Exploring the Profile of Simple Trend-Following Strategies: A Sensitivity Analysis

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Contents

Abstract

Systematic traders employ fully systematic strategies to manage their investments. As a result of the fully defined algorithmic nature of such strategies, it is possible to determine their exact responses to any conceivable set of market conditions. Consequently, sensitivity analysis can be conducted to systematically uncover undesirable strategy behavior and enhance strategy robustness by adding controls to reduce exposure during periods of poor performance / unfavorable market conditions, or increase exposure during periods of strong performance / favorable market conditions.

In this paper, we formulate both a simple systematic trend-following strategy (i.e., trading model) to simulate investment decisions, and a market model to simulate the evolution of instrument prices. We then map the relationship between market model parameters and strategy performance under a particular set of trading model parameters to explore the sensitivity of the strategy to different market conditions. We focus, in particular, on identifying the performance impact of changes in both serial dependence in price variability and changes in the trend.

The sensitivities derived provide an effective set of metrics for for determining the fundamental profile of the simple trading strategy and suggest an explanation for the functions of trading model components commonly found in trend-following strategies.

keywords: trend-following, Monte Carlo, sensitivity analysis

Introduction

For the class of market participants employing fully systematic approaches to manage their investments, it is possible to determine the exact responses of their strategies to any conceivable set of market conditions. As a result, they can conduct sensitivity analysis to systematically uncover undesirable strategy behavior and enhance strategy robustness.

Systematic traders generally use sensitivity analysis to identify the set conditions under which the system will operate within acceptable bounds. In the this paper, we refer to this set of conditions as the *operational domain* of the strategy (for a specific set of trading model parameters). The broader the spectrum of market conditions over which a trading system can perform within acceptable performance bounds (i.e. the broader the operational domain of the strategy), the more *robust* the system.

In general, the operational domain of a trading strategy can be broadened through the introduction of feedback and feed-forward risk controls. Feedback risk controls operate to reduce the impact of unpredictable phenomena or events on strategy performance, while feed-forward controls exploit regularities in market structure to make local predictions that aid in the enhancement of strategy performance. We use feedback controls when poor trading performance is not driven by something we can predict. We use feed-forward controls when we understand the drivers of poor performance and there is enough persistence in the market conditions for us to effectively anticipate future poor performance.

In the following sections, a simple systematic investment approach - a so called trend-following strategy - is explored through the use of Monte Carlo simulation. In particular, a market model is specified and used to generate realistic realizations of financial instrument prices across of broad spectrum of market conditions. Sensitivity analysis is then conducted, mapping the relationship between market model parameters and the strategy performance under a particular set of trading model parameters.

The market model (i.e., the model used to simulate instrument prices) has been designed to capture a set of essential stylized facts believed to be critical to the effective functioning of the strategy. As a model is a simplification of reality by definition, we do not attempt to reproduce all empirical stylized facts. We also limit the complexity and scope of the work by focusing on the instrument-level strategy. Portfolio-level meta-strategies that determine how to allocate across instrument-level strategy instances are not explored.

Literature Review - Stylized Facts

There exists a vast literature on the empirical characteristics of financial markets, documenting extensively the basic stylized facts. A similarly broad literature also exists on the derivation of financial derivative sensitivities. To price and risk manage products with path-dependent payoffs similar to a trend-following strategy, Monte Carlo simulation is often required. Despite a seemly obvious link between the analysis of systematic trading strategies and the analysis of replication strategies used to manufacture financial derivative products, little published work exists leveraging the findings in these two areas of research to the analysis of systematic trading strategies.

Although the scope of this paper does not allow for a detailed exploration of the stylized facts, a number of comprehensive surveys [3,4,6,7,12,15,18,20,22] exist.

The most basic and commonly agreed upon facts upon which we rely in this paper are as follows: 1) Price returns of financial instruments show insignificant serial correlation; 2) The unconditional distributions of returns are heavy-tailed, and; 3) Price variability for all financial instruments is both time-varying and serially dependent.

Methodology

Typically, systematic traders *backtest* the strategies that they employ (i.e., they use historical data to evaluate potential performance). Such backtesting allows systematic traders to determine the response of a strategy to the exact mix of market conditions that actually occurred, but not the response of a strategy to conditions that have not yet occurred or that may occur in different proportions in the future. Typically, the longer the historical period used, the more varied the market conditions, and the more likely that historical data can be used to build a relatively complete picture of the operational domain.

There are two main ways to supplement the historical data available for testing, namely market model-based Monte Carlo simulation, and Monte Carlo resampling. In this paper, we focus on the former approach to explore the characteristics of a simple trend-following strategy.

In order to simulate financial prices, a market model is designed, implemented, and calibrated to financial market data. The market model reproduces key well-established stylized facts, particularly focusing on time-varying, serially dependent price variability. Trading strategy sensitivities are created by simulating price scenarios - consisting of many realizations - for a range of key market model parameters, then computing the performance of the trading strategy for all realizations under each scenario.

In the following sub-sections, we provide overviews of the data acquisition and transformation process, the trading model, and the market model used in later sections of the paper to generate sensitivities.

Data Acquisition and Transformation

Prices, dividends, and corporate actions for each of the constituents of the S&P500 index over the period between 2000-01-01 and 2016-11-30 were acquired from Bloomberg. For each instrument that existed over the entire period, a *volatility-normalized* total return index accounting for changes in prices, accrued dividends and corporate actions was constructed[1] (Figure 1).

The index for each instrument represents the total return on a quarterly re-balanced position sized to equate a move of 3 units of price variability (i.e., average true range) to a 1% loss. Use of the volatility-normalized total return index facilitates comparison of model parameters across the instrument universe[2].

Trading Model

We implement a very simple version of a common systematic trend-following strategy [11][3]. The instrument-level logic of the trading system has a several core components: 1) The *entry signal*, determines timing for initiating a position (either long or short) in a particular instrument; 2) The *position sizing* algorithm determines the size of the position; and, 3) The *trailing stop loss* determines the timing of a exit from the position[4].

Both the position size and the distance of the trailing stop from the current price level are functions of the true range, R_t, a commonly used measure of the daily price range of a financial instrument that accounts for gaps from the close of the previous period to open of the current period:

$$R_t = \max[P_{t,H} - P_{t,L}, \text{abs}(P_{t,H} - P_{t-1}), \text{abs}(P_{t,L} - P_{t-1})]$$

where $P_{t,H}$ and $P_{t,L}$ are the current daily high and low prices respectively, and P_{t-1} is the previous close price.

[1] It is important to note that use of a data sample consisting of only the instruments that survived over the entire period can significantly bias backtest results. For the purposes of calibrating the market model, the range of conditions observed across the 397 instrument sample was deemed sufficient.

[2] The volatility-normalization process was also used to meet the conditions of the data agreement.

[3] See the reference for the definition of the EMA

[4] Although trend-following models used in practice have a layer of controls at the portfolio level, in this paper we focus only on the instrument-level components of the strategy.

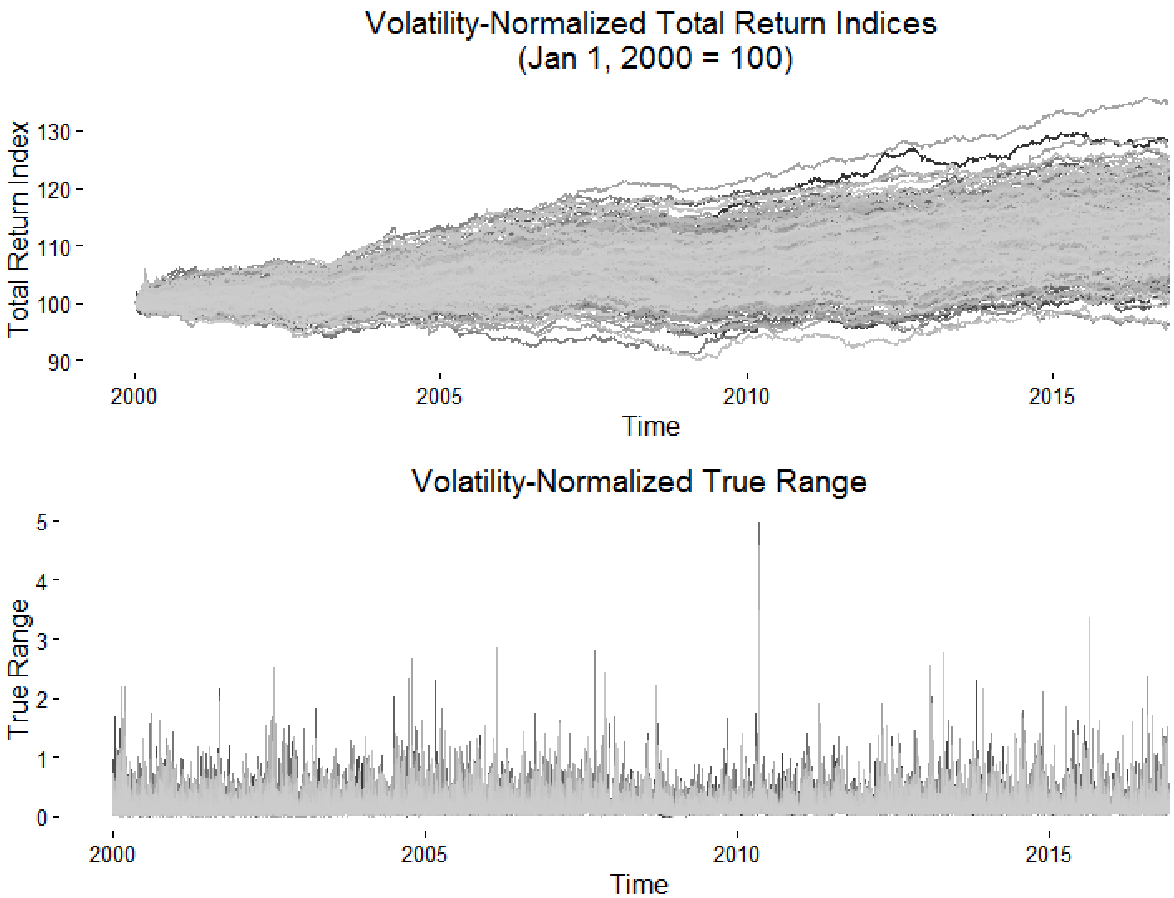

Figure 1: Normalized Price and True Range

Filters are commonly used to smooth price series. We use exponentially weighted moving averages (EMAs) to smooth both price and the true range time series.

The core rules of our simple trading model are detailed briefly in the next two sub-sections.

Long Position

At t, if the fast $\text{EMA}_{t-1,F}$ is *above* the slow $\text{EMA}_{t-1,S}$ and we have no position, we enter a *long* position of p_t units:

$$p_t = \text{floor}\left[\frac{f \times A_{t-1}}{\max[\text{ATR}_{t-1} \times M, L]}\right]$$

where f is the fraction of account size plus accrued realized P&L, A, risked per bet, ATR_{t-1} is the EMA of the true range for the previous time step, M is the risk multiplier, and L is the ATR floor.

We set our initial stop loss level M units of ATR *below* the entry price level, p_t. For each subsequent time, t, we update our stop level as follows:

$$s_t = \max[P_t - \text{ATR}_{t-1} \times M, s_{t-1}]$$

We exit our long position if the price, p_t moves below the stop loss level, s_{t-1}.

Short Position

At t, if the fast $\text{EMA}_{t-1,F}$ is *below* the slow $\text{EMA}_{t-1,S}$ and we have no position, we enter a *short* position of p_t units:

$$p_t = -\text{floor}\left[\frac{f \times A_{t-1}}{\max[\text{ATR}_{t-1} \times M, L]}\right]$$

We set our initial stop loss level M units of ATR *above* the entry price level, p_t. For each subsequent time, t, we update our stop level as follows:

$$S_t = \min[P_t - \text{ATR}_{t-1} \times M, S_{t-1}]$$

Regardless of whether we are long or short, for each trade we budget for a loss of f percent of our account size plus accrued realized P&L. The effectiveness of this crude risk budgeting system is a function of the characteristics of the true range. Serial dependence in the true range can transform this simple mechanism from a feedback control to a feed-forward control.

Market Model

We define and use a simple discrete time model to simulate a broad set of market conditions. Each scenario consists of realizations of both price and true range.

Model Specification

The following discrete time process is used to generate price realizations for a single stock:

$$P_t = P_{t-1} \exp\left(\mu \Delta t + \sigma_t \epsilon_t\right)$$

Where $t = 1 \ldots T$, $\Delta t = 1/T$, $\epsilon_t \sim N(0,1)$, and μ is the constant annual drift for the instrument over time period, T.

The volatility at time, t, is a function of *true range* [5]:

$$\sigma_t = \sqrt{\frac{\pi}{8}} R_t$$

Following Lunde 1999 [17], C. Brunetti & P. Lildholdt 2002 [5], and Chou 2005 [8], the true range is modeled according to a CARR(q,p) process:

$$R_t = \lambda_t \gamma_t$$

The conditional mean of true range at time, t is:

$$\lambda_t = \omega + \sum_{i=1}^{q} \alpha_i R_{t-i} + \sum_{j=1}^{p} \beta_j \lambda_{t-j}$$

where the normalized range, $\gamma_t = \frac{R_t}{\lambda_t}$, is gamma distributed.

The coefficients (ω,α_i,β_j) in the conditional mean equation are all positive to ensure that λ_t is positive. R_t and its expected value, λ_t, are both positive, so γ_t must also be positive. The process is stationary if $\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j < 1$. Finally, the unconditional (long-term) mean of the range, $\bar{\omega}$, is:

$$\bar{\omega} = \frac{\omega}{1 - \left(\sum_{i=1}^{q} \alpha_i + \sum_{j=1}^{p} \beta_j \right)}$$

Our model has two sources of uncertainty, ϵ and γ. Bursts in volatility driven by the true range process can generate price momentum that looks very similar to that observed in real markets.

Model Calibration

For each instrument in the universe under study, we fit a CARR(1,1) model with a gamma-distributed error. We then use the cross-section of parameters to define the starting range of parameters for use in our sensitivity analysis.

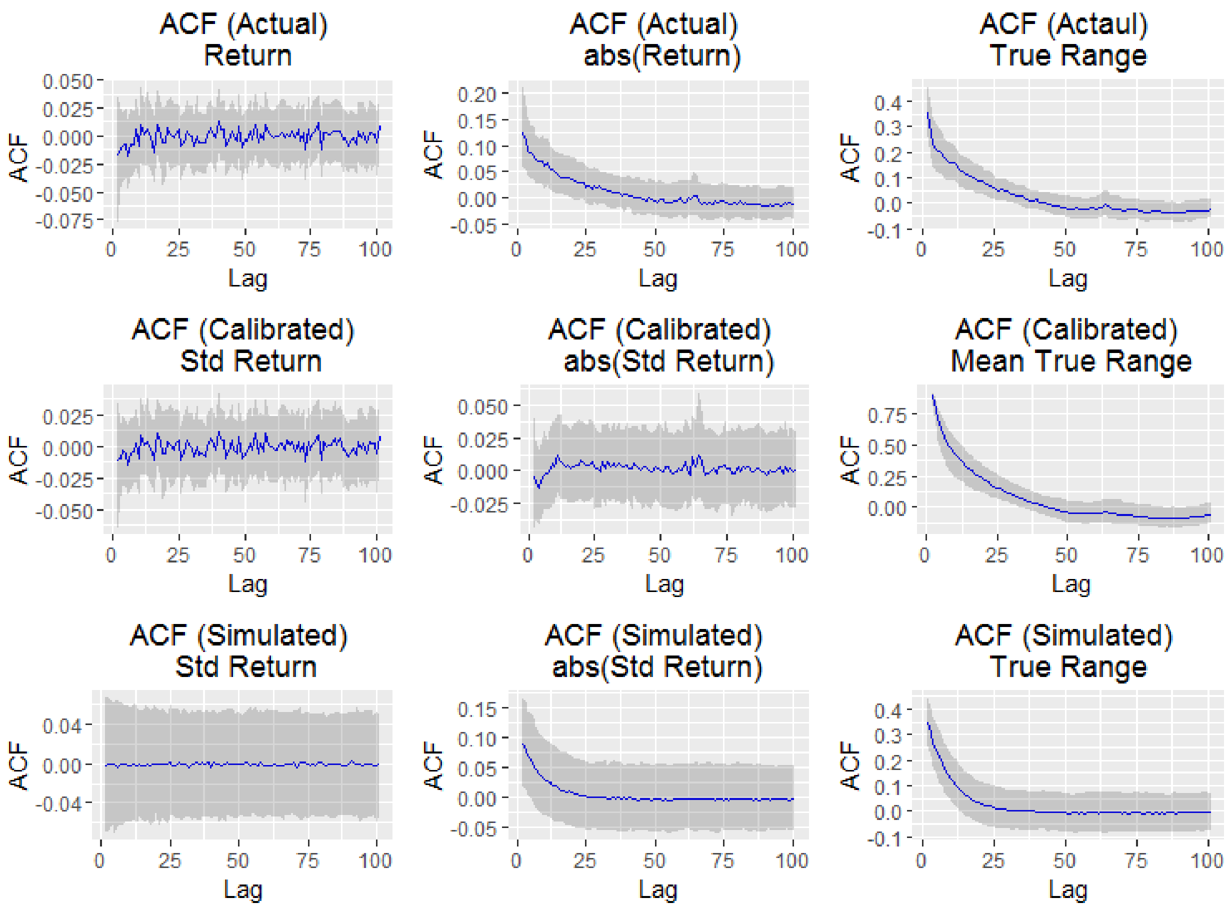

Figure 2: Investment Universe Autocorrelation Functions: Actual, Calibrated, and Simulated

The first row of the illustration above was derived by computing the autocorrelation functions (ACFs) for the log returns, absolute value of the log returns, and the true ranges for each instrument in the universe under study, then computing the median and 95% confidence interval (Figure 2). The second row shows the autocorrelation of the standardized log returns, the absolute value of the standardized log returns, and the conditional true range (λ) based on the calibrated model. The last row shows the median and 95% confidence interval for the standardized log return, the absolute value of the standardized log return and the true range for a for 1000 realizations generated for a sample instrument using the market model.

Notice that the standardized residuals of the fitted model show little autocorrelation across all instruments in the sample, indicating that the model accounts reasonably well for serial dependence in-sample. The shape of the ACF for the simulated true range, however, shows a faster decay than that observed in practice. In is apparent from the difference in the actual and simulated ACF that a model based on an underlying long-memory process may provide a better fit than the short-memory process chosen.

Results: Sensitivity Analysis

In the previous section, we specified a market model, then calibrated it to each instrument in the equity universe under study. In this section, we create sensitivities by simulating price scenarios for a set of market model parameters and computing the performance of the trading model under each scenario.

The parameter space of the combined market and trading models is vast. To reduce the dimension of the problem, an initial study was conducted to coarsely explore the impact of different trading model parameters on the strategy backtest results. A set of trading model parameters was selected from stable areas of the response curves[5].

Following the selection of the trading model parameters, the range of market parameters observed over the entire instrument universe under study was examined and used to determine realistic starting parameter ranges for sensitivity analysis. These ranges were then extended to account for realistic conditions that may be observed in in the future. Once ranges were selected, another coarse study was conducted to determine which market model parameters had the largest impact on performance. Based on these results, the drift (μ), ω, α, and β parameters were selected for the final sensitivity analysis. 1000 paths, each with a 1250 day length (roughly 5 years), were used for all simulations. Parameter sets for each of the final simulations appear in Appendix C. The strategy performance measure (TWR) is defined in Appendix B.

[5] The process required to select robust trading parameters is beyond the scope of this paper. An extensive literature associated with a number of disciplines, including machine learning, addressing over-fitting and robust parameter selection

Sensitivity to Trend Conditions

Trend-following strategies operate on premise that the emergence of a trend in a particular instrument can not be predicted. The system is designed to maintain a position in an instrument as long as it is trending and exit the position when the trend has reversed beyond M times the typical daily range. Any predictability in the characteristics of true range, is thus expected to enable strategy enhancement.

First we use our market model defined above to determine the sensitivity of the strategy to trends of different magnitudes by computing trading model performance under different drift rates (μ) (Figure 3).

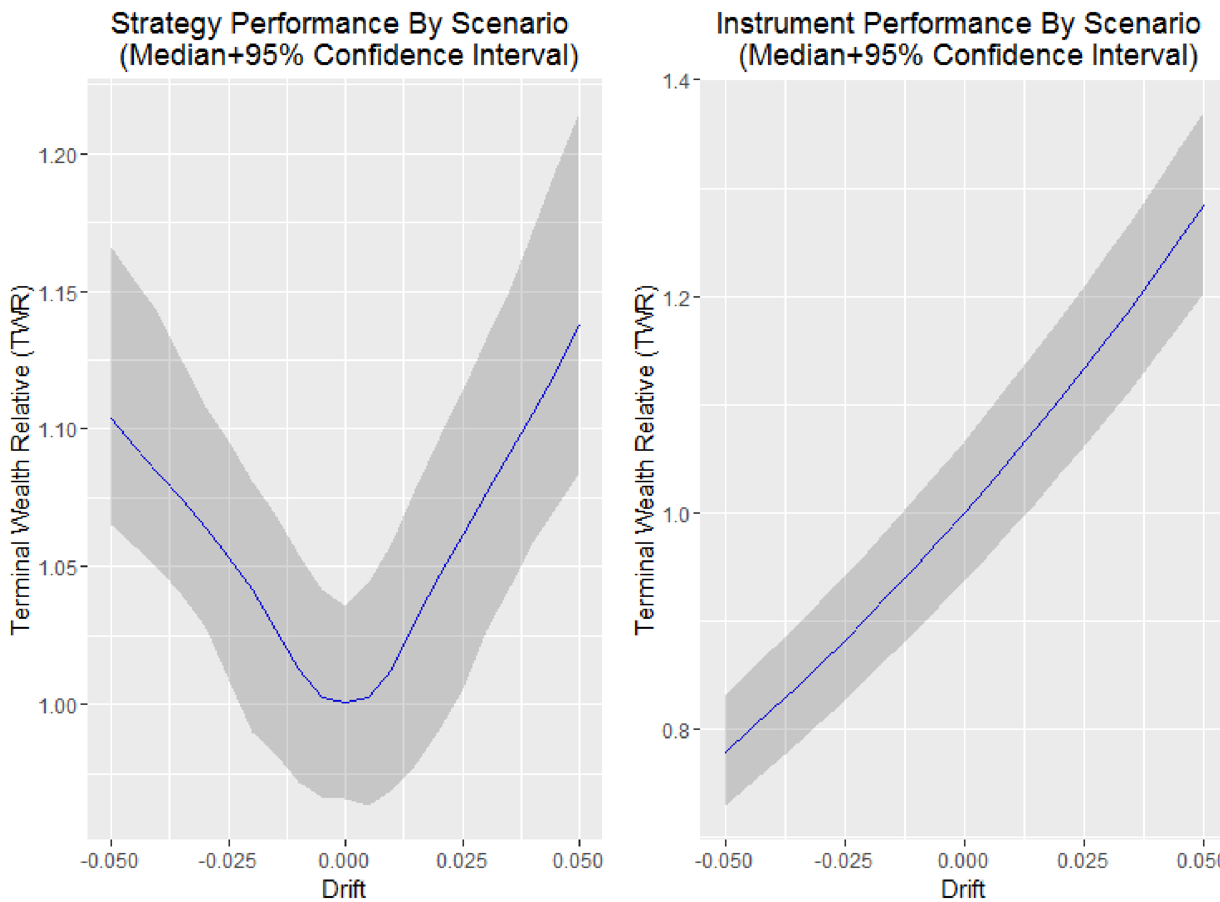

Figure 3: Trading Model Performance Sensitivity to Changes in Trend (μ)

The profile that emerges from this sensitivity analysis of the strategy performance with respect to changes in the drift illustrates the essence of the strategy. From the profile, it is clear that as the price moves up or down strongly, the strategy performance increases. The less variability around the trend, the better the strategy performance. Choppy, sideways movement in prices produces a condition where the strategy repeatedly enters and gets stopped out, generating losses for roughly half of the paths.

By holding both the trading model parameters and the α and β parameters of the market model constant, and perturbing the ω parameter of the market model up or down, we determine the impact of changes in variability for the same drift scenarios depicted above (Figure 4):

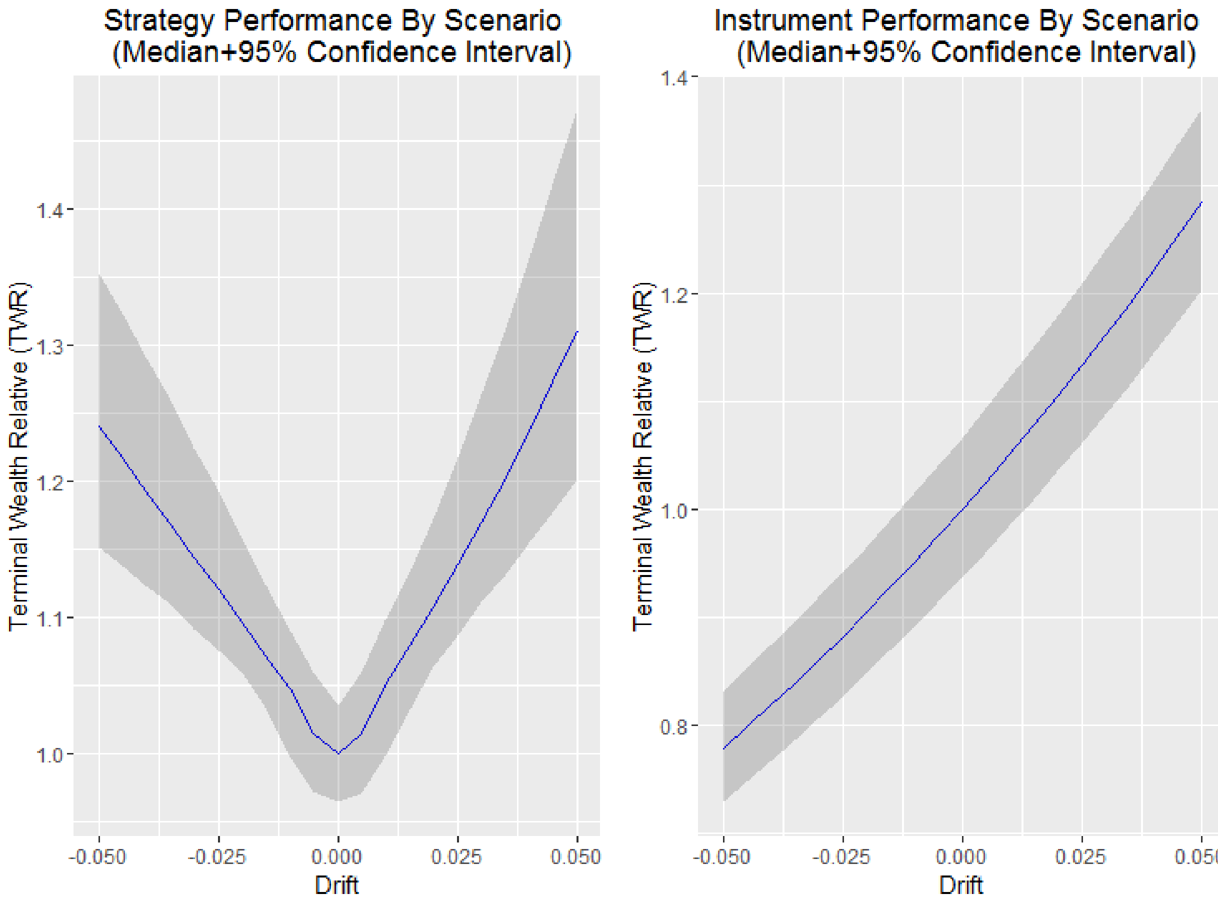

Figure 4: Trading Model Performance Sensitivity to Changes in Trend (μ) Under a Reduction in General Level of Variability

Decreasing the ω parameter roughly 50% to the lower end of the range observed across all of the instruments in the universe under study (i.e., roughly the 1^{st} percentile), we see the profile steepen and shift up - a marked improvement in performance.

Sensitivity to Volatility Conditions

Given the observed serial dependence in the true range, a natural question arises as to the sensitivity of the performance of our simple trading model to the strength of autocorrelation. To determine the link between strategy performance and autocorrelation we perturb the α and β parameters along the line depicted in the following figure, generate price and true range scenarios, then evaluate strategy performance under each scenario (Figure 5):

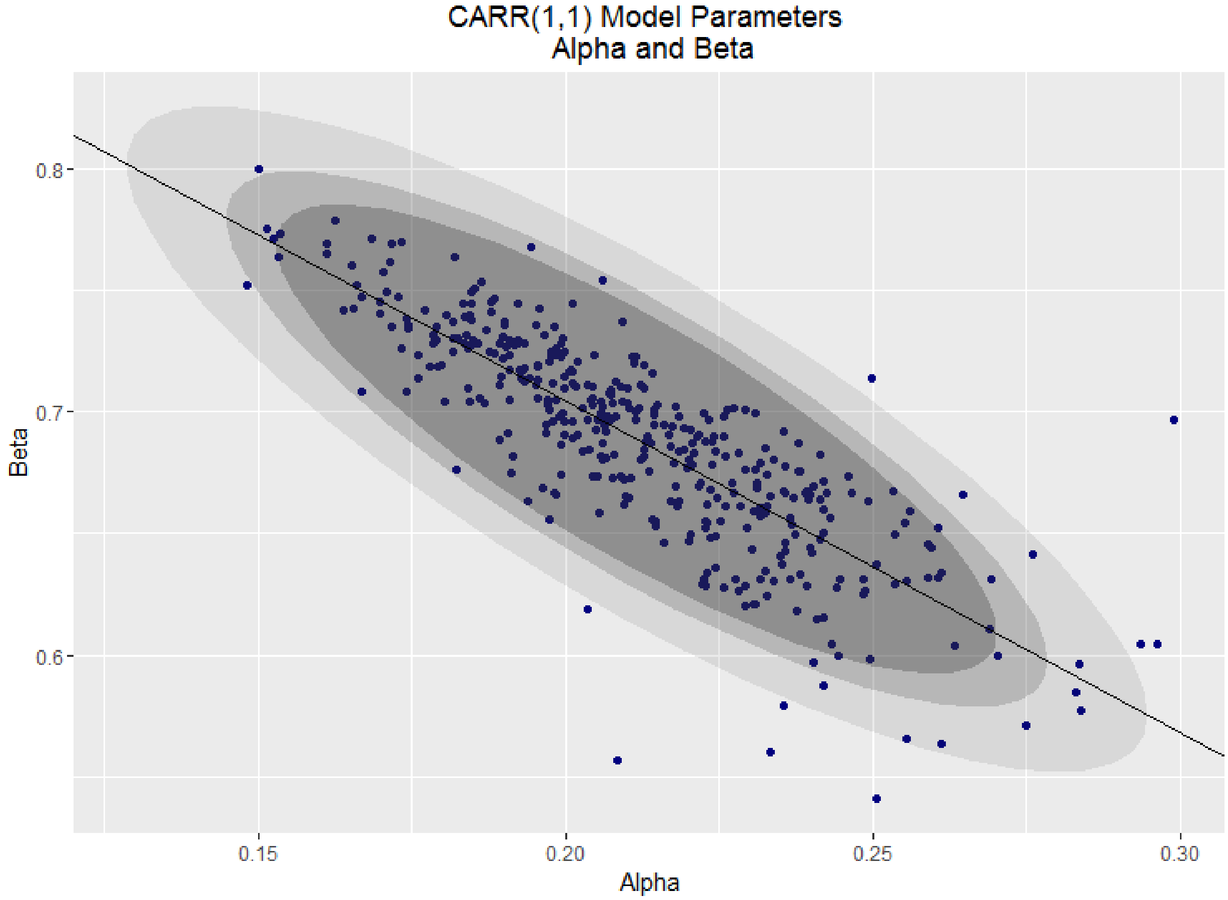

Figure 5: Relationship Between Market Model Parameters α and β

Using the mean trend across the instrument universe we see a minor performance increase as serial dependence increases (Figure 6):

Increasing the trend to twice the long-run maximum drift range observed across the instrument universe, we observe significant performance improvement as serial dependence increases (Figure 7):

Conclusion

In this paper, we formulated both a simple systematic trend-following strategy (i.e., trading model) to simulate investment decisions, and a market model to simulate the evolution of instrument prices. We explored the sensitivity of our strategy to different market conditions (for a particular set of trading model parameters) and provided a map between the market model parameters for each scenario representing a particular market condition and strategy performance. In particular, we focused on identifying the performance impact of

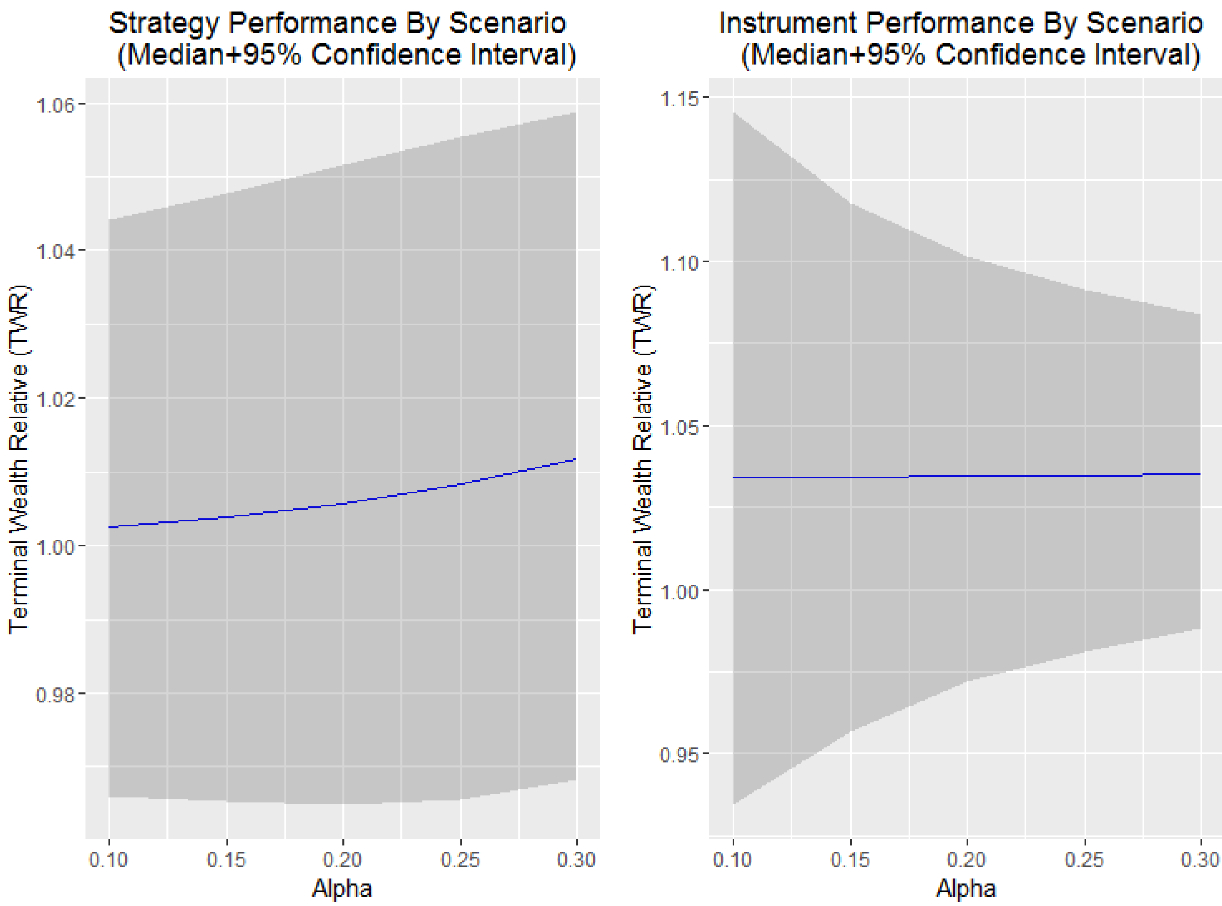

Figure 6: Strategy Performance Sensitivity to Changes in Serial Dependence in the True Range Under Typical Trend Conditions

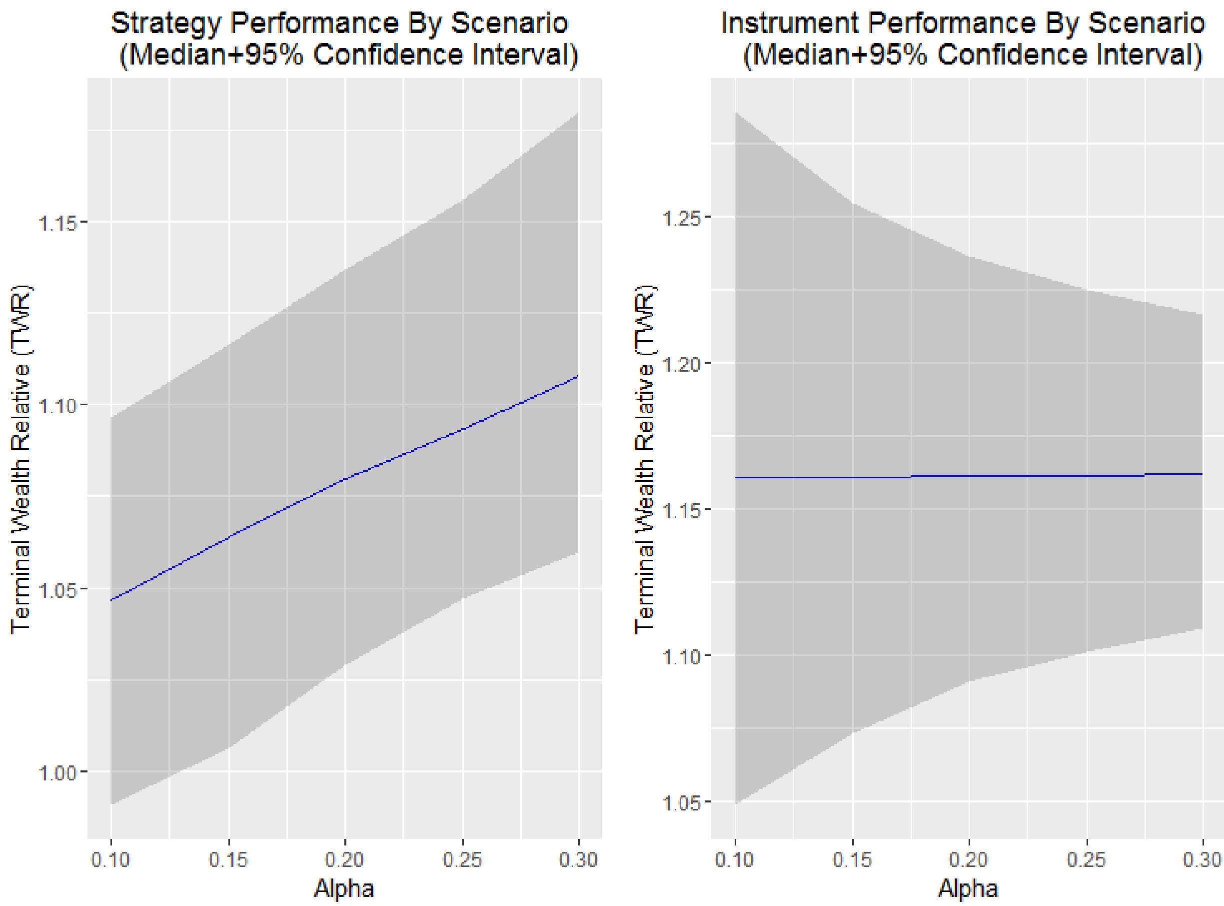

Figure 7: Strategy Performance Sensitivity to Changes in Serial Dependence in the True Range Under Strong Trend Conditions

changes in 1) serial dependence in price variability, and; 2) changes in the trend.

The sensitivities derived provide an effective visual depiction of the fundamental profile of the simple trading strategy and suggest an explanation for the functions of trading model components commonly found in trend-following strategies. The serial dependence in the true range appears to enhance strategy performance, particularly during periods of strong performance, by reducing conditions under which the strategy enters and exits repeatedly from a sideways moving market. Our simple model suggests that a slightly more complex feed-forward controller could be created to further improve performance of the strategy.

An extension of our simple single instrument market market model to a multiple instrument model could provide useful sensitivity analysis relating to the cross-dependence between instruments. Incorporation of long range dependence into the true range piece of the market model would also allow us to improve the realism of our results.

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Appendix A: Project Github Repository

All of the volatility-normalized data and code used to generate this paper is available under the following github repository.

https://github.com/dgn2/IS604

The repository includes Python code used to both fetch data from Bloomberg (i.e., monthly S&P500 index constituent, daily price, dividend, and split data) and perform the volatility normalization.

The repository also includes the R/C++ source file implementing the simple trading model, and the .Rmd file used to generate the paper. The simulations have been disabled with the .Rmd file by setting the 'eval' flag to FASLE. To run the .Rmd, a significant amount of RAM is required[6].

Appendix B: Strategy Performance Measurement

We can define the *terminal wealth relative* (TWR) as the multiplier that we apply to our starting equity to get our ending equity. In other words, the terminal wealth relative is one plus our total return [24].

$$TWR_T = \prod_{t=1}^{T} (1 + r_t) = \prod_{t=1}^{T} (HPR_t)$$

Where:

r_t is our return over period t

HPR_t is our holding period return or one plus our return over the t^{th} period

TWR_T is our terminal wealth relative or one plus our total return over T periods

We can approximate our TWR_T with the following formula [24]:

$$approxTWR_T = \left(\sqrt{(AHPR_T^2 - SDHPR_T^2)}\right)^T = EGM^T$$

Where:

[6]The simulation was run on a recent quad-core workstation with 64 gigs of RAM.

N is the number of sub-periods over which we have returns

$approxTWR_T$ is the approximate terminal wealth relative (i.e., one plus the total return over the T periods)

HPR_t is the holding period return (i.e., the return over the t^{th} period)

$AHPR_T$ is arithmetic average of the holding period returns over the T periods:

$$AHPR_T = \frac{1}{T}\sum_{t=1}^{T}(HPR_t)$$

$SDHPR_T$ is the standard deviation of the holding period returns over the T periods:

$$SDHPR_T = \frac{1}{T-1}\sum_{t=1}^{T}(AHPR_T - HPR_t)^2$$

EGM_T is the estimated geometric mean (EGM) over the T periods

$$EGM_T = \sqrt{(AHPR_T^2 - SDHPR_T^2)}$$

This equation illustrates that:

[1] If $AHPR_T$ is less than or equal to 1, then regardless of the other two variables, $SDHPR_T$ and T, our result can be no greater than 1 (i.e., our total return will be less than or equal to zero).

[2] If $AHPR_T$ is less than 1, then as T approaches infinity, TWR_T approaches zero. This means that if $AHPR_T$ is less than 1, we will eventually go broke.

[3] If $AHPR_T$ is greater than 1, increasing T increases our TWR_T.

[4] If we reduce our $SDHPR_T$ more than we reduce our $AHPR_T$ our TWR_T will rise.

Reducing variability or increasing average return by the same amount has an *identical* impact on compound return.

We can use this equation to understand how changes in the average return, return variability, or both impact our compounded return.

We can also extend this result to show how the cross-dependence between strategies/investments - which ultimately drives portfolio variation - impacts compound return.

TWR and EGM_T - which are composed of $AHPR_T^2$ and $SDHPR_T^2$ - are our primary measures of trading strategy performance. All other performance metrics are a function of these three metrics.

Appendix C: Simulation Parameters By Figure

Figure 3

Drift (μ) scenario from -0.05 to 0.05 by increments of 0.005

Market Model Parameters - CARR(1,1)

	nRows	nPaths	nYears	nBurn	S0	Omega	Alpha	Beta	Kappa	Gamma
Parameter	1250	1000	5	100	100	0.0130	0.1900	0.7180	15000	0.0200

Trading Model Parameters

	Indicator Lookbacks (In Days)				Long/Short
	atrLookback	atrMultiplier	fastLookback	slowLookback	longOnly
Parameter	20	6	120	180	FALSE

	Cost	Risk			
	commissionPerShare	accountSize	fPercent	minRisk	stopTWR
Parameter	0.0000	100000	0.0050	0.0050	0.85

Figure 4

Drift (μ) scenario from -0.05 to 0.05 by increments of 0.005

ω at roughly the 1^{st} percentile of observed universe parameter range.

Market Model Parameters - CARR(1,1)

	nRows	nPaths	nYears	nBurn	S0	Omega	Alpha	Beta	Kappa	Gamma
Parameter	1250	1000	5	100	100	0.0060	0.1900	0.7180	15000	0.0200

Trading Model Parameters

	Indicator Lookbacks (In Days)				Long/Short
	atrLookback	atrMultiplier	fastLookback	slowLookback	longOnly
Parameter	20	6	120	180	FALSE

	Cost	Risk			
	commissionPerShare	accountSize	fPercent	minRisk	stopTWR
Parameter	0.0000	100000	0.0050	0.0050	0.85

Figure 6

α scenario from 0.10 to 0.30 by increments of 0.01

Typical in-sample long-term drift of 0.0069

Market Model Parameters - CARR(1,1)

	nRows	nPaths	nYears	nBurn	S0	Omega	Alpha	Beta	Kappa	Gamma	Drift
Parameter	1250	1000	5	100	100	0.0130	variable	variable	15000	0.0200	0.0069

Trading Model Parameters

	Indicator Lookbacks (In Days)				Long/Short
	atrLookback	atrMultiplier	fastLookback	slowLookback	longOnly
Parameter	20	6	120	180	FALSE

	Cost	Risk			
	commissionPerShare	accountSize	fPercent	minRisk	stopTWR
Parameter	0.0000	100000	0.0050	0.0050	0.85

Figure 7

α scenario from 0.10 to 0.30 by increments of 0.01

Strong drift scenario of 0.03

Market Model Parameters - CARR(1,1)

	nRows	nPaths	nYears	nBurn	S0	Omega	Alpha	Beta	Kappa	Gamma	Drift
Parameter	1250	1000	5	100	100	0.0130	variable	variable	15000	0.0200	0.0300

Trading Model Parameters

	Indicator Lookbacks (In Days)				Long/Short
	atrLookback	atrMultiplier	fastLookback	slowLookback	longOnly
Parameter	20	6	120	180	FALSE

	Cost	Risk			
	commissionPerShare	accountSize	fPercent	minRisk	stopTWR
Parameter	0.0000	100000	0.0050	0.0050	0.85