“Market timing using asset rotation on exchange traded funds: a meta-analysis on trading performance”

Panagiotis Schizas (Greece), Dimitrios D. Thomakos (Greece)

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Abstract

The ultimate goal of any "paper" investment strategy is to achieve real-life profitability. This paper measures the performance of a trading rule based on the relative pricing and relative volatility of a rotation strategy between two assets, using data from passive ETFs. To avoid problems of pair selection we work with meta-data obtained after the evaluation of a large number of 351 pairs of ETFs. In this way the authors analyze the performance of the proposed strategy on the cross-section of different ETFs. The results show that rotation trading, as applied in this paper, offers advantages even when the simplest model is used in generating trading signals. Furthermore, the authors find that the differences in the actual mean returns (over the evaluation period), the correlation of the pair components and to (a lesser extend) the volatilities of the ETFs can explain the success of the rotation strategies.

Keywords: market timing, sign forecasting, rotation trading, exchange traded funds, mean reversion, rotation trading, equity directional quantitative strategies, volatility timing.
JEL Classification: C22, C53, G15.

Introduction

We present empirical results on the statistical and economic viability of a market timing trading strategy that is based on rotation between two risky assets. The underlying intuition for the use of such a strategy rests with literature on sign and volatility predictability[1]. Christoffersen and Diebold (2006), and Hong and Chung (2003) propose ways of testing and assessing sign predictability for asset returns. Using data on exchange traded funds (ETFs), and models for both the returns and the volatility of the underlying assets, we compare the performance of the suggested models with the standard benchmarks of a buy-and-hold strategy and an equally weighted portfolio, as Shilling (1992) argues that market timing can beat the buy-and-hold strategy. Brooks et al. (2006) compare and evaluate a number of different market timing strategies.

Breen, Glosten and Jagannathan (1989) and Vandell and Stevens (1989) are early references, that employed market timing switching strategies between pairs of assets and establish the superior performance of a market timing approach between two assets. Pesaran and Timmermann (1994, 1995) examine the predictability and profitability of a similar market timing approach. Schizas and Thomakos (2012) also address the issue of asymmetric response terms for the relative returns on the pair of assets that is being rotated and similar to the above applied technical trading strategies and tried to identify and group the asymmetric response of volatility and market timing. The above goal is achieved in this paper through an empirical meta-analysis of 351 ETFs pairs.

The work of Christoffersen and Diebold (2006) and Christoffersen et al. (2007) suggests that there is potential value in using signs for the predictability of asset returns (the sign forecasts depending on volatility) and Johannes et al. (2002) showed that there is superior performance of a strategy based on volatility timing than that of market timing. A similar approach, based again on volatility timing, is taken by Fleming, Kirby and Ostdiek (2001, 2003). Lam et al. (2004) find that the efficiency of market timing strategies is strongly related to the percentage of correct sign predictions and, finally, Benning (1997) discusses the prediction skills of traders that apply timing methodologies in the real world.

The rotation strategy is not risk-neutral and assumes the presence of arbitrage opportunities in the markets. Furthermore, the model specification uses the interplay between relative returns and relative volatilities in picking-up the asset with the highest return. The conditional expected return and volatility for the rotation strategy is positive when the relative realized return is greater than a negative threshold that depends on the probability of making a positive prediction. Therefore, when both returns are positive the strategy's expected return is also positive. We can also see that the volatility of the rotation strategy is maximized when the probability of making a positive prediction is close to one-half or when the difference between the two realized returns is increasing or both.

Further to the properties of the trading strategy, there is one crucial factor in the success of the asymmetric response the day of the week effect. Day-of-the-week effect is crucial on the final performance of the trading strategy (Conrad and Kaul, 1988, and Chordia et al., 2001) as have been reported. In our analysis we experimented with different days of the week, however, we present only Wednesday since we found them to be the most profitable.

[1] Here it's important to note that sign and directional predictions have been found to heavily depend on volatility forecastability for which there is a rather large literature which we will not review here.

A feature of our analysis is that we use the class of US exchange traded funds (ETFs) to apply our rotation methodology. Transparency, liquidity, and with no doubt, the tremendous favorability that they enjoy among asset managers favor are the distinctive pros in the implementation of our trading strategy.

The paper is organized as follows. Section 1 presents the model used to generate predictions. The empirical results are shown in section 2. The final section provides some concluding remarks.

1. Model and data

In this section, we present the rotation methodology and the models and approach we use to implement it – they are taken from Schizas and Thomakos (2012). As in most forecasting exercises we leave out part of our sample for testing and use a rolling window of observations to forecast and trade in historical "real time". Our current results are for a rolling window of T_0 = 104 weeks but other results for different estimation lengths are also available[1]. We denote the evaluation period by $T_1 = T - T_0$, for a total of T available return observations.

The weekly return of the i^{th} asset is denoted by $R_{ti} = \log\left(C_{ti} / C_{t-1,i}\right)$ $R_{ti} = \log(C_{ti}/C_{t-1,i})$ and is defined as the logarithmic difference of the weekly ETF closing price C_{ti}; by V_{ti} we denote its corresponding volatility. For the measurement of volatility we use the realized, weekly range-based volatility estimator – with the range-based estimator being that of Parkinson (1980):

$$V_{ti} = \sum_{s=1}^{5} \sigma_{st,i}{}^{2} \tag{1}$$

In our rotation-based models the dependent variable is either the relative return (difference in returns) or the relative volatility between two assets, i and j. The relative return is defined as:

$$y_t = R_{ti} - R_{tj} \tag{2}$$

which is equivalent to the return of relative prices, i.e. to $y_t = \log(C_{ti} / C_{tj}) - \log(C_{t-1,i} / C_{t-1,j})$, with C_{ti} being the closing price. This is an attractive feature of rotation modeling, i.e. that deals with the economically interpretable notion of relative prices. The relative volatility is defined using levels and logarithms as:

$$V_t = V_{ti} - V_{tj} \text{ and } v_t = \log(V_{ti}) - \log(V_{tj}) \tag{3}$$

and we experiment with the direct modeling of v_t but also with the modeling of the individual log-volatilities as well. All rotation models we consider are using either y_t or v_t as their dependent and decision variables and follow a standard regression specification:

$$y_t = x_t^T \beta + u_t, \tag{4}$$

where x_t is the regressor vector, whose dimension and included variables differs across model specifications, and u_t is the regression error. The simplest rotation model we consider is the naïve model that does not include any explanatory variables other than the mean of relative returns and ignores dynamics potentially present, i.e. is given as:

$$y_t = \beta_0 + u_t. \tag{5}$$

Another simple model comes if we include any dynamics that are present in the regression error term using, as we do, a moving average such as:

$$y_t = \beta_0 + u_t(\varepsilon_t;\theta), \text{ with}$$

$$u_t(\varepsilon_t;\theta) = \varepsilon_t + \sum_{k=1}^{q} \varepsilon_{t-k}\theta_k. \tag{6}$$

A more plausible alternative to these benchmarks is a model that includes some explanatory variables in the right-hand side. We experimented with the inclusion of a lagged dependent variable, lagged values of the relative volatility and asymmetric response terms for both of them, as well as cross-terms. For a model with a single lag this specification is given by:

$$\begin{aligned} y_t &= \beta_0 + \beta_1 y_{t-1} + \beta_2 V_{t-1} + \beta_3 I_t^y + \beta_4 I_t^V + \beta_5 y_{t-1} I_t^y + \\ &+ \beta_6 V_{t-1} I_t^V + \beta_7 y_{t-1} I_t^V + \beta_8 V_{t-1} I_t^y + u_t, \end{aligned} \tag{7}$$

where $I_t^y = I(y_{t-1} < 0)$ is a dummy variable capturing the asymmetric response of relative returns, and similarly for $I_t^V = I(V_{t-1} < c)$ of relative volatilities – c being a fixed threshold which we discuss later. This approximation is piecewise linear and can capture the potentially different behavior of relative returns in periods when one of the two assets outperforms the other depending on both the asymmetric response of relative returns and relative volatilities.

Finally, we consider the following autoregressive models for the individual log-volatilities and for the relative volatility of the form:

$$\log(V_{it}) = \phi_0 + \sum_{k=1}^{p_{AIC}} \phi_k \log(V_{t-k,i}) + \eta_t, \text{ and}$$

$$v_t = \alpha_0 + \sum_{k=1}^{p_{AIC}} \alpha_k v_{t-k} + w_t, \tag{8}$$

where the orders of both models are selected by the AIC criterion, which is known to overfit and is suitable for the presence of long-memory in the volatility series.

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[1] We also run the rotation models for 26, 52, 200, 300 and 350 weeks. Results are available on request.

[2] Where $\sigma_{st,i}$ is the daily range-based volatility estimated from the high-low formula as: $\sigma_{st,i} = [4\log(2)]^{-1}[\log H_s - \log L_s]^2$.

The rotation trading strategy we implement is based on the forecasts generated by the above models and it involves a binary decision for the asset that is to be invested. The strategy is "always in the market": we are fully invested all the time and the capital rotates from one asset to another when a suitable trading signal is given. Given a sample of T observations suppose that a rolling window of T_1 observations is to be used for the historical evaluation of the strategy. The steps involved in the computations are as follows, for all

$t = T_0 + 1,..., T_0 + T_1$

At time t estimate the models m = 1, 2,..., M and compute the one-week ahead forecasts

$\hat{y}^{(m)}_{t+1|t}, \log\left(\hat{V}_{t+1|t,i}\right), \hat{v}_{t+1|t}$.

Based on the forecasts enter into a positions as follows: if $\hat{y}^{(m)}_{t+1|t} > 0$ then enter a long position for asset i, else enter a long position for asset j. Note that a switch occurs at time t only if the position was in a different asset than the current signal at time t-1. Similarly for $\hat{v}_{t+1|t} > 0$ and for $\log\left(\hat{V}_{t+1|t,i}\right) >$ $\log\left(\hat{V}_{t+1|t,j}\right)$. Note that in the context of the naïve model the rotation strategy coincides with a momentum strategy based on local smoothing: the comparison is between two moving averages of the same size since $\hat{y}_{t+1|t} = \hat{\beta}_0 = \bar{y}_{n_0} = \bar{R}_{i,n_0} - \bar{R}_{j,n_0}$.

The return for implementing the above strategy for model m = 1, 2,..., M and each pair $n = (i,j)$ is then calculated as follows:

$$R^{(m)}_{t+1,ij} = R_{t+1,i} I[\hat{y}^{(m)}_{t+1|t} > 0] + R_{t+1,j} I[\hat{y}^{(m)}_{t+1|t} \leq 0] \qquad (9)$$

which now becomes the data for our meta-analysis.

Let $E^{(m)}_{T_1,n} = E^{(m)}_{T_1,n}\left(R^{(m)}_{T_0+1,m},..., R^{(m)}_{T_0+T_1,m}\right)$ to be any evaluation measure based on the returns of the strategy from model m and the total T_1 evaluation observations for pair n. For example, this can be the average return or the Sharpe ratio, etc. Given a total of N possible (i,j) pairs we compute and present statistics and results for the data on the evaluation measures across all models m = 1, 2,..., M. For example, when we present an average based on the meta-data we imply the following:

$$\bar{E}^{(m)}_{T_1} = \frac{1}{N} \sum_{n=1}^{N} E^{(m)}_{T_1,n} \qquad (10)$$

which is computed across all available (i,j) pairs for model m. In essence we are analyzing the results of the evaluation measures on the cross-section of all available ETF pairs.

The implementation of this strategy is based on 27 passive ETFs which we selected from the entire universe that is traded on the US stock exchanges. Specifically, we consider the largest ETFs, based on market capitalization, from the top 100 ETFs listed on US stock exchanges and then we applied 3 specific criteria based on (a) the inception date (cut off as of July 30 2007); (b) the investment objective (not to overlap on the same investment strategy) and (c) the trading volume (not less than 1.000.000 trading shares per day), in order to avoid any market microstructure effects. The data span is from January 4, 1999 and we add up each ETF since its inception. The last ETF was launched on July 26, 2011. The last estimation observation has been taken on June 08, 2010. After the construction of the corresponding volatility series we match the data according to the pairs that we form, which come out to a total of N = 351 pairs.

2. Results

Table 1 presents the basic statistics of our rotation specifications and responds to our goal to examine the degree of asymmetric response[1]. Thus, there is a separate examination based on quartiles while we present only the means and the medians[2]. The evaluation of the performance is examined both on absolute and relative terms. In order to implement the latter, we compared the proposed rotation methodology with respect to a buy-and-hold strategy as implemented by investing on each of the underlying assets and by an equally weighted portfolio.

A careful look at Panel A demonstrates that average return across the rotation models outperformed the equally weighted portfolio and at least one of the underlying assets. The moving average model of equation (6) is the only exception. The poor outcome of moving average supports our more extensive methodology since the information included in the error term is inadequate to time the market. In absolute terms, the naive model is the top performer, followed by the models based on volatility timing − volatility ratio and differences on volatility. Those trading rules outperformed all the applied benchmarks. On the contrary, only the naive specification outperformed both ETFs and the equally weighted portfolio in means of the Sharpe ratio. This outcome supports the perception that volatility timing rules achieve a higher average return, albeit, with a higher risk than the buy-and-hold strategy. The opposite behavior is indicated by the trading behavior of equation (7), as it exhibits the lowest risk among the suggested trading models.

[1] We present the mean return of each ETF separately on each technical trading strategy in the Appendix, section B.
[2] Different quartiles are available on request.

Furthermore, the piecewise linear specification is the second closes in having the smallest minimum return and exhibits an almost similar dip to the MA strategy and ETF2. So, the combination between market and volatility timing in equation (7) probably has a more robust performance on a bounce back market rather than on a bull market.

The end wealth assumes that $1 is invested at the beginning of the evaluation period. Comparing the terminal wealth performance of all the rotation models with the terminal wealth of the best performing asset in each pair and with that of the equally weighted portfolio we find that the active trading outperforms the buy-and-hold strategy. Moving average is the laggard of the rotation modeling with a poor behavior affected by the second underlying asset.

Panel B identifies the asymmetry of each model, since it is based on the median evaluating across pair. The most asymmetric behavior is coming from the volatility models of equation (3). Volatility ratio generates the best mean return, risk and Sharpe ratio followed by the naive model. Asymmetry in the piecewise linear specification is found to improve performance in terms of minimum realized return, while it outperforms both the alternative trading rules and the two underlying assets.

Overall these results indicate that, on average, the suggested trading specifications that use a market timing strategy are superior than investing in the best asset buy-and-hold strategy or the equally weighted portfolio. Note, however, that due to the strategies being non-neutral the superior performance in terms of mean return and wealth comes at a price of higher risk. We also find that the rotation strategy of equation (7) improves the risk profile for an investor, even though average return is coming from both volatility models. Comparing both panels, we can see that as the spread between the two underlying assets is widening, the range between the best and the worst rotation model is expanding.

Table 1. Trading models and performance

The table illustrates the basic statistics for meta-data analysis of 351 pairs of ETFs. The results correspond to the quantile analysis of mean and median under the 5 different trading models, the underlying ETFs and an equally weighted portfolio. The implementation of the trading strategies is based on 27 passive ETFs, while the data span is extended from February 4, 1999 until June 8, 2010. All quantities are on a percentage and yearly basis. The estimation period is 104 weeks and the results correspond to out of sample one step ahead forecasts.

Panel A. Mean								
Rotation models	Naive	MA	Volatility ratio	Diff. in volatilities	Piecewise linear	ETF1	ETF2	Eq. weighted
Average return	9.98	7.75	9.72	9.67	8.68	9.05	7.75	8.42
Volatility	27.14	26.69	29.94	29.98	26.68	26.60	26.18	24.57
Sharpe ratio	0.37	0.29	0.32	0.32	0.33	0.34	0.30	0.34
Min. realized return	-18.31	-17.32	-19.54	-19.53	-17.82	-18.55	-17.45	-16.88
Max. return	11.40	12.28	13.70	13.80	11.88	12.30	11.73	11.39
End wealth	1.40	1.33	1.40	1.39	1.38	1.36	1.33	1.34
Panel B. Median								
Rotation models	Naive	MA	Volatility ratio	Diff. in volatilities	Piecewise linear	ETF1	ETF2	Eq. weighted
Average return	7.80	6.03	8.63	8.32	7.23	7.44	5.67	6.66
Volatility	24.09	24.81	26.98	27.11	24.67	24.08	22.92	22.73
Sharpe ratio	0.32	0.24	0.32	0.31	0.29	0.31	0.25	0.29
Min. realized return	-19.73	-17.43	-19.95	-19.95	-17.43	-17.73	-17.73	-18.34
Max. return	11.06	11.31	12.50	12.50	11.14	11.29	10.45	10.64
End wealth	1.47	1.34	1.42	1.39	1.40	1.34	1.33	1.34

Table 2 presents point estimates and significance for the regression of average mean return across all pairs against the actual correlation, the mean difference and the volatility ratio of the ETFs. The difference in the means found to be significant across all strategies. The naive model and the two volatility models exhibits the higher coefficient which let us assume that the greater the difference in means the higher the mean return. This finding can be further supported, if we look at the results for the moving average model, which is found to be unrelated to the difference in means (and recall its worst average performance from the previous table). The trading strategy based on moving average and volatilities we found to be affected positively by the factor of correlation, which explains the finding of a riskier rule since the diversification benefit is limited.

Panel B presents point estimates of the Sharpe ratio. Whitelaw (1997) used a Sharpe ratio-based approach to construct market timing strategies and found evidence that such strategies can outperform a buy-and-hold strategy. The triggering outcome in comparison to Panel A, is the positive link between the four rotation strategies (MA, volatility ratio, differences in volatility, piecewise linear) and the factor of correlation. Differences in means are significant across trading strategies, where the naive model and the difference in volatilities illustrate the highest coefficient.

Table 2. Determinants of pairs trading performance – total

The table illustrates the basic statistics for meta-data analysis of 351 pairs of ETFs. The results correspond to the regression output based on point estimates of the average return and the Sharpe ratio against to the actual correlation, mean difference and the volatility ratio of the 5 different models, the underlying ETFs and an equally weighted portfolio. The implementation of the trading strategies is based on 27 passive ETFs, while the data span is extended from February 4, 1999 until June 8, 2010.

Panel A. Mean					
	Intercept	Correlation	Diff. in means	Vol. ratio	R^2
Naive	0.002***	-0.001	0.219***	0.000	0.063
MA	0.001	0.001†	0.056	0.000	0.016
Volatility ratio	0.001†	0.001*	0.174***	0.000	0.046
Diff. in volatilities	0.001*	0.001†	0.220***	0.000	0.055
Piecewise linear	0.001*	0.001	0.105*	0.000	0.020
ETF1	0.001**	0.001	0.631***	0.000	0.379
ETF2	0.001**	0.001	-0.369***	0.000	0.188
Eq. weighted portfolio	0.001**	0.001	0.131**	0.000	0.027
Panel B. Sharpe ratio					
	Intercept	Correlation	Diff. in means	Vol. ratio	R^2
Naive	0.069***	-0.005	7.316***	-0.011	0.061
MA	0.013	0.045**	2.571†	-0.003	0.037
Volatility ratio	0.018	0.048***	4.593***	-0.006	0.070
Diff. in volatilities	0.027†	0.043**	6.013***	-0.011	0.074
PL	0.030*	0.032*	3.615**	-0.007	0.035
ETF1	0.061***	0.025†	17***	-0.030***	0.308
ETF2	0.008	0.037**	-8.936***	0.008	0.147
Eq. weighted portfolio	0.048***	0.018	4.708***	-0.012	0.039

Note: Significance levels: *** less than 1%, ** less than 5%, * less than 10%, † less than 0,1%.

To further examine whether these factors are important in explaining profitability, in Table 3 we present results of the main drivers of the *correct trades* through an OLS regression against the correlation and the two measures of volatility-difference in means and difference in volatility. A casual look suggests that the outcome that a strategy works is related with the percentage of the correct sign predictions and the correct trades. The results indicate that the success of trading is linked to the correlation between the underlying assets only for the models based on relative pricing and most precisely on market timing – so the naive model, the moving average model and the piecewise linear. The highest degree of the correct trading is generated by the piecewise linear model with a coefficient of 4.7 bps, followed by the naive strategy with a coefficient of 2.8 bp, and with a coefficient of 2.7 bp for the moving average. The piecewise strategy is also negatively linked to the difference in means. This factor relies on the power of the strategy since it reveals the inherent dynamics of the relative pricing and the asymmetric response. Volatility ratio is positive influenced by the difference in volatilities with a coefficient of 1.5 bp, which explains the superior performance versus the alternative strategy of differences in volatilities.

Table 3. Determinants of pairs trading performance – correct trades only

The table illustrates the basic statistics for meta-data analysis of 351 pairs of ETFs. The results correspond to the regression output of the percentage of correct trades across all pairs to the actual correlation, mean difference and the volatility ratio under the 5 different models. The implementation of the trading strategies is based on 27 passive ETFs, while the data span is extended from February 4, 1999 until June 8, 2010.

Panel A. Wednesday					
	Intercept	Correlation	Diff. in means	Diff. in vol.	R^2
Naive	0.476***	0.028**	1.342	0.018**	0.053
MA	0.475***	0.027*	-0.407	0.004	0.019
volatility ratio	0.494***	0.006	1.388	0.015*	0.029
Diff. in volatilities	0.491***	0.012	1.599	0.010	0.023
Piecewise linear	0.461***	0.047***	-2.021†	0.010	0.067

Table 3 (cont.). Determinants of pairs trading performance – correct trades only

Panel B. Friday					
	Intercept	Correlation	Diff. in means	Diff. in vol.	R^2
Naive	0.499***	0.018†	5.295***	0.016*	0.121
MA	0.451***	0.058***	-1.000	0.007	0.093
Volatility ratio	0.495***	0.007	1.516	0.010	0.015
Diff. in volatilities	0.496***	0.005	2.290*	0.012†	0.030
Piecewise linear	0.465***	0.037***	0.994	0.013*	0.058

Note: Significance levels: *** less than 1%, ** less than 5%, * less than 10%, † less than 0,1%.

To examine the strength of the trading behavior now, in relative terms, of the rotation models we compute statistics with respect to the number of times that a rotation model was better either of the two ETFs or the equally weighted portfolio. Table 4 presents the results in terms of average mean return, Sharpe ratio and end wealth. Based on average mean return, the naïve model outperformed the equally weighted portfolio 26 times compared with 14 times and 10 times of the first and second ETF respectively. The rotation based on volatility timing exposes the most symmetric and successful behaviour versus the benchmarks. Differences in volatility outperformed ETF1 20 times versus 22 times of ETF2 and the equally weighted portfolio. On the contrary, the moving average model found to be the weakest link among the rotation models.

Turning our attention to the Sharpe ratio all the rotation models are driven by the ETF2. The Naïve model outperformed the benchmarks, followed by the ratio of volatilities. Panel C, represents the end wealth where there is a significant improvement in performance for the majority of the rotation models. Therefore, the volatility models and the naïve model found to be the outperformers, with almost a symmetric behavior between the two underlying assets. Volatility ratio was better 24 times than the first ETF, 23 times than the ETF2 and 22 times than the equally weighted portfolio. Difference in volatility was better 22 times than the ETF1 and 23 times than the equally weighted portfolio. The piecewise linear model exhibits the maximum outperformance on ETF2 (19 times) and the least on ETF1 (17 times).

Table 4. Number of times that rotation models outperformed the benchmarks

The table illustrates the basic statistics for meta-data analysis of 351 pairs of ETFs. The results correspond to the number of times that a rotation model was better than either of the two ETFs or the equally weighted portfolio (the benchmarks). The implementation of the trading strategies is based on 27 passive ETFs, while the data span is extended from February 4, 1999 until June 8, 2010.

	Panel A. Average mean			Panel B. Sharpe ratio			Panel C. End wealth		
	ETF1	ETF2	Eq. weighted	ETF1	ETF2	Eq. weighted	ETF1	ETF2	Eq. weighted
Naive	14	19	26	15	23	18	18	23	23
MA	6	14	7	7	14	6	7	14	10
Volatility ratio	20	18	22	12	21	15	24	23	22
Diff. in volatilities	20	22	22	14	20	11	22	21	23
Piecewise linear	14	17	17	14	20	10	17	19	18
Average	14,8	18	18,8	12,4	19,6	12	17,6	20	19,2

Conclusion

This work exploits the relationship between sign predictability and volatility predictability of two risky assets, to present results from meta-data analysis framework of 351 pairs and a rotation methodology. Our results suggest that, on average, rotation trading based on market timing is better off than using the best asset buy-and-hold strategy or the equally weighted portfolio. The suggested rules exhibit better average return than a buy-and-hold strategy, however, the come a cost of higher risk. The rotation strategy which includes relative pricing and relative volatility is to be an overall most robust performer. The success of trading is highly linked to the correlation between the underlying assets only for the models based on relative pricing but is also strongly linked with the differences in means across all models we examined.

The results of our paper give some hints as to what could perhaps drive investors' decisions' criteria in quantitative trading rules; it seems that currently our theoretical understanding of this heterogeneity is still very limited. Our analysis suggests that one key to explaining trading performance is to understand the forces that make quantitative algorithms to specialize into diverse categories and lead them to follow heterogeneous trading decisions. Investors should, therefore, look into models that move in unison (i.e. assets with similar trading charatestics, sectoral properties etc). Our results clearly suggest when the spread between the two underlying assets is widening, the range between the best and the worst rotation model is also expanding and, perhaps, this is associated with the levels of volatility. We are currently pursuing further research on the above issues in trying to explain why asset rotation works and how it's linked with volatility.

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Appendix

List of underlying ETFs. The list of our series is bellow accompanied by their ticker: SPDRs S&P500 (SPY), Oil Services HOLDRs (OIH), Financial Select Sector SPDR (XLF), PowerShares QQQ (QQQQ), Energy Select Sector SPDR (XLE), SPDR Gold Shares (GLD), iShares MSCI Emerging Markets Index (EEM), iShares MSCI EAFE Index (EFA), iShares S&P 500 Index (IVV), Vanguard Emerging Markets Stock ETF (WVO), Vanguard Total Stock Market ETF (VTI), iShares Russell 2000 Index (IWM), iShares Russell 1000 Growth Index (IWF), iShares FTSE/Xinhua China 25 Index (FXI), DIAMONDS Trust Series 1 (DIA), SPDR S&P MidCap 400 ETF (MDY), iShares S&P MidCap 400 Index (IJH), iShares Russell 3000 Index (IWV), iShares S&P SmallCap 600 Index (IJR), iShares MSCI Japan Index (EWJ), iShares Silver Trust (SLV), Ishares Russell 1000 (IWB), Vanguard FTSE All-World ex-US ETF (VEU), Vanguard REIT Index ETF (VNQ),Technology Select Sector SPDR (XLK), iShares Russell Midcap Index (IWR), Vanguard Europe Pacific ETF (VEA).

Table 1A. Annual mean return of each underlying ETF vis-a-vis the correspond annual mean return from the application of rotation models on that ETF

ETFs	Naive	MA	Volatility ratio	Diff. in volatilities	PL	ETF1	ETF2	Eq. weighted
SPY	6.55	4.45	7.52	7.13	6.07	3.55	8.16	5.86
OIH	9.58	10.87	8.36	8.72	7.93	7.86	11.13	9.50
XLF	7.24	6.08	2.62	3.08	5.51	-0.86	6.92	3.03
QQQQ	9.13	6.45	7.83	7.70	8.32	7.73	8.58	8.14
XLE	8.36	7.75	8.26	7.97	7.91	7.20	8.74	7.97
GLD	20.74	10.71	7.38	8.34	13.16	17.65	6.55	12.09
EEM	13.98	11.96	16.10	15.52	15.10	14.77	9.31	12.03
EFA	9.63	6.50	8.51	8.59	8.02	7.07	7.70	7.38
IVV	7.33	5.51	8.88	7.91	7.35	6.22	6.86	6.55
VWO	4.72	5.15	7.40	7.69	6.00	6.65	3.10	4.37
VTI	9.62	7.75	9.37	9.10	7.24	8.16	7.28	7.72
IWM	9.90	8.22	10.28	10.14	9.52	10.36	8.37	9.38
IWF	6.96	5.30	7.64	7.17	5.83	7.10	6.08	6.59
FXI	14.88	7.54	13.30	11.41	10.88	7.47	9.26	8.36
DIA	6.42	4.58	7.85	7.81	5.38	6.93	4.89	5.91
MDY	9.07	7.59	8.99	9.36	8.50	9.18	7.28	8.23
IJH	10.37	8.74	10.81	11.12	9.77	10.60	8.32	9.46
IWV	7.82	5.56	7.76	7.43	6.13	7.82	4.80	6.31
IJR	10.47	9.26	10.65	11.46	10.85	10.46	8.48	9.47
EWJ	4.21	4.70	7.07	6.43	5.12	5.38	2.17	3.78
SLV	5.82	3.57	10.30	8.42	2.19	1.60	9.78	5.69
IWB	7.65	5.62	9.03	8.41	7.24	9.09	4.52	6.81
VEU	37.21	33.75	37.50	38.70	32.89	35.73	36.66	36.18
IWR	10.66	9.93	10.48	10.55	10.38	10.23	8.48	9.34
VNQ	2.61	0.35	6.70	7.68	6.16	4.73	2.80	3.76
XLK	5.90	4.03	4.92	4.83	4.99	7.96	3.33	5.65
VEA	12.56	7.85	6.72	7.78	6.12	14.72	-0.26	7.23