PBW	PowerShares WilderHill Clean Energy Portfolio
TAN	MAC Solar Index
USO	United States Oil Fund
VFINX	Vanguard 500 Index Fund

SUMMARY

We analyze four alternative energy mutual funds using a multi-factor capital asset pricing model with generalized autoregressive conditionally heteroskedastic errors (CAPM-GARCH). Our findings will help portfolio managers and others who seek to predict the return on investment in alternative energy firms. We find that alternative energy firms tend to be riskier than the general US stock market, have a low, but significant and positive response to oil prices, and have a significantly high and negative response to the value of the dollar relative to other currencies. Our results also suggest that alternative energy firms should hedge against currency exchange rate fluctuation.

1. INTRODUCTION

“The process of selecting a portfolio may be divided into two stages. The first stage starts with observation and experience and ends with beliefs about the future performances of available securities. The second stage starts with the relevant beliefs about future performances and ends with the choice of portfolio” (Markowitz, 1952).

This paper is concerned with the first stage of portfolio selection.

Recent growth in environmental consciousness has spurred the creation of alternative energy firms and investment vehicles. Alternative energy mutual funds are relatively new to the stock market and have not been studied extensively. This paper examines four mutual funds that invest exclusively in the alternative energy industry. We use a multi-factor capital asset pricing model with generalized heteroskedastic errors (CAPM-GARCH). In common with recent studies, we find that the excess returns of alternative energy stocks have low correlation with oil prices and that different sectors--solar, wind, and nuclear--have different levels of correlation with the broad market. Our contribution beyond examining new data is to add foreign exchange rates into the model. All four mutual funds in our sample have strong negative correlation with the Nominal Broad Dollar Index, indicating that alternative energy firms do not generally practice hedging against currency fluctuation.

Portfolio Selection

The purpose of this paper is to inform the second stage of portfolio selection, as described by Markowitz. Investors do not simply pursue maximal expected returns, but also seek minimal risk--variance of returns. By choosing a group of assets each with a

particular expected return and risk, an investor creates a portfolio with the same expected return but lower risk than any of its component assets. The portfolio reduces risk to the degree that the returns on investment of its components are not correlated with each other. Portfolio selection based on diversification assumes the investor has knowledge of assets' expected return and their correlation with each other. Our estimation of alternative energy funds' correlation with the market and other factors provides some of that essential information.

An efficient portfolio of assets is one constructed such that no other portfolio can have a greater expected return with equal or less risk. In other words, an efficient portfolio cannot benefit from more diversification. The minimum expected return of an efficient portfolio is that of one completely invested in an asset without risk.

Capital Asset Pricing Model

Sharpe (1964) provides a method of predicting an asset's risk and return. At equilibrium, the set of all efficient portfolios forms a ray originating from this point of zero risk and minimum expected return. Sharpe calls this the capital market line. Every possible asset is a part of at least one efficient portfolio. Therefore the returns of every asset will be at least partly correlated with the returns of an efficient portfolio. This is the systematic risk, or Beta, and this variance cannot be eliminated through diversification. The returns of the stock market do not have constant variance. Instead, a large movement appears to be followed by a temporary increase in variance. To account for this we use CAPM-GARCH as described by Bollerslev (1988). Najand (2007) summarizes some of the evidence supporting CAPM-GARCH as better predictor of stock returns than the traditional CAPM.

Following Bollerslev (1988) we are only concerned with the excess returns of assets--the returns above or below that of a risk-free asset. This starts our capital market line at zero risk and zero excess return and eliminates the movement of the returns of a risk-free asset from the variance detected in the returns of other assets.

Bollerslev (1988) uses New York Stock Exchange value-weighted equity returns as a proxy for an efficient portfolio, but adds that "wider definitions of the market would allow the model to do better." Henriques (2008) models the returns of alternative energy firms with oil prices as a factor. Sadorsky (2001) models the returns of Canadian oil and gas companies with US-Canadian dollar exchange rates as a factor. We also use a multi-factor approach to our analysis, including a stock market index, spot oil prices, and an index of US foreign exchange rates as the systemic risk factors for alternative energy stocks.

2. DATA

We downloaded historical stock, mutual fund, and exchange traded fund prices from Yahoo! Finance, oil spot prices and futures contract prices from the US Energy Administration, and US Treasury bill rates from the US Federal Reserve. All data are daily closing price for one share or one barrel or percent return on U.S. Treasury bill.

Alternative Energy

To represent alternative energy stocks, Henriques (2008) used the exchange-traded PowerShares WilderHill Clean Energy Portfolio (PBW), which is based on the WilderHill Clean Energy Index. The index selects “companies that focus on greener and generally renewable sources of energy and technologies that facilitate cleaner energy” (Invesco PowerShares, 2010).

The PowerShares WilderHill Clean Energy Portfolio has the advantages of being exclusively alternative energy focused, containing only US exchange traded stocks, and having a longer history than many other funds. Other funds are newer, include non-US traded stocks, or include non-energy sector stocks. We expand on Schmidt (2009) by examining not only the same MAC Solar Index (TAN), but also the iShares S&P Global Nuclear Index ETF (NUCL) and the First Trust Global Wind Energy ETF (FAN).

The Market

Henriques (2008) used the Arca Tech 100 Index (PSE) in their model. Contrary to their findings, our estimation using GARCH on daily returns from Jan 2005 to April 2010 determined that the PowerShares WilderHill Clean Energy Portfolio is more highly correlated with the S&P 500 than with the Arca Tech 100 Index. To represent the S&P

500, we use the Vanguard 500 Index Fund (VFINX), the oldest mutual fund to track the S&P 500 Index. Though the S&P 500 Index only covers approximately 75% of the stock market, results were not qualitatively different when using the S&P 1500 Index, which covers 90% of the market (Standard & Poor's, 2010).

Oil

We compared the United States Oil Fund (USO) with spot prices and First Month Future Contracts (Future Contract 1) on barrels of West Texas Intermediate in Cushing, OK. Weekly returns on the United States Oil Fund have an approximately 0.25 correlation coefficient with weekly returns on spot price, despite the fund's prospectus. There is no statistically significant correlation between their daily returns. Future Contract 1 and spot price have a correlation coefficient of approximately 1 for both daily and weekly returns. Because spot price appears to have a handful of large outliers, we use Future Contract 1 to represent the price of oil in our model.

Foreign Exchange Rates

Because many firms traded on the New York Stock Exchange may cater to the global market, rather than solely to the US market, one expects their growth to be correlated with the movements of foreign exchange rates. If the dollar is stronger, the firms will have a harder time exporting and their share prices should decrease. All countries demand energy, not only major trade partners. Therefore, we use the Nominal Broad Dollar Index (NBDI) to check for a negative relationship between the dollar's exchange rates and alternative energy stocks. The Nominal Broad Dollar Index was more significantly correlated with our alternative energy funds than was the Nominal Major Currency Dollar Index (NMCDI), which is a subset of the Nominal Broad Dollar Index.

Risk-Free Asset

To represent the risk-free asset, we follow Najand (2007) in the use of 3-month US Treasury bills, gathering data from the Federal Reserve Bank of Saint Louis.

Table 1. Summary Statistics of Excess Returns

<i>Statistic</i>	<i>PBW</i>	<i>TAN</i>	<i>FAN</i>	<i>NUCL</i>	<i>VFINX</i>	<i>OIL</i>	<i>NBDI</i>
Mean	-0.0044	-0.0042	-0.0038	-0.0041	-0.0043	-0.0036	-0.0044
Min.	-0.1491	-0.2328	-0.1714	-0.1827	-0.0933	-0.1228	-0.0298
Max.	0.1327	0.2175	0.1932	0.1781	0.1066	0.1782	0.0143
Var.	0.0007	0.0036	0.0018	0.0026	0.0002	0.0008	0.0000
Skew.	-0.1772	-0.0283	0.0911	0.0395	0.2688	0.5134	-0.3973
Kurt.	4.3584	1.8788	3.3848	2.6131	8.4623	4.9006	1.4514

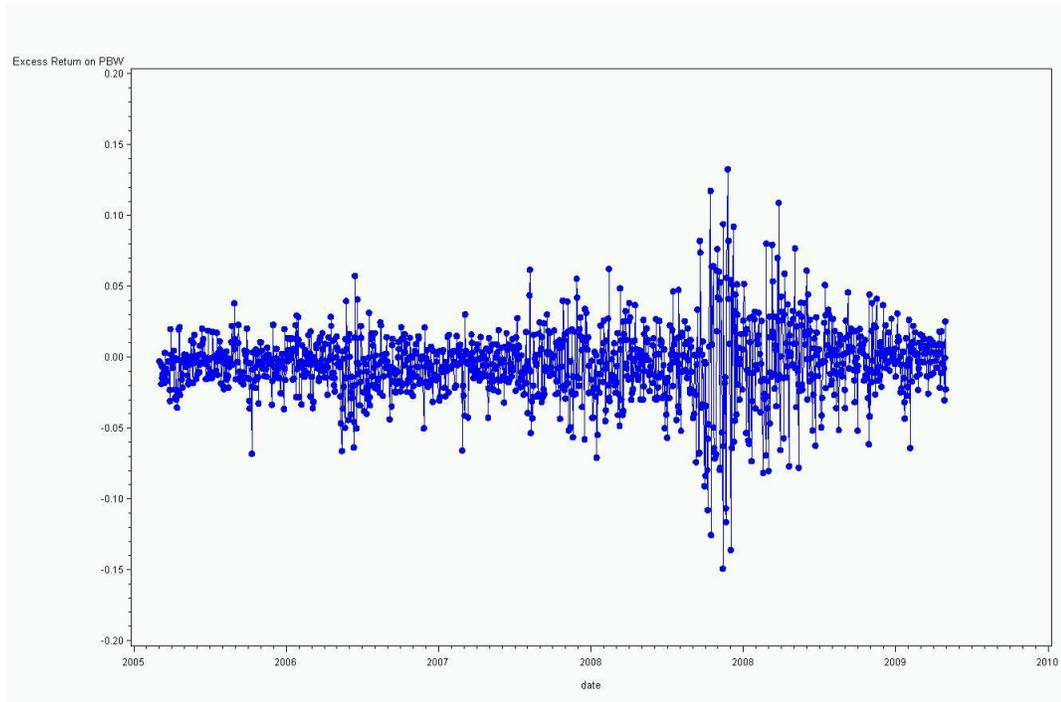


Figure 1. Weekly Excess Return on PBW, 2005-2010

3. METHODS

We experimented with sampling our time-series at several different intervals and concur with Najand (2008) that weekly data provides "a good compromise on the use of noisy daily data and a relatively short span of monthly data." However, some of our time-series are not long enough to use even weekly data. Instead of using Wednesday closing prices, we picked an arbitrary starting date and iterated through the time series keeping the next date that was at least a set number of days after the previous kept date. This allowed us to easily experiment with different time intervals to balance noise-reduction with sample size. We used weekly intervals when possible and slightly shorter when necessary. Each estimation used the maximum duration available for the explained alternative energy mutual fund--5 years for the generic alternative energy fund and approximately 2 and a half years for the solar-, wind-, and nuclear-specific funds.

Excess Returns

We transformed the closing prices of our time-series into excess returns. We calculate the return of our risk-free asset, 3-month U.S. Treasury bills, over a short interval:

$$(1) \quad R_{tbill}(t) = [1 + AR(t)]^{\frac{Date(t) - Date(t-1)}{365}} - 1$$

$R_{tbill}(t)$ is the return of a 3-month U.S. Treasury bill at time t .

$AR(t)$ is the annualized interest rate of a 3-month U.S. Treasury bill at time t .

$Date(t)$ is the calendar date at time t .

We use the excess returns time-series as the data sets for our econometric model.

Econometric Model

We extend Najand (2007) and Henriques (2008) in using a multi-factor CAPM-GARCH(1,1) model to estimate conditional volatility in alternative energy mutual fund excess returns.

$$(2) \quad ER_{altenergy}(t) = \alpha + \beta_{market} ER_{VFINX}(t) + \beta_{oil} ER_{oil}(t) \\ + \beta_{FX} ER_{NBDI}(t) + \varepsilon(t)$$

$$(3) \quad \varepsilon(t) \sim N(0, h(t))$$

$$(4) \quad h(t) = \omega + \beta_1 \varepsilon(t-1)^2 + \beta_2 h(t-1)$$

$ER_{asset}(t)$ is the excess return of a particular asset at time t .

4. RESULTS

In all four of our explained time-series—the PowerShares WilderHill Clean Energy Portfolio, the MAC Solar Index, the First Trust Global Wind Energy ETF, and the iShares S&P Global Nuclear Index ETF—all three factors—the U.S. stock market, oil prices, and U.S. foreign exchange rates--were found to be statistically significant and the null hypothesis of no ARCH(1) effects was rejected, indicating the appropriateness of the GARCH(1, 1) method.

Alternative Energy

The PowerShares WilderHill Clean Energy Portfolio, representing alternative energy firms in general, is highly responsive to the broad stock market. A 1% movement in the Vanguard 500 Index Fund will correspond to a 1.4% movement in the PowerShares WilderHill Clean Energy Portfolio. As found in Najand (2008), alternative energy is not highly responsive to oil prices, although the relationship is significant. For a 1% movement in the price of oil, the PowerShares WilderHill Clean Energy Portfolio only moves 0.11%. Interestingly, the PowerShares WilderHill Clean Energy Portfolio is significantly negatively correlated with movements of the Nominal Broad Dollar Index. If the Nominal Broad Dollar Index increases 1%, then the PowerShares WilderHill Clean Energy Portfolio will decrease 0.7%. In comparison, large modern firms heavily engaged in export, such as The Coca-Cola Company (KO), have very small response to the Nominal Broad Dollar Index.

Solar

At the time of this writing, the major holdings of the PowerShares WilderHill Clean Energy Portfolio are primarily firms engaged in solar energy. As might be expected, MAC Solar Index is largely similar to the PowerShares WilderHill Clean Energy Portfolio. Solar energy firms have a 1.44 correlation coefficient with the broad stock market and a 0.09 correlation coefficient with oil. However, solar energy firms appear to respond even more highly to fluctuations in foreign exchange rates, having a -1.56 correlation coefficient with the Nominal Broad Dollar Index.

Wind

Wind energy firms appear to be on par with the broad market systemic risk, having a 0.98 covariance with the Vanguard 500 Index Fund. The First Trust Global Wind Energy ETF responds more than the PowerShares WilderHill Clean Energy Portfolio to foreign exchange rates, having a covariance of -1.06 with the Nominal Broad Dollar Index, and less response than the PowerShares WilderHill Clean Energy Portfolio to oil prices, having a covariance with oil futures contract 1 of 0.06.

Nuclear

Similar to wind energy, nuclear energy firms are nearly one-to-one correlated with the broad stock market's systemic risk. The iShares S&P Global Nuclear Index ETF has a 1.02 covariance with the Vanguard 500 Index Fund. The iShares S&P Global Nuclear Index ETF has a -0.73 covariance with the Nominal Broad Dollar Index and a 0.13 covariance with oil Future Contract 1.

Table 2. Market Risk Comparisons

<i>Parameter</i>	<i>PBW</i>		<i>TAN</i>		<i>FAN</i>		<i>NUCL</i>	
Alpha	-0.01	(-1.85)	-0.00	(-1.73)	-0.00	(-2.52)	-0.01	(-3.41)
Beta_VFINX	1.43	(19.28)	1.45	(15.13)	0.98	(21.55)	1.02	(23.48)
Beta_NBDI	-0.73	(-5.99)	-1.56	(-3.98)	-1.06	(-5.51)	-0.73	(-4.26)
Beta_OIL	0.11	(3.03)	0.09	(1.76)	0.06	(2.26)	0.13	(4.54)
GARCH(1)	0.00	(9.21)	0.00	(7.68)	0.00	(7.19)	0.00	(4.42)
ARCH(1)	0.18	(2.28)	0.34	(2.39)	0.50	(3.56)	1.00	(3.26)

Each parameter estimate is displayed with its t-statistic in parentheses to the right.

5. CONCLUSION

The results of these estimations reinforce the findings of past studies such as Henriques (2008) and Schmitz (2009) that including alternative energy firms in a portfolio is a good way to increase a portfolio's risk and therefore its expected return. We also find that alternative energy is good hedge against the weekly fluctuations of oil prices, having a low correlation with oil prices. Henriques (2008) suggests that investors view alternative energy companies more as generic technology companies than as having a strong relationship with oil. Though the price of oil affects all stocks, due to its use as an input in production and an indicator of inflation, oil cannot be shown to influence alternative energy companies much more than the stock market as a whole. Further work could search for a relationship between alternative energy firms and critical levels of oil prices or sustained increases in oil prices, rather than a relationship between weekly excess returns.

One of our contributions is the separate analysis of solar, wind, and nuclear energy. We find that the bulk of alternative energy's greater response to systemic risk resides in solar energy firms. However, we caution that these type-specific alternative energy mutual funds are still young and that behavior may change as the industry matures.

Another contribution is the addition of foreign exchange rates to the model. The highly negative correlation of alternative energy firms to the Nominal Broad Dollar Index suggests that these young firms are too small to have well-developed currency hedging activities. Large modern firms have low response to currency fluctuations, even export-

dependent firms such as The Coca-Cola Company. However, these large firms also have treasury departments that actively engage in currency markets. Currently, alternative energy firms provide a good hedge against a rising dollar for interested investors.

However, as the industry matures and the firms grow to a size that they can engage in non-core activities, we expect this negative correlation to reduce. Small firms do have the ability to outsource their treasury operations to a broker or other agency, such as Oanda Forex Consulting, but the evidence shows that few of these firms have done so. Indeed, the firms that survive the years are likely to be ones that have the foresight to manage currency fluctuation.

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