FACULTAD ECONOMÍA Y NEGOCIOS UNIVERSIDAD DE CHILE

PORTFOLIO PERFORMANCE: THE CASE OF SERIAL AUTOCORRELATION

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Portfolio performance:

The case of serial autocorrelation

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Abstract

The use of the Sharpe ratio for the measurement of the performance of the financial assets is widely generalized, although there is empirical evidence of serious problems with the assumptions behind the distribution functions. This paper explores the conditions under which the Sharpe ratio is efficient to analyze the performance of financial asset portfolios, a situation that is not true in the presence of strong autocorrelation. We demonstrate the effect that autocorrelation has in determining the best means of performance measurement, defining a robustness function of the variance of the Spearman coefficient degradation, allowing to define monitoring and control criteria in the task of tracking the evolution of financial assets and makes an adequate selection of a combination of risk and return, expanding the spectrum of analysis for the performance measurement of the financial series, placing an alarm for the evaluation of the performance of the financial assets.

Contents

I Introduction

The assessment of financial assets determines how an investment has behaved against some contrast parameter, delivering signals if a decision exceeds or falls short of the investor's expectations. This evaluation improves the financial activity to make an investment decision in a base of a number of alternatives who makes an adequate selection of a combination of risk and return. The investor, using information on the yields of financial assets, can make decisions about the composition of his portfolio, eventually modifying his investment preferences on the selection of a set of portfolios, being a fundamental part of the risk management.

What is the role of the autocorrelation in the evaluation of the assets? Understanding that the existence of autocorrelation in the time series is common, it is necessary to comprehend the effect that can bring the work with these time series. The problems generated by autocorrelation in the adequate estimation of yield parameters and subsequent estimations of the evaluation methods have been developed in the financial literature, as mentioned by Lo (2002), Eling (2006), between other authors. However, the dimension of the evaluation of the performance of the financial assets subject to the presence of autocorrelation is an area that has not heavily explored.

The first developments in the assessment of financial assets can found in the seminal contribution of Sharpe (1966), who developed the one that has been considered the main means to evaluate the returns of the financial assets for the investors. The Sharpe ratio shows an inverse relationship between the expected return and the risk level of the asset measured by its standard deviation. Amenc et al. (2008) mention that 80% of managers use Sharpe's ratio for the evaluation of their portfolios. This measurement of market returns and risk is widely used by investors when they consider that the property responds to a generation of data from the normally distributed returns, and it has widely accepted by the direct linkage that can draw from Modern Portfolio Theory initiated by Markowitz (1952).

When the normality assumptions of the distribution of the returns fulfilled, these can be characterized directly by the first and the second moment of their distribution. However, the fundamentals in the use of the Sharpe ratio as a means to measure the efficiency of financial assets diminished by the need for investors to diversify their portfolios. Besides the characteristics of the distribution of returns that, in general terms, are quite different from normality assumptions (see Agarwal and Naik (2004), Malkiel and Saha (2005), Van Dyk et al. (2014)), with Sharpe's ratio being an inadequate measure of risk (see Zakamouline (2011)). Brooks and Kat (2002) performs an analysis of various funds, showing that these do not meet the normality criteria, present a highly significant positive first order autocorrelation, correlation with other assets, among other phenomena.

Even with the strong theoretical problems of Sharpe's ratio in the measurement of the goodness of financial asset, as mentioned by Van Dyk et al. (2014), one can ask why its extensive use by investors, compared with other performance measures, such as Sortino and Van Der Meer (1991), Sortino et al. (1999), Keating and Shadwick (2002), Dowd (2000), Young (1991), Kestner (1996), and Kaplan and Knowles (2004) that in principle are able to capture the problems of characterization of the distributions of the returns that usually appear in the financial market.

The measures of performance presented may represent an adequate optimization solution within the selection criteria of portfolios. However, it is not clear the dominance of an evaluation method over the other in the strategy defined by an investor, as mentioned by Biglova et al. (2004).

Eling and Schuhmacher (2007) perform an analysis of the Sharpe ratio evaluation compared to 12 other evaluation measures, showing that the Sharpe ratio presents a high correlation with them, implying that the decision criteria of the Investors do not change if another valuation measure is used to the detriment of Sharpe's ratio. Similarly, Eling (2008) indicates that the measure of valuation followed by investors does not substantially change the ranking assigned to financial assets, focused on the mutual fund market. Hass et al. (2010) repeat the analysis and incorporate other evaluation measures, showing different results that expand the robustness of Sharpe's ratio in the assessment of mutual funds, highlighting a particular evaluation means that separates from the rest, the Manipulation-Proof Performance Measure (MPPM), which observed sensitive to the parameters with which it computed.

Gallais-Hamonno and Nguyen-Thi-Thanh (2007) perform an analysis of the time series, showing econometric estimates for the parameters of autocorrelated series. In this paper, a contrast of the evaluation method is realized using the Sharpe ratio estimation and a correction based on the method introduced by Geltner (1991), Geltner (1993) and Okunev and White (2003). The authors found that the assessment does not differ when used the correction or using the uncorrected Sharpe criterion, corroborating the previous analyses on the robustness of the Sharpe ratio method as a standard for evaluating the performance of financial assets.

The present paper covers the effect on the robustness of the use of the Sharpe ratio in the evaluation of the financial assets, using a numerical analysis with Monte Carlo simulations in the construction of the distributions of the returns of assets, observing the effects that can case autocorrelated series in measures of evaluation of financial assets. The paper presents the following distribution: in section II a synthesis of the influence of autocorrelation in the estimation of Sharpe ratio is presented. In Section III a simulation process is developed to characterize the effect of the components of an autocorrelated model. Section IV performs an analysis of the elements of the autocorrelated model to perform a verification of the effects in real series, analyzing its empirical effect on investments in a panel dataset. Finally, section V corresponds to a section of conclusions.

II Effect of Autocorrelation

The phenomenon of serial autocorrelation is present in the series of returns of financial assets, can cause strong biases in decision making and errors that can impact the decisions of investors. There are at least two significant problems with which investors constantly deal, one of them is the management of the information they have about the funds and the second corresponds to the statistical properties of the returns of the funds that impact the investment strategies. In this section, we will focus on the second problem that affects decisions made by investors.

One of the main statistical elements that impact on returns of financial assets corresponds to the serial correlation in the monthly measurements, as mentioned by Brooks and Kat (2002). In this case it is shown that many of the evaluated indexes present a strong presence of serial correlation with parameters of an autoregressive model of order 1 of at least 0.4 for the coefficient that corresponds to the return of the previous period and a level of significance of 1%, showing a strong bias in which the volatility underestimated. On the other hand Avramov et al. (2006) mention in their article that there is strong evidence that the illiquidity of financial markets has an effect on the autocorrelation of returns. In a similar way, we can cite Chordia and Swaminathan (2000) who mention that the problems of autocorrelation and cross autocorrelation are related to the trade volume of financial assets.

Zakamouline (2011) mentions how the high degree of correlation between the different measures of performance with Sharpe's ratio represents a puzzle, focusing on explaining the reasons for this phenomenon described by Eling and Schuhmacher (2007) and Eling (2008). In this same study, he concludes that the correlation depends on the properties of the sample, finding that financial assets with significant Sharpe ratios computed lead to substantial changes in the ranking if other performance measures used. However, it uses a limited sample, which can bias and condition its results.

II.1 Autocorrelation Model

This section describes the general model of time series that will be used for the measurement of performance ratios and will analyze the effect it has on the Sharpe ratio. The data generator model described below.

$$y_t = \alpha + \sum_{j=1}^{J} \rho_j y_{t-j} + \sum_{i=1}^{I} \theta_{t-i} \mu_{t-i} \tag{1}$$

where y_t corresponds to the time series returns of the asset y, α corresponds to an adjustment parameter, ρ_j corresponds to a parameter of the model related to the lags of the time series of y_t, θ_{t-i} corresponds to a parameter of the model associated with the lag of the time series error or innovation and μ_{t-i} corresponds to a white noise error term.

This document assumes a stationary process of the returns of the financial assets and contemplates the process of autocorrelation using an autoregressive process of order 1 (AR (1)) to exemplify and characterize the effects on the function that defines the ranking of financial assets using the Sharpe ratio criterion.

For the case of an AR (1) model the average of the process, its variance and its autocovariance, respectively are:

$$E(y_t) = \frac{\alpha}{1-\rho}$$

$$\gamma_0 = \frac{\sigma^2}{1-\rho^2}$$

$$\gamma_j = \frac{\rho^j}{1-\rho^2}\sigma^2$$

Autocorrelation is defined as follows:

$$\phi_j \equiv \frac{\gamma_j}{\gamma_0} \tag{2}$$

The effect of autocorrelation is shown in Asness et al. (2001), showing that the tested funds have positive autocorrelation factors, statistically significant and that generate a bias that underestimates the true variance of the returns series. However, in a more thorough analysis of the nature of the bias, we can show that in the case of negative autocorrelations the effect is the reverse of that described previously, and the traditional estimate of variance overestimates the true volatility of the series.

For the adequate calculation of the returns of the financial assets[1], we can describe the procedure developed by Geltner (1991) and Geltner (1993)[2], allowing to correct the bias produced by the autocorrelation of the time series of the financial assets, where r_t^o corresponds to the observed return in the period t weighted by r_t^c which corresponds to the true value of the return and the observed return in the period $t-1$.

[1] Returns are defined as the percentage change in the price of the financial asset in successive periods, $r_t = \frac{p_t - p_{t-1}}{p_{t-1}}$.

[2] This methodology was generalized by Okunev and White (2003) and allows to perform the correction procedure for any structure of a stationary series.

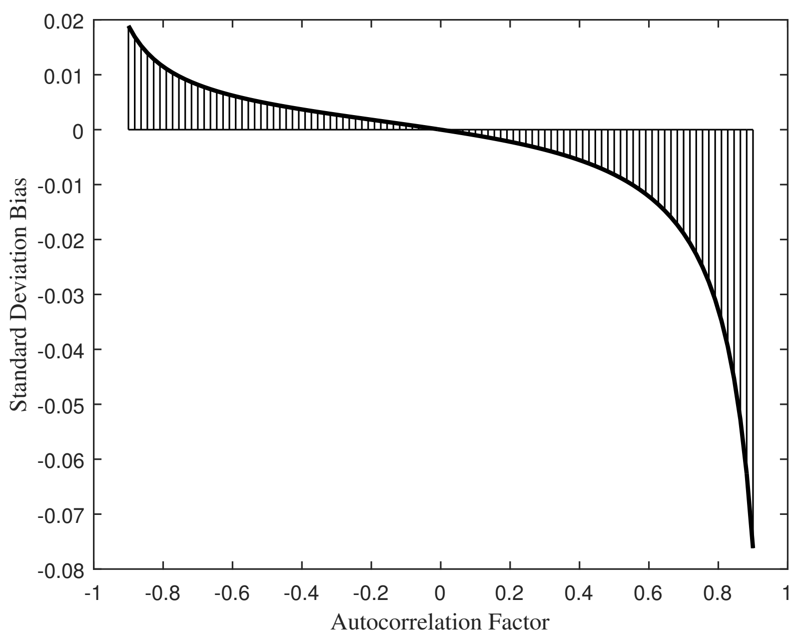
$$r_t^o = (1-\rho)r_t^c + \rho r_{t-1}^o \tag{3}$$

ρ corresponds to a parameter of the model that represents the correlation factor and $\rho \in (-1,1)$. By clearing a true value of the return we get:

$$r_t^c = \frac{r_t^o - \rho r_{t-1}^o}{1-\rho} \tag{4}$$

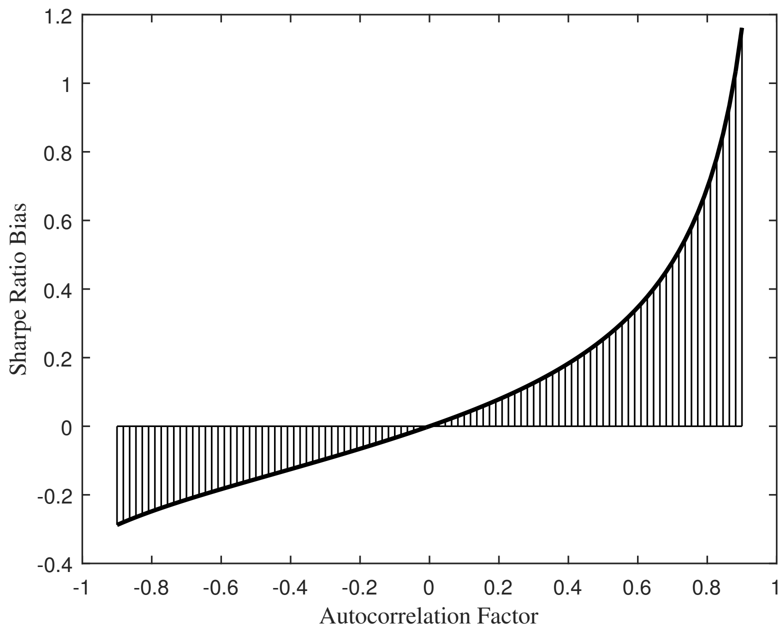
Figure 1 shows the effect of the computed standard deviation difference compared to the standard deviation corrected by the procedure described by Geltner. It is shown that at a higher level of negative autocorrelation, the difference between computed volatilities tends to increase explosively. A similar phenomenon observed in the presence of positive autocorrelation where bias tends to grow very rapidly, corroborating the overestimation of the computation of the standard deviation for the case that the series is negatively autocorrelated and underestimated for the event of a positively correlated series.

Figure 1: Standard Deviation Bias



The effect of the bias produced by the autocorrelation affects performance measures such as the Sharpe ratio, causing strong losses due to an inadequate investment strategy due to errors in its measurement by the investors. Figure 2 shows the bias arising out in the Sharpe ratio calculation, failing to make the proper estimation of the values of the returns, indicating the effect that the parameter has in the proper estimation of the variance or standard deviation of the time series.

Figure 2: Sharpe Ratio Bias



III Monte Carlo Simulation

In this section, we proceed to develop the simulation of the series of returns to be able to characterize the phenomena that affect them. We will explore three phenomena in particular: the effect of the autocorrelation factor; The effect of the variance or the standard deviation of the innovation in the series of returns; And the effect of the scale factor or the intercept of the model.

A time series of 500 periods generated for each of the 1000 hypothetical investment funds that have fixed parameters for the definition of the data model of an AR (1) model. This procedure is repeated 1000 times for values of the correlation element of the model, ρ, which defined between the values of $(-0.99; 0.99)$. In the same way, we proceed with the analysis of the standard deviation of the innovation of the model, μ_t, which will define between (4.5%; 30%). Also, the scaling factor, alpha, will also be characterized by values of $(-1.0\%; 1.0\%)$. The data generator model is shown below.

$$r_{i,t} = \alpha + \rho r_{i,t-1} + \mu_{i,t} \tag{5}$$

$r_{i,t}$ corresponds to the return of the fund i in the period t, α corresponds to the adjustment factor that defines the unconditional mean of the model. ρ is the factor of the model that is the source of the autocorrelation of the returns and μ_t is an innovation that responds to a Gaussian distribution belonging to the time series, $N(0, \sigma)$.

Once the simulated financial series are defined, the Spearman[3] correlation will be used to measure the degree of robustness of the Sharpe ratio compared to other evaluation methods due to the extensive use of the literature. Alternatively, we can use the Kendall correlation. However, Conover (1999) mentions that for large samples there is not strong evidence to prefer one to the detriment of the other. The report of the findings will correspond to the simple average of the Spearman correlation of the rankings defined by each measure of performance against the classification of the financial assets specified by the ratio of Sharpe.

[3] This methodology was originally described by Spearman (1904).

Spearman's correlation coefficient is an attempt to measure the power of the relationship between two variables, in this case, the Sharpe ratio between the ranking of financial asset portfolios and other performance measures. This methodology allows measuring the relationship between variables that are not necessarily of quantifiable characteristics. In the case of the measurement of rankings, we are in the presence of a classification that naturally is of ordinal characteristics.

Below is a chart of the various performance measures and method of calculation used in this document.

Table 1: Performance Measure

Ratio	Calculation	Reference
$Sharpe$	$(r_t - r_f)/\sigma$	Sharpe (1966)
$Omega$	$(r_t - \tau)/LPM_1 + 1$	Keating and Shadwick (2002)
$Sortino$	$(r_t - \tau)/\sqrt{LPM_2}$	Sortino and Van Der Meer (1991)
$Kappa_3$	$(r_t - \tau)/\sqrt[3]{LPM_3}$	Kaplan and Knowles (2004)
$Upside$	$HPM/\sqrt{LPM_2}$	Sortino et al. (1999)
$Calmar$	$(r_t - \tau)/-D$	Young (1991)
$Sterling$	$(r_t - r_f)/[(1/K)\sum_{k=1}^{K} -D]$	Kestner (1996)
$Dowd$	$(r_t - r_f)/VaR$	Dowd (2000)

r_t= mean return;

r_f= risk free interest rate;

τ= Target parameter;

LPM_n= lower partial moment of order n;

HPM_n= higher partial moment of order n;

D= drawdown of fund;

III.1 Effect of Correlation Coefficient

In this section we will focus on analyzing the effect of the Spearman correlation coefficient on variations of the autocorrelation factor, ρ. For the modeling, we used the parameters of $\alpha = 0.4\%$ and the standard deviation of the error $\sigma = 10\%$.

Figure 11 shows the ratio of Omega and Sortino, which degrade the robustness of the Sharpe ratio as the correlation factor increases, showing that when approaching values greater than 0.6, the degradation rate returns exponentially. Figure 12 shows the Kappa ratio, which shows a deterioration similar to what happened with the Omega and Sortino ratios. For the case of the Upside ratio, a similar degradation observed, but in the two tails. For the case of the Calmar ratio, a rapid degradation noted that stabilizes around 0.75 to reach a point of high autocorrelation where it again degrades strongly. The case of the Sterling ratio is highly stable, showing minimal observable degradation in the lower tail. The case of the Dowd ratio is similar to what happened with the Omega, Sortino and Kappa ratios.

The following table shows the summary of the performance ratios and their correlation with the Sharpe ratio.

Table 2: Rank Correlation Compared with the Sharpe Ratio

	ρ										
	-1	-0.8	-0.6	-0.4	-0.2	0	0.2	0.4	0.6	0.8	1
Omega	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.95	0.34
Sortino	0.99	0.99	0.99	0.99	0.98	0.98	0.98	0.97	0.96	0.91	0.33
$Kappa_3$	0.99	0.98	0.97	0.97	0.96	0.96	0.95	0.95	0.93	0.87	0.33
Upside	0.21	0.88	0.93	0.94	0.95	0.96	0.96	0.96	0.95	0.91	0.34
Calmar	0.95	0.73	0.68	0.66	0.66	0.67	0.67	0.67	0.68	0.70	0.33
Sterling	0.99	0.99	1	1	1	1	1	1	1	1	1
Dowd	1	1	1	1	1	1	1	1	1	-0.60	NaN

*Parameters $\sigma = 10\%$ and $\alpha = 0.4\%$

III.2 Variance Effect

The effect of the variance of random shock on the series of returns will have a direct impact on the risk estimation of the different measures of performance. In most literature, the variance of returns is the primary means for analyzing or measuring the risk of a financial asset. In this part of the paper, we will characterize the effect of the random shock variance on the robustness of the Sharpe ratio. For the modeling, the parameters of $\rho = 0.6\%$ and $\alpha = 0.4\%$ will consider.

The figure 14 shows that the increase of the variance of μ has a positive effect on the degree of robustness for the case of the proportions of Omega and Sortino. Similar to the case of the Omega and Sortino ratios, Kappa, Upside, Calmar and Dowd ratios have a positive effect of Sharpe ratio robustness as the μ variance increases. A different case is the Sterling ratio, which is stable against variances of the error term. Therefore, for the case of highly volatile time series, the Sharpe ratio criterion is consistent with the other means of evaluating the performance of financial assets.

The following table shows the summary of the performance ratios and their correlation with the Sharpe ratio.

Table 3: Rank Correlation Compared with the Sharpe Ratio

	$\sigma\%$										
	7	12	15	18	21	23	25	27	29	30	31
Omega	0.85	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Sortino	0.77	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
$Kappa_3$	0.70	0.97	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Upside	0.77	0.97	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Calmar	0.53	0.77	0.89	0.94	0.97	0.98	0.99	0.99	0.99	0.99	0.99
Sterling	1	1	1	1	1	1	1	1	0.99	0.99	0.99
Dowd	-0.37	1	1	1	1	1	1	1	1	1	1

*Parameters $\rho = 0.6$ and $\alpha = 0.4\%$

III.3 Scale Effect

In this section, we will measure the relationship of the AR(1) scale parameter (α) to the Spearman correlation to characterize this effect against different structures of the data generator model the series of returns. For the modeling, the parameters of $\rho = 0.6\%$ and the standard deviation of the error $\sigma = 4.5\%$.

Figure 17 shows the effect of α on the robustness of the Sharpe ratio, indicating a strong degradation of the value of the parameter moves away from zero in the Omega and Sortino ratios. The above implies that periods where the time series of financial assets show a strong upward or downward persistence[4], Sharpe's ratio criterion loses consistency, which can lead to strong distortions to investors about their ideal investment status. A similar effect observed for the Upside and Calmar ratios which show a high degradation of the Spearman correlation when moving away from its central value. For the case of the Kappa and Dowd ratios, Spearman correlation degradation

[4]Phenomenon described by Carhart (1997).

occurs with increases in the scaling factor on the positive side, unlike the Sterling ratio that undergoes degradation for negative values although a low degradation observed in comparison with other performance measures.

Table 4: Rank Correlation Compared with the Sharpe Ratio

	$\alpha\%$										
	-1	-0.8	-0.6	-0.4	-0.2	0	0.2	0.4	0.6	0.8	1
Omega	0.71	0.84	0.93	0.98	0.99	0.99	0.99	0.98	0.93	0.84	0.72
Sortino	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.96	0.89	0.77	0.64
$Kappa_3$	0.98	0.98	0.98	0.98	0.99	0.99	0.98	0.93	0.82	0.69	0.57
Upside	0.71	0.83	0.92	0.97	0.98	0.99	0.98	0.95	0.88	0.76	0.63
Calmar	0.68	0.75	0.83	0.91	0.97	0.99	0.83	0.69	0.59	0.53	0.49
Sterling	0.96	0.96	0.97	0.98	0.99	0.99	1	1	1	1	1
Dowd	1	1	1	1	1	1	1	1	1	0.91	-0.51

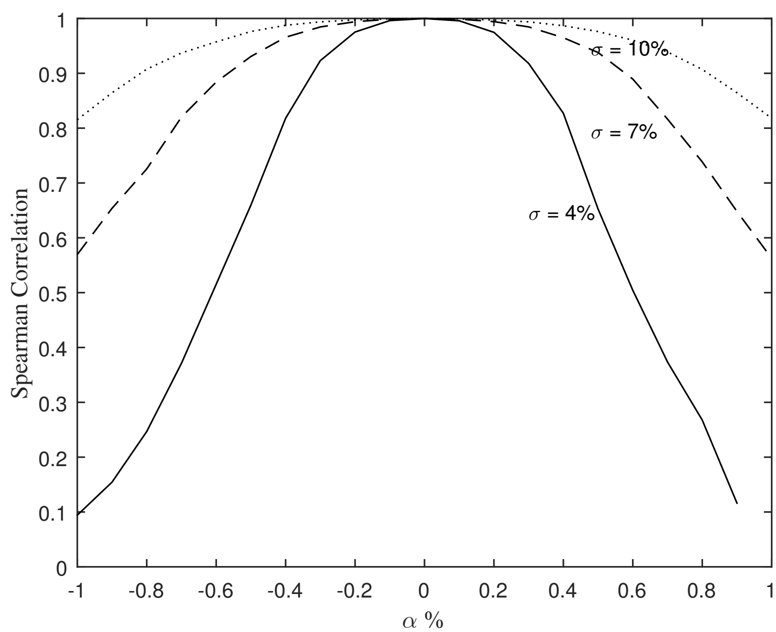
*Parameters $\sigma = 10\%$ and $\rho = 0.6\%$

III.4 Joint analysis

The effects of the parameters of the AR(1) model have been characterized in isolation to understand the effect that each of them has over a time series. However, it is still not clear that in a joint analysis degradation of the evaluation increases or cancel it.

Figure 3 shows the effect of an autocorrelated model ($\rho = 0.45$) with various scale constants (α) and multiple standard deviations of the innovation element (σ) in the which has the robustness of the Sharpe ratio compared to the ranking of the financial assets defined by the Omega ratio. It is chosen the Omega ratio only for illustrative purposes, being able to characterize the phenomenon against the other performance criteria.

Figure 3: Spearman correlation, Omega, multiple standard deviations



The joint analysis demonstrates that the degradation effect is enhanced as the values of α move away from zero and with small values of σ. This relationship allows us to define:

$$Robustness_i = F(\rho, \alpha, \sigma, ratio_i) \tag{6}$$

where *Robustness* corresponds to the Spearman correlation degree of the Sharpe ratio, ρ corresponds to the value of the correlation factor, α corresponds to the scale factor, σ corresponds to the standard deviation of error of the autocorrelated model and $ratio_i$ corresponds to the type of ratio with which the Sharpe ratio compared.

The results of the joint analysis of this financial series show us the effects and dominance of the different parameters of the autocorrelated model. In principle, it is shown that the scale constant in the autocorrelated model has a dominance effect against the parameters of serial correlation and volatility, indicating that this parameter must be observed with special care at the time of evaluations of the funds investment and thus determine the efficiency of Sharpe's ratio in the evaluation of the funds.

IV Is Sharpe suitable for measuring performance?

The results established in this document show that asserting that the use of the Sharpe ratio is the accurate measure to measure financial assets is at least questionable and deserves a deeper review due to the high impacts that can cause when defining investment procedures.

The extensive use of Sharpe's ratio in the financial industry as a criterion of performance can have a critical influence, unlike the one raised by Eling (2008), which may lead to potential arbitrage opportunities with the understanding that the evaluation criteria performance of investments is inadequate over certain time periods.

To verify the potential problems that may arise from the use of the Sharpe ratio as the main means of performance evaluation, we proceed to evaluate a sample 1336 investment funds in the same spirit of Eling (2008) and Zakamouline (2011) to observe the phenomena that are happening in these portfolio assessments. The data used to correspond to financial series of mutual funds of daily quotation in the United States, evaluated from January 1, 2004, to December 31, 2015.

For the computation of the parameters of the AR(1) model, we used 250 rolling sub-sample data for each value reported (1 horizon year), delivering $N - 250(3022)$ periods with the parameters of the computed model.

The descriptive statistics of the whole sample, mean value, standard deviation, skewness, and kurtosis are shown below:

Table 5: Descriptive statistics for 1336 mutual fund daily return distributions

	Mean	Median	Std. dev.
Mean value (%)	0.0354	0.0416	0.0196
Std. deviation (%)	0.6260	0.7124	0.3264
Skewness	-0.1849	-0.1898	0.1236
Kurtosis	2.8513	2.7414	2.1236

*Data between percentile 5 and percentile 95

The table 6, 7 and 8 shows descriptive statistics in three periods. The first period corresponds to January 1, 2004 until June 30, 2007, the pre-crisis Subprime period. The second period corresponds to July 1, 2007 to December 31, 2011, the crisis Subprime period. Finally, the third period corresponds to January 1, 2012 to December 31,2015, the post-crisis Subprime period.

Table 6: Descriptive statistics for mutual fund 2004/01-2007/06

	Mean	Median	Std. dev.
Mean value (%)	0.0481	0.0416	0.0358
Std. deviation (%)	0.4864	0.5104	0.2660
Skewness	-0.1502	-0.1541	0.2567
Kurtosis	2.7699	2.4624	4.4341

*Data between percentile 5 and percentile 95

Table 7: Descriptive statistics for mutual fund 2007/07-2011/12

	Mean	Median	Std. dev.
Mean value (%)	0.0121	0.0108	0.0226
Std. deviation (%)	0.9504	1.1134	0.4983
Skewness	-0.2159	-0.2173	0.1130
Kurtosis	2.8126	2.7911	0.4966

*Data between percentile 5 and percentile 95

Table 8: Descriptive statistics for mutual fund 2012/01-2015/12

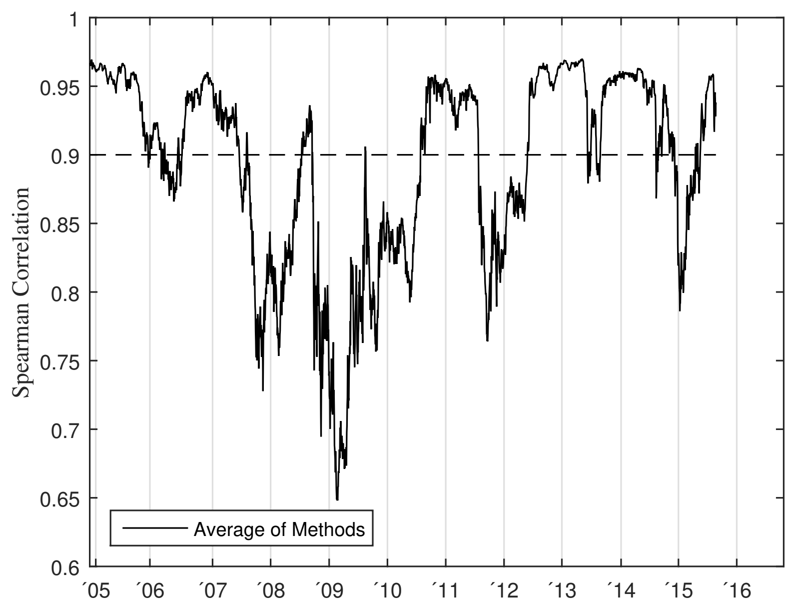
	Mean	Median	Std. dev.
Mean value (%)	0.0334	0.0411	0.0236
Std. deviation (%)	0.5695	0.6567	0.2990
Skewness	-0.1817	-0.1726	0.1933
Kurtosis	2.8303	2.6398	1.9651

*Data between percentile 5 and percentile 95

The statistical data show that the financial series are far from a Gaussian distribution for all reporting periods. The data included between the percentiles 5 and 95 were reported to avoid large deviations due to extreme data that can deliver abnormal values.

In figure 4 we can observe how the average Spearman correlation among all the evaluation methods of this study, varies with time, putting particular emphasis on those values that decrease of 0.9[5].

Figure 4: Average performance methods



[5]Value of the parameter defined for a risk level of a hypothetical investor.

In figure 5 we observe the variation in the Spearman correlation time on each performance method, observing substantial differences between them. In particular, the methods of Calmar, Upside, and Sterling present a significant difference on the analysis of the portfolio rankings against those reported by the Sharpe method.

Figure 5: Performance methods

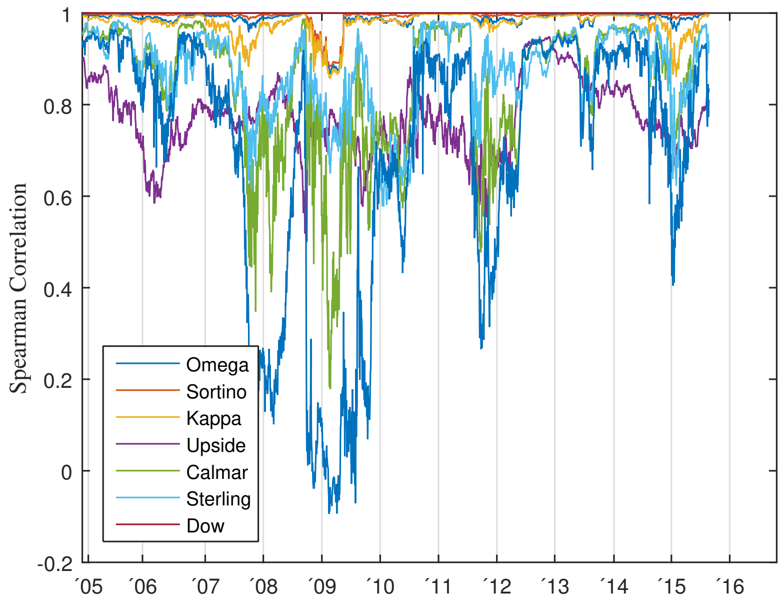


Table 9: Rank Correlation Compared with the Sharpe Ratio

	'06	'07	'08	'09	'10	'11	'12	'13	'14	'15	Whole Sample
Omega	0.99	0.99	0.98	0.98	0.95	0.98	0.99	0.99	0.99	0.99	0.98
Sortino	0.99	0.99	0.99	0.98	0.96	0.99	0.99	0.99	0.99	0.99	0.99
$Kappa_3$	0.98	0.98	0.95	0.97	0.94	0.98	0.98	0.98	0.99	0.99	0.97
Upside	0.80	0.71	0.77	0.76	0.71	0.75	0.69	0.84	0.86	0.79	0.77
Calmar	0.94	0.91	0.80	0.75	0.61	0.82	0.83	0.84	0.92	0.95	0.84
Sterling	0.93	0.89	0.85	0.84	0.78	0.77	0.91	0.88	0.91	0.95	0.87
Dowd	1	1	1	1	1	1	1	1	1	1	1

Figure 6: Spearman Correlation, Average of α

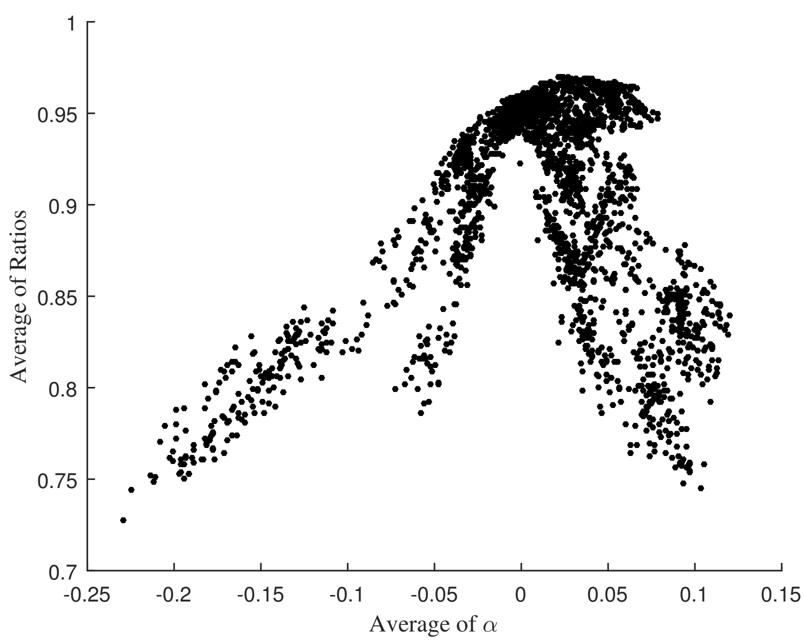
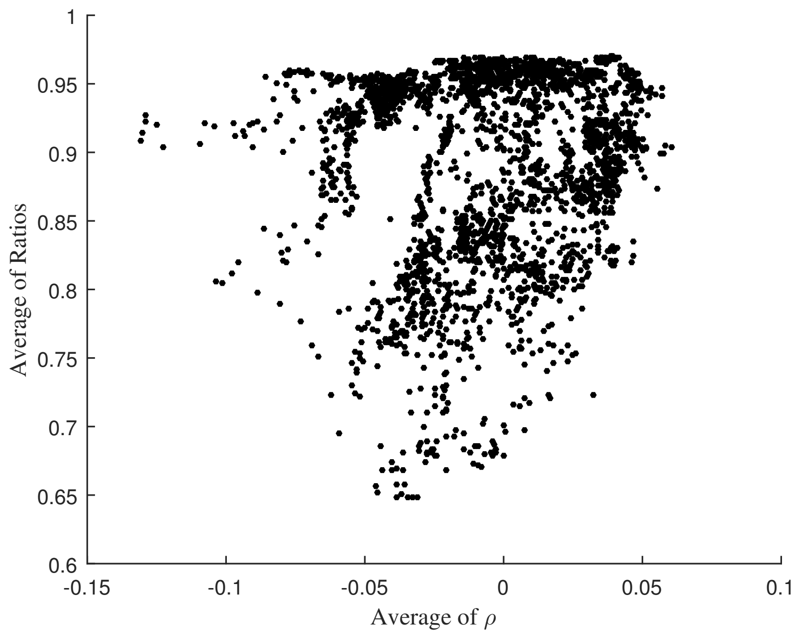


Figure 6 the average Spearman correlation of the ratios as a function of the average alphas of the whole sample, showing a nonlinear function that describes it, as can be seen in the Monte Carlo simulation. Similarly, we proceed with the autocorrelation factor where we do not observe a clear relation that describes a function. However, it can not be discriminated a priori, since the sample concentrates many of the points near the zero value.

Figure 7: Spearman Correlation, Average of ρ



We continue with the estimation of the model defined in equation 6, testing several specifications. The model described as:

$$(7) \qquad Robustness = \lambda + \sum_{j=1}^{J} \psi_j \alpha^j + \sum_{i=1}^{I} \phi_i \rho^i + \sum_{k=1}^{K} \tau_k \sigma^k + \epsilon$$

where the parameter λ corresponds to an adjustment parameter, the parameter ϕ corresponds to the factor of the different powers of ρ; the parameter ψ corresponds to the power factor of α, τ corresponds to the factor of the different powers of σ and ϵ corresponds to an error factor. The use of the parameters in powers is used to capture the nonlinear effect observed in the simulation of Monte Carlo. These parameters will estimate by techniques of ordinary linear regression.

Table 10 shows a summary of the tested models, where a simple linear model with the ρ, α, and σ factors tested (1), a model that incorporates the quadratic factor of α (2), a model that integrates quadratic factors of ρ and α (3), a model that integrates quadratic factors of three parameters (4) and finally a model incorporating a factor of α in the third power (5).

Within the models tested we can observe that a complete model, model (5), is the one that presents a lower value of information criterion, so the inclusion of these parameters is appropriate, being able to capture 59% of the variance of the dependent variable. The effect of ρ is significant at 0.1% for the three parameters tested, therefore from the statistical point of view the autocorrelation factor is part of the robustness model of the Sharpe ratio as criterion of evaluation. The effect of α is statistically significant at 0.1% for the three parameters tested, showing the strong effect it has on the robustness of the Sharpe ratio. Finally, the effect of the standard deviation is also significant at 0.1%.

Table 11 reports the same exercise for each of the performance measures, observing highly significant parameters, as described in the previous table.

The analysis of the nature of this function allows defining criteria for the use of the Sharpe ratio within this framework of analysis so that the evaluation of the financial assets can actively employ by the investors in the definition of their purse. Below we show its utilization against his-

Table 10: Spearman Correlation Regression

	(1)	(2)	(3)	(4)	(5)
ψ_1	0.116***	-0.181***	-0.211***	-0.212***	0.308***
	(0.0226)	(0.0179)	(0.0185)	(0.0184)	(0.0276)
ϕ_1	-0.207***	-0.121***	-0.210***	-0.183***	-0.168***
	(0.0434)	(0.0320)	(0.0353)	(0.0358)	(0.0323)
τ_1	-0.580***	0.210***	0.208***	0.916***	1.435***
	(0.0794)	(0.0610)	(0.0606)	(0.182)	(0.166)
ψ_2		-7.053***	-7.320***	-7.275***	-11.49***
		(0.153)	(0.159)	(0.159)	(0.229)
ϕ_2			-3.908***	-3.767***	-2.763***
			(0.667)	(0.666)	(0.604)
τ_2				-2.859***	-3.970***
				(0.694)	(0.629)
ψ_3					-41.67***
					(1.762)
λ	0.965***	0.908***	0.913***	0.871***	0.829***
	(0.00878)	(0.00659)	(0.00661)	(0.0122)	(0.0112)
N	2521	2521	2521	2521	2521
R^2	0.057	0.488	0.494	0.498	0.589
AIC	-7253.9	-8789.2	-8821.4	-8836.4	-9340.6

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Spearman Correlation Regression

	Omega	Sortino	Kappa	Upside	Calmar	Sterling
ψ_1	0.0277***	0.0153***	0.375***	0.446***	0.252***	0.301***
	(0.00370)	(0.00122)	(0.0104)	(0.0541)	(0.0549)	(0.0341)
ϕ_1	-0.0129**	-0.000983	-0.0151	0.122	-0.439***	-0.279***
	(0.00434)	(0.00143)	(0.0122)	(0.0635)	(0.0643)	(0.0399)
τ_1	0.470***	0.233***	0.689***	3.878***	2.382***	1.749***
	(0.0223)	(0.00733)	(0.0628)	(0.326)	(0.330)	(0.205)
ψ_2	-1.272***	-0.418***	-2.865***	-4.353***	-23.09***	-21.88***
	(0.0308)	(0.0101)	(0.0867)	(0.450)	(0.456)	(0.283)
ϕ_2	-0.416***	-0.110***	-2.165***	-9.815***	-3.388**	-9.474***
	(0.0811)	(0.0267)	(0.229)	(1.185)	(1.201)	(0.746)
τ_2	-1.194***	-0.786***	-0.753**	-9.736***	-5.940***	-2.585***
	(0.0845)	(0.0278)	(0.238)	(1.235)	(1.251)	(0.777)
ψ_3	-4.443***	-1.637***	-17.67***	-32.87***	-64.14***	-86.95***
	(0.237)	(0.0778)	(0.667)	(3.460)	(3.504)	(2.176)
λ	0.958***	0.983***	0.921***	0.486***	0.747***	0.792***
	(0.00150)	(0.000493)	(0.00422)	(0.0219)	(0.0222)	(0.0138)
N	2521	2521	2521	2521	2521	2521
R^2	0.515	0.550	0.505	0.132	0.629	0.743

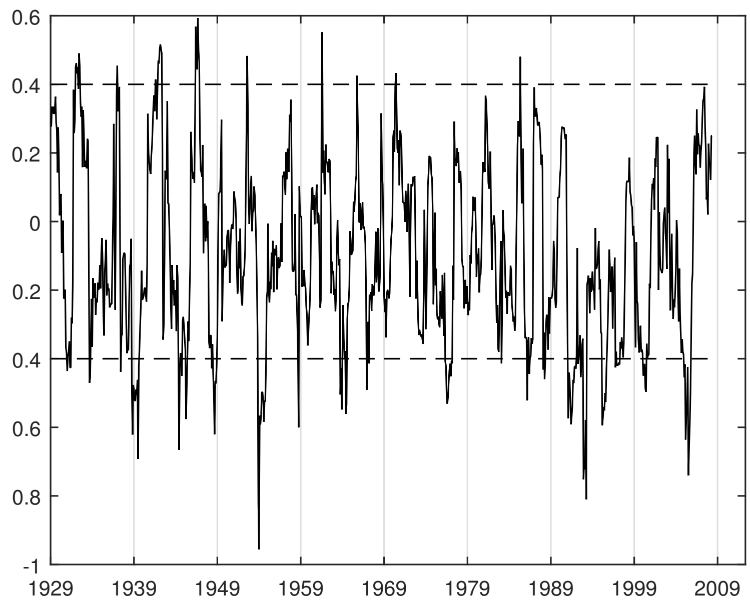
Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

torical Dow Jones indexes, with their monthly measurements from 1928 to 2009.

The following graph demonstrates the effect of ρ measured with data of 30 months of mobile window [6], Defining as a care limit a value of $\rho = 0.4$.

Figure 8: Evolution of ρ

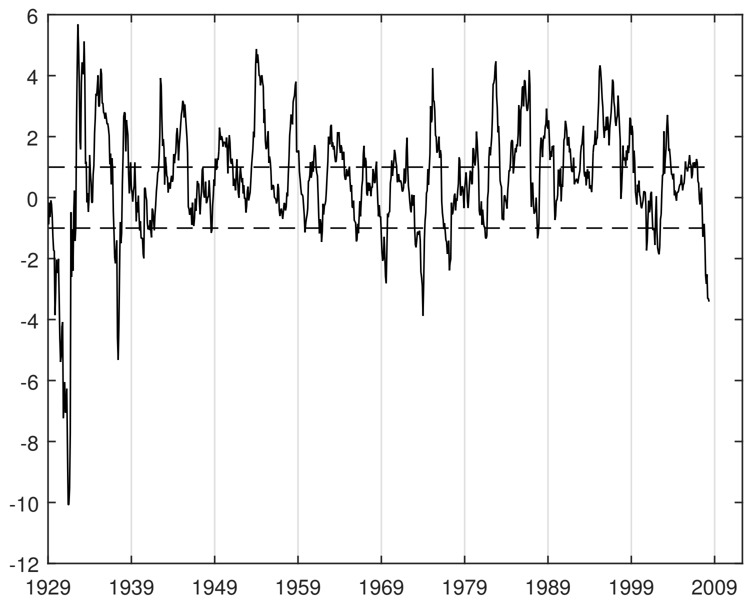


[6]The mobile window defined as the measurement that is performed on the last N periods, taking this sample as the universe for the calculation of The mean, variance, or another indicator. It is also known as ’rolling’.

It can see that there are numerous cases in which the ρ factor exceeds the limit, which defines an element of observation, for the effects that have been described in the document.

The following graph shows the effect of α measured with 30 months rolling data, defining as precautionary limit a value of 1, which corresponds to $\alpha = 0.6$.

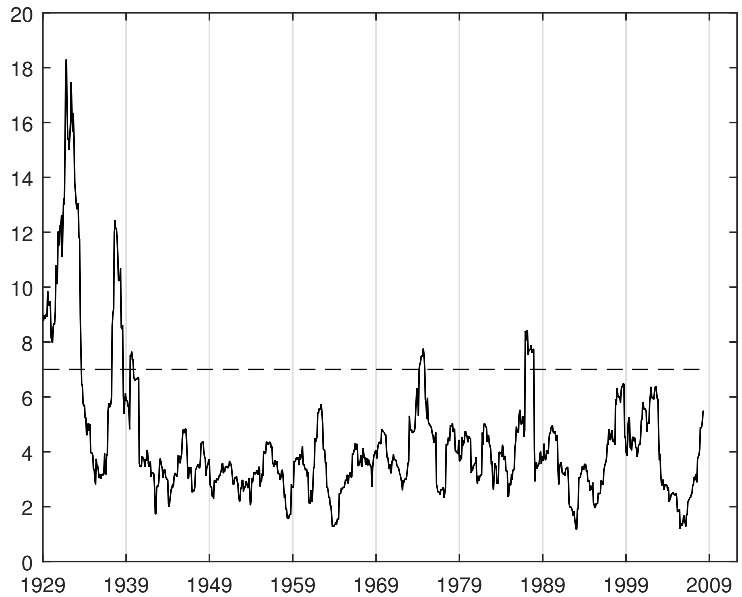
Figure 9: Evolution of α



It can see that the limit imposed for the evaluation is exceeded in various episodes, especially careful in the values associated with the financial crisis of the year 1928 which are much higher than the ones that continue, showing the importance that this crisis had in the markets The definition of investment strategies.

The following graph indicates the effect of the standard deviation, σ, measured with 30 months rolling data, defining as a precautionary limit, a value of $\sigma = 7\%$.

Figure 10: Evolution of σ



V Conclusions

The results presented in this document confirm the hypothesis raised about the importance of the autoregressive processes in the determination of the performance of financial assets and the care that must take in working with them. These results are allowing to characterize the robustness of the Sharpe ratio as a means to the analysis of the yield of said financial assets.

The robustness function, described in this document, captures 60% of the variance of the Spearman coefficient degradation, allowing to define monitoring and control criteria in the task of tracking the evolution of financial assets and makes an adequate selection of a combination of risk and return.

Within the main findings is the quantification of the bias that arises when a serious one is found against an autocorrelated process under the measurement without corrections of average or standard deviation, which in principle allows to intuit that to work with series that are far from the assumptions of normality can lead to problems in calculations and subsequent investment decisions.

The effect of autocorrelation, variance, and scale are not contradictory, but rather complement and generalize the results presented by Eling and Schuhmacher (2007) and Eling (2008) showing in turn that if the financial series approach a process of normality, it is indifferent to the valuation method, as mentioned Zakamouline (2011), giving a more global view of the selection of the method of evaluation of financial assets, focusing on the phenomenon of autocorrelation, introducing a dimension of temporality in the assessment of financial assets.

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Appendix

Figure 11: Spearman Correlation Omega, Sortino

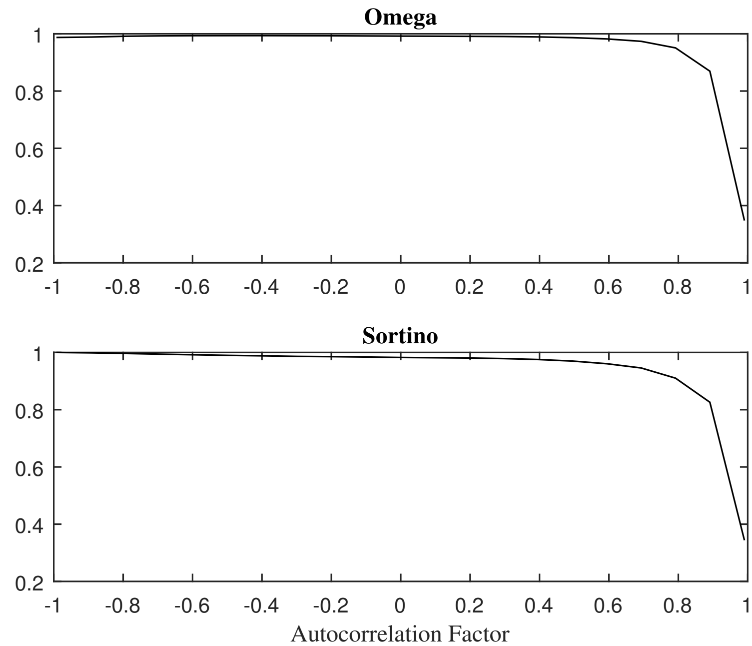

Figure 12: Spearman Correlation Kappa, Upside

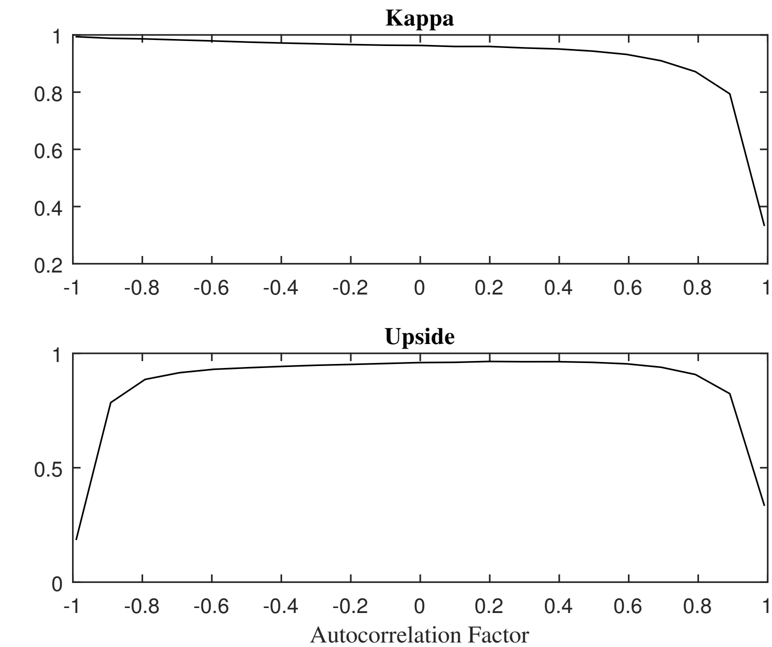

Figure 13: Spearman Correlation Calmar, Sterling, Dowd

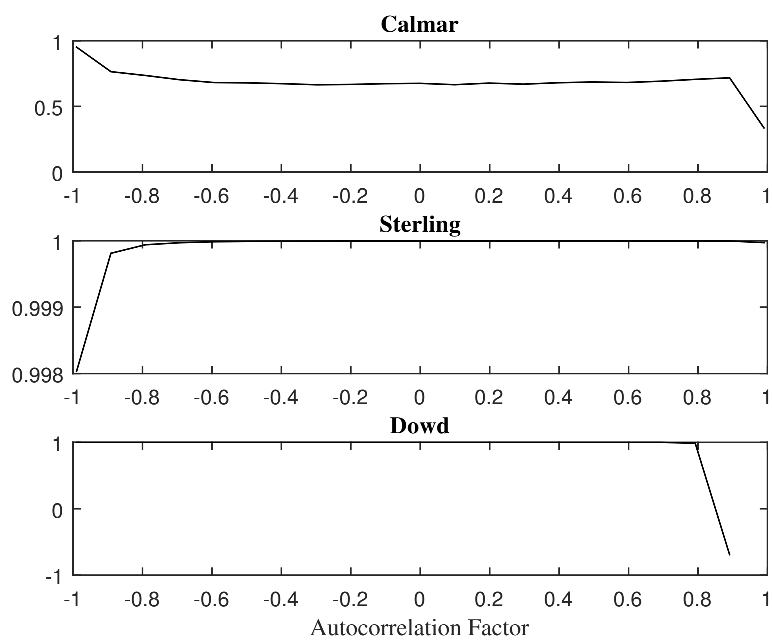

Figure 14: Spearman Correlation Omega, Sortino

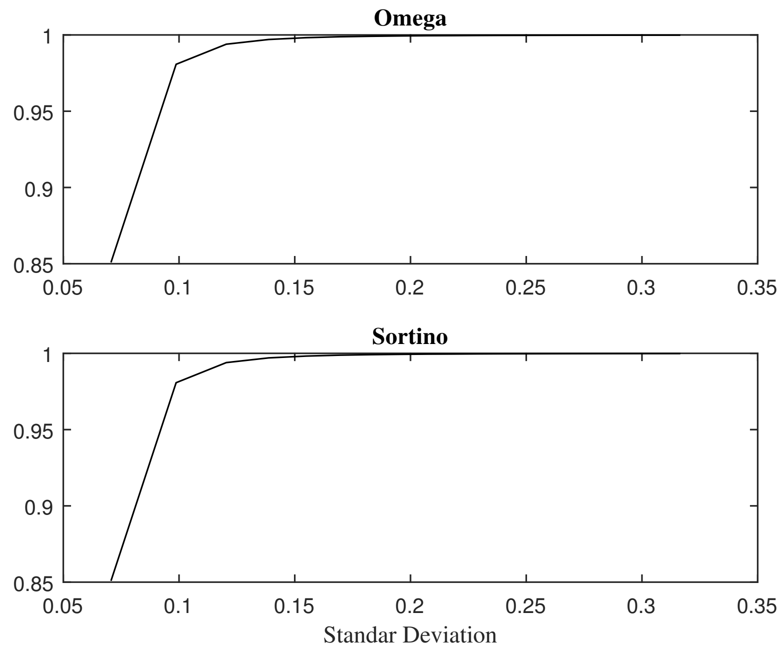

Figure 15: Spearman Correlation Kappa, Upside

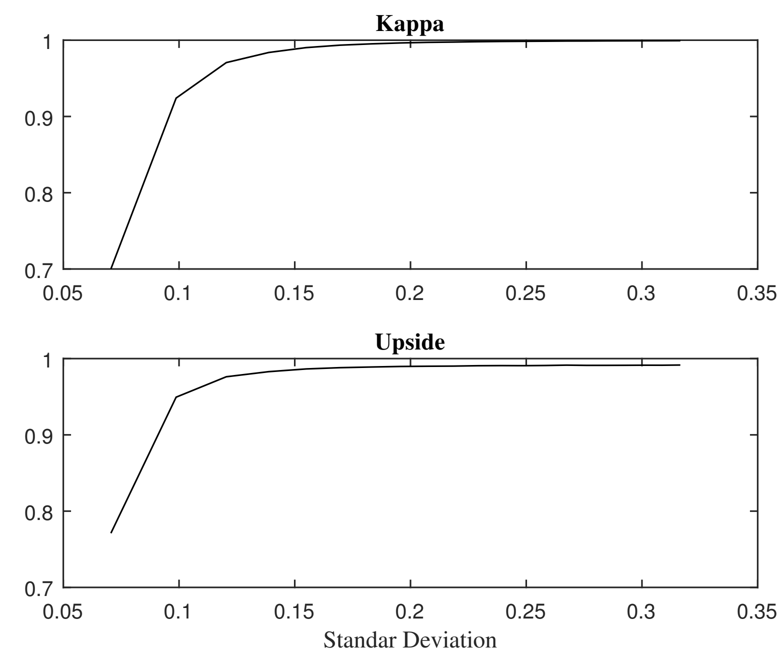

Figure 16: Spearman Correlation Calmar, Sterling, Dowd

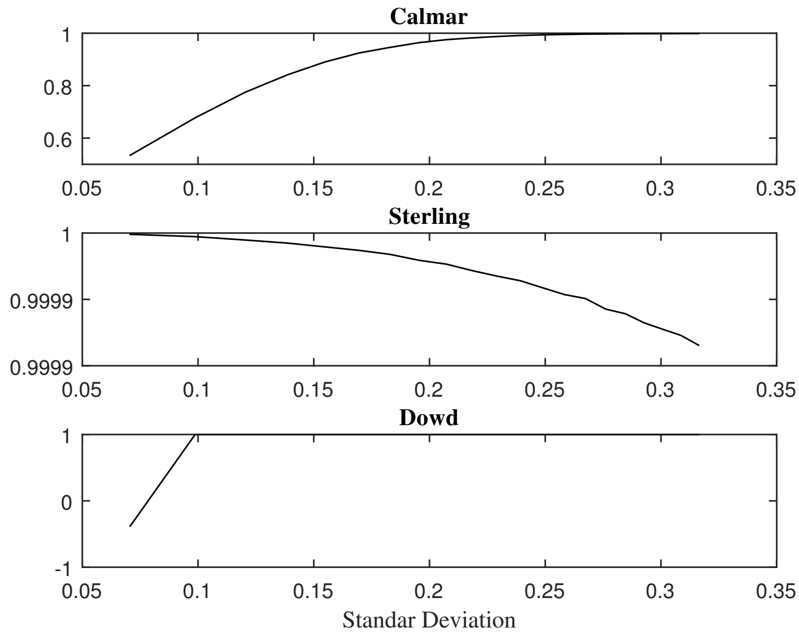

Figure 17: Spearman Correlation Omega, Sortino

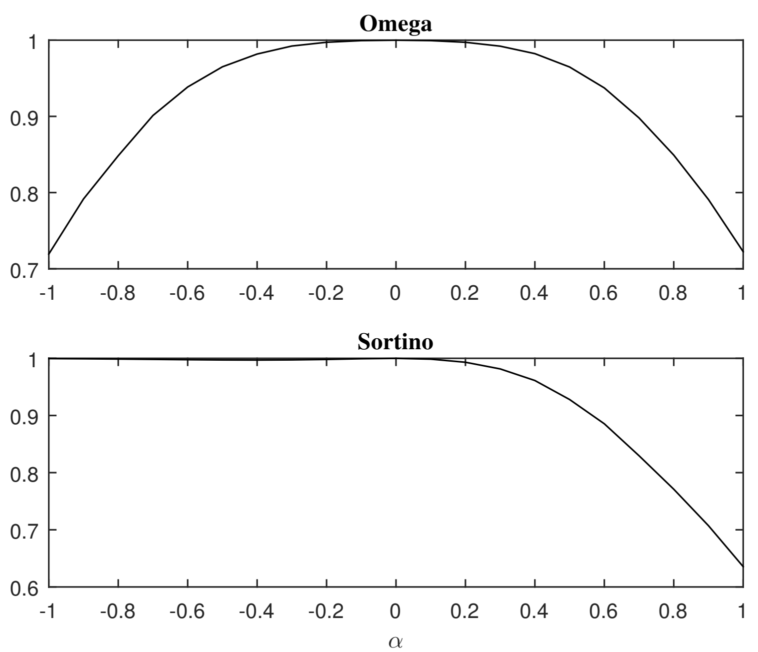

Figure 18: Spearman Correlation Kappa, Upside

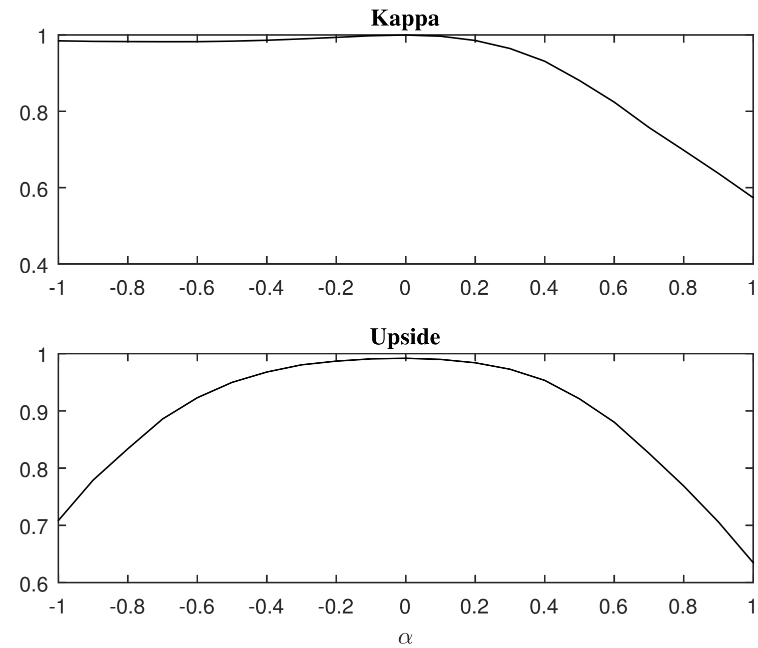

Figure 19: Spearman Correlation Calmar, Sterling, Dowd